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Integrated bottom-up modeling of renewable energy systems

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Table of Contents

Part A: Introduction

Part B: Appended Papers

I. *Schmidt, J., Cancella, R., Pereira Junior, A.O., 2016.* The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal electricity system. Energy (in press).

II. *Schmidt, J., Cancella, R., Pereira Junior, A.O., 2016.* The effect of windpower on long-term variability of combined hydro-wind resources: *The case of Brazil. Renewable and Sustainable Energy Reviews 55, 131-141.*

III. *Schmidt, J., Cancella, R., Pereira Jr., A.O., 2016.* An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil. *Renewable Energy 85, 137-147.*

IV. *Schmidt, J., Wehrle, S., Rezania, R., 2016.* A reduction of distribution grid fees by combined PV and battery systems under different regulatory schemes*, In: 2016 13th International Conference on the European Energy Market (EEM).*

V. *Mayr, D., Schmid, E., Trollip, H., Zeyringer, M., Schmidt, J., 2015.* The impact of residential photovoltaic power on electricity sales revenues in Cape Town, South Africa. *Utilities Policy 36, 10-23.*

VI. *Höltinger, S., Salak, B., Schauppenlehner, T., Scherhaufer, P., Schmidt, J., 2016.* Austria's wind energy potential – a participatory modeling approach to assess socio-political and market acceptance. *Energy Policy 98, 49-61.*

VII. *Schmidt, J., Lehecka, G., Gass, V., Schmid, E., 2013.* Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines. *Energy Economics 40, 269-276.*

VIII. *Kirchner, M., Schmidt, J., Kindermann, G., Kulmer, V., Mitter, H., Prettenthaler, F., Rüdisser, J., Schauppenlehner, T., Schönhart, M., Strauss, F., Tappeiner, U., Tasser, E., Schmid, E., 2015.* Ecosystem services and economic development in Austrian agricultural landscapes — The impact of policy and climate change scenarios on trade-offs and synergies. *Ecological Economics 109, 161-174.*

IX. *Schmidt, J., Schönhart, M., Biberacher, M., Guggenberger, T., Hausl, S., Kalt, G., Leduc, S., Schardinger, I., Schmid, E., 2012.* Regional energy autarky: Potentials, costs and consequences for an Austrian region. *Energy Policy 47, 211-221.*

Part C: CV, scientific activities, publications & teaching portfolio

Part A: Introduction

"C*hange my identity? Are you crazy?*"
Burning Spear (Spear, 2004)

"*The trouble with having an open mind, of course, is that people will insist on coming along and trying to put things in it.*"
Terry Pratchett, (Pratchett, 2009, chap. 3)

Foreword

After finishing my studies in Computer Science, I wanted to use my methodological background to study the transformation of our societies to resilient ones, i.e. to societies that are able to deal with the huge challenges implied by current global change processes. I had the chance to do so in the inter- and transdisciplinary doctoral school "Sustainable Development" at the University of Natural Resources and Life Sciences, Vienna. Conducting inter- and transdisciplinary research, a "research borderland", "did not seem all too comfortable" to my peers and me, as Felt et al. (2012, p. 522) acknowledged in their (meta-) research on the doctoral school. Still, the school gave me the exciting opportunity to learn about the integrated modeling of renewable energy systems. Although I somehow felt homeless in academia due to an unclear disciplinary attachment, I continued to explore the field after finishing my doctorate - as I found it both relevant as well as worthwhile. Now, after nine years of research as a doctoral student and Post-Doc, this treatise should eventually shed some light on how my work relates to different research fields, and where I see my past and future contributions in academia.

In a transdisciplinary setting, research questions should relate to real-world problems. Those problems depend very much on local contexts: I therefore had the challenging opportunity to learn about perceptions of renewable energies by different actors in different social contexts. I listened to (potential) neighbors of wind turbines in small Austrian municipalities and in the poor Brazilian semi-arid region[1]. I discussed the opportunities of renewable energies with officials of the Ministry of Energy and Mines and the Empresa da Pesquisa Energética in Brazil. Members of WWF Brazil voiced environmental concerns associated with biomass production in the Amazon forest, and the staff in the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management told me about their views on the reform of the European Common Agricultural Policy. I am very grateful to all people who, during my research projects, shared their perspectives with me.

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[1] Many thanks to Thomas Bauer and his family for their support during my trip to Bahia.

As transdisciplinary research involves interdisciplinarity, a big challenge was to learn about different disciplinary approaches. Consequently, I know little about any single one of them. I therefore had and have to rely on many fellow researchers with whom I had the opportunity to work with - and I am very grateful to all of them: my colleagues at UFRJ in Rio de Janeiro (in particular Rafael Cancella and Julian Hunt), the fellow students at the Santa Fe Institute in the Complex Systems Summer School (in particular Bruno Pace, Holly Arnold, David Masad, Giuliano Andrea Pagani, Elena Stepanova, Jody Wright, and Puduru Reddy), researchers from all over Europe at the Joint Research Center in Petten (in particular Ioulia Papaioannou, Arturs Purvins, Sofia Simões, Kiti Suomalainen, Vendula Rajdlova, Nicolás Pardo Garcia, and Christian Thiel), research collaborators at diverse institutions in Austria and Europe (in particular Luiz Ramirez Camargo, Johannes Rüdisser, Gerhard Streicher, David Leclère, Sylvain Leduc, and Erik Dotzauer) and, of course, my colleagues at BOKU in Austria (in particular Bernhard Mittermüller, Andreas Huber, Thomas Schauppenlehner, and Boris Salak).

Some people, who were fundamental for my professional and personal development, I want to mention in particular: Erwin Schmid was my doctoral supervisor and continued giving me immense support throughout my post-doc years. He supervised my research activities and, at the same moment, gave me a lot of freedom to develop my own research agenda. He taught me about the pitfalls of a research career and always encouraged me to take the next important steps forward. His comments also very much improved this treatise. I am deeply thankful for all of his support and hope to continue having him as a close mentor.

Ulrich Morawetz, Martin Schönhart, Hermine Mitter, and Martin Kniepert not only read early and late versions of this treatise and contributed significantly in improving it – they are also great work colleagues. Many thanks to them – and to all other fellow researchers at the Institute for Sustainable Economic Development. I am also very grateful to Iris Richter and Eva Krickler for their support during my time at the institute – they made life in academia much easier for me.

During the last five years, I closely collaborated with Viktoria Gass, Dieter Mayr, Mathias Kirchner, Marianne Zeyringer, and Stefan Höltinger during their doctoral thesis. Their research greatly improved my own research activities and this treatise contains parts of their work. They heavily influenced my ideas about integrated modelling of renewable energy systems, commented on this treatise and shared a lot of time inside and outside the work context with me. I am very thankful for their contributions and the time we spent together.

I had and have the great pleasure to work with Georg Lehecka and Sebastian Wehrle: with both, I explored the economic side of integrated modelling of energy systems. Both are very sharp economic thinkers and collaborating with them has very much improved the rigor of my work. I am very grateful to them and hope for a further continuation of our collaboration.

I owe very much to Anja Bauer and Patrick Scherhaufer. They had a sharp eye on my modelling activities from a social sciences point of view, they shared numerous lunch breaks with me, discussing anything from research to science-fiction literature. Also, they read this treatise and provided substantial input and improvements. I hope to continue sharing one or the other glass of wine with them. Elisabeth Wetterlund has also read this treatise and significantly contributed in shaping it. I am very much looking forward to our future collaboration with her.

Amaro Pereira Jr. was my supervisor during my Post-Doc stay at the Federal University of Rio de Janeiro. I am very thankful for his support in Rio, for involving me in his research projects, for teaching me about the regulation of the Brazilian electricity system and for traveling with me to the remote state of Acre.

Many thanks go to all my friends and in particular to Alex, Alexander, Babsi, Birgit, Herbert, Johanna, Josh, Lisi, Lucas, Luis, Martina, René, Rosa, Sonja, Stephan, Uli, and my Caxinguelê people for the good times we have shared and continue sharing. For making me enjoy life so much more, and for being present in troubled times and keeping up my spirit.

I am so grateful to my parents, for their support, their caring, and their interest in my life. I want to thank my two sisters and my brother, for being there for me – and my grandfather, for his example of endurance.

I am deeply grateful to Ulla for her love, her close company during good and bad times, her support in this and many other endeavours, and for bringing the fire of Iansã into my life.

"But in truth the source of life is a difference in air pressure, the flow of air from spaces where it is thick to those where it is thin. […] When the pressure everywhere in the universe is the same, all air will be motionless, and useless; one day we will be surrounded by motionless air and unable to derive any benefit from it." (Chiang, 2008)

1. Introduction

When Malthus assessed future prospects of food supply for human societies in 1798, he used a simple model for predicting human population and food supply growth:

> *"Population, when unchecked, increases in a geometrical ratio. Subsistence increases only in an arithmetical ratio. A slight acquaintance with numbers will shew the immensity of the first power in comparison of the second. By that law of our nature which makes food necessary to the life of man, the effects of these two unequal powers must be kept equal."* (Malthus, 1998, pp. 4–5)

He concludes that mankind was doomed to ever repeating hunger catastrophes, if population growth was not controlled. He proved to be wrong – at least for the time being – as technological progress and the conversion of pristine natural ecosystems to agricultural land allowed for growth in food supplies that outperformed population growth[2]. It seems that the position of utopians, such as William Godwin, a fellow scientist of Malthus, had prevailed: human ingenuity would allow solving the problem of food scarcity – by inventing new institutions and technologies (Godwin, 1842). Still, Malthus argument was retaken in a different form by others. Nicholas Georgescu-Roegen (1971) argued that a maximization of the life-time of all humans living today and in the future should be the aim of the economic process. Georgescu-Roegen stresses that while the first law of thermodynamics teaches that neither energy nor matter are ever lost, the second law of thermodynamics implicitly implies that any economic process causes an increase in entropy[3]. The human population basically feeds on only three sources of limited low entropy: the stock of natural resources available on earth[4], gravity[5], and the flow of low entropy from sun in the form of solar light[6]. Georgescu-Roegen additionally introduces his "fourth law of entropy" which states that perfect recycling is impossible (Georgescu-Roegen, 1971), i.e. that any kind of transformational process applied to material is irreversible. This implies that material resources are also limited. Therefore limited stocks of low entropy and materials should be used sufficiently slowly to allow survival of future generations. This line of thought is however contested: physicists do not agree on the "heat death" theory that

[2] At least for the period 1961-2012, per capita food intake has increased for all world regions (FAOSTAT, 2015), although there are single countries where per capita food intake has decreased, e.g. Afghanistan and Somalia. Floud et al. (2011) have shown for some European countries that per capita calorie intake has increased from around 2000 kcal/cap/day in the year 1800, around the time when Malthus published his book, to above 3600 kcal/cap/day in the year 2000. Average per capita intake may be a misleading indicator when income is distributed unevenly within a region or country. Therefore there are still around 780 Million undernourished people, but numbers have fallen absolutely and relatively since 1990/1992 from 991 Million (Food and Ariculture Organization of the United Nations et al., 2015).

[3] Entropy measures the amount of work that a thermodynamic system can carry out at a given temperature. Entropy never decreases for irreversible processes (Lemons, 2013).

[4] Which also includes stock of materials that may be used for energy conversion using principles from nuclear physics, such as Uranium for nuclear fission and Hydrogen for nuclear fusion.

[5] As used by tidal power plants.

[6] Which drives processes such as water transport (hydropower), biomass production (bioenergy), and differences in atmospheric pressure (wind energy).

suggests a state of thermodynamic equilibrium in the universe at some point in the future (e.g. Krauss and Starkman, 2000) [7,8,9]. Georgescu-Roegen's approach is also criticized as, first on any relevant human time scale (i.e. thousands or even millions of years) the amount of low entropy available on earth is high, and that second his fourth law of entropy, i.e. limited recycling, does not hold (Schwartzman, 2008). The options for human survival (at least considering periods of millions of years) are therefore much more constrained by the technological options allowing humans to transform sources of low entropy to useful energy than by the total amount of low entropy available to the system earth.

Shortly after Georgescu-Roegen, Meadows et al. (1972) published "Limits to Growth", a first attempt of a quantitative dynamic global assessment of resource and sink availability based on empirical data about the resource base that had provided human survival at that time: they introduce a global integrated modelling exercise to assess the limits that the availability of resources and the environment pose on population and economic growth. They conclude that ruling growth rates in population and wealth could not infinitely be sustained. Therefore, resource limitations would cause total global population to decline as early as in the 21st century:

> "*We can thus say with some confidence that, under the assumption of no major change in the present system, population and industrial growth will certainly stop within the next century, at the latest.*" (Meadows et al., 1972, p. 126)

They tested different assumptions for the most important parameters and even if resource availability was higher than initially assumed, the turning point at which growth cannot be sustained any longer would be only slightly postponed. In that case, pollution of the environment by industrial residuals and the availability of arable land set a definite end to the growth of population and wealth, although the authors also concluded that there are still options available to "*alter these growth trends and to establish a condition of ecological and economic stability that is sustainable far into the future*" (Meadows et al., 1972, p. 24). Forty years after the first publication of Limits to Growth, Turner (2012) compared model forecasts with real-world data and concluded that model predictions in the business as usual scenario represented the observed outcome with respect to some of the core variables reasonably well. However, de-growth of population and wealth was predicted later than today in the original publication[10], i.e. only the growth section of the curve can be currently validated.

Contrary to the positions of Malthus, Georgescu-Roegen, and Meadows some economists argued that almost anything may be substituted and that there are no absolute limits to growth therefore. Solow (1974) tried to operationalize intergenerational equity by introducing a normative component into his models: he argued that if consumption over time is maintained at constant

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[7] First ideas about the heat death developed in the 19th century and were even discussed by Friedrich Engels who rejected that idea (Foster and Burkett, 2008). To Engels, the theory needs a meta-physic entity to explain the initial hot state of the universe from which it is cooling down.

[8] Thermodynamic equilibrium implies that, as there are no more significant differences in entropy left in the universe, no more work can be done. Ted Chiang (Chiang, 2008) creates a wonderful metaphor for the "warm death" in his short story "exhalation" from which the introducing citation is taken. He creates a world that is solely driven by differences in air pressure – and as the source of high pressurized air is limited in this world, "*one day we will be surrounded by motionless air and unable to derive any benefit from it"*.

[9] Assuming that the universe does not end in the heat death however does not imply that long-term survival of life is guaranteed in the universe, as Krauss and Starkman (2000) demonstrate: in an ever expanding universe, energy that can be collected by any lifeform which depends on quantum mechanics, will be limited.

[10] Actually, Meadows et al. (1972) did not determine the exact date when growth stops. But they assume that this event is going to take place latest at some point in the 21st century.

levels, this criterion was satisfied[11]. Consumption was however measured by the consumption of substitutable goods and equity was therefore reachable by substituting natural resources by reproducible capital, or as Solow (1974, p. 41) put it: "*Earlier generations are entitled to draw down the pool (optimally, of course!) so long as they add (optimally, of course!) to the stock of reproducible capital*". Under the assumption of exogenous technological progress, constant consumption can even be guaranteed in the case of a growing human population.

Recent research (Steffen et al., 2015) however emphasized that the limits of global eco-systems to safely support human activities had already been surpassed for some indicators such as the loss of biodiversity, and the nitrogen and the phosphorus cycle. This concept highly questions perfect substitutability for all goods, and in particular for services that are provided by the global bio-physical system to humans. The emphasis on the impossibility of substitution of environmental services and goods is sometimes coined "strong" sustainability (Dietz and Neumayer, 2007). In any case, energy as source of work cannot be substituted. Availability of primary energy sources, energy conversion and use are therefore at the core of the discussion of the long-term sustainable development of human societies[12].

Renewable energies[13] fit quite well into the debate presented above: In Solow's framework, drawing down the pool of fossil fuels to build up a renewable infrastructure would be a feasible solution for achieving a long-term sustainable energy supply with constant consumption if the elasticity of substitution between fossil and renewable resources is equal to or larger than one (Erdmann and Zweifel, 2010). Obviously, no non-energetic restrictions may apply, such as a lack of important inputs in the production process of renewables or limited sinks for residues. Proponents of strong sustainability however point to the fact that the inputs to renewable production technologies (e.g. rare earth elements for the construction of wind turbines (Willis et al., 2013), or land for the large scale deployment of PV panels) are limited and that the expansion of renewables is therefore also physically limited. And while renewables are considered to contribute to climate change mitigation by strong sustainability proponents, they also emphasize negative environmental effects of renewable energies in other areas than climate change, for instance a possible reduction of biodiversity (Hastik et al., 2015). Research questions such as *how much fossil fuels resources are (left) to power the world? Which alternative resources are available? What is the elasticity of substitution between fossil fuels and alternative energies? And what is the impact of energy conversion activities on the global emission balances, on ecosystems, and on human well-being in general?* therefore continue to be of outmost importance.

The debate on long-term sustainable energy supply is no longer an academic one only: first, the impact of resource scarcity has been discussed to a larger extent on a political level after the oil price shocks in the 1970ies (Hall and Day, 2009; Ikenberry, 1986). The academic discourse and real world events lead to the United Nations Conference on Environment and Development in

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[11] He derived that rule from Rawl's Max-Min criterion

[12] The debate on sustainability does not only involve renewable supply side measures. There is a huge debate on options ranging from technical fixes such as capturing greenhouse gases, nuclear fission and fusion, and energy efficiency measures (Hoffert et al., 2002), to de-growth strategies and a complete restructuring of the whole economic system to delink it from the need for (economic) growth (Kallis, 2011). Those issues are not going to be further discussed in detail in this text.

[13] Of course, Georgescu-Roegen would at all reject the term renewable energies from a thermo-dynamical point of view (although he was an advocate of solar energy), as independent of the energy conversion process, entropy increases in any energy conversion process. However, a more pragmatic definition of "renewability" is proposed here: a resource is considered to be renewable if its consumption is lower than the reproduction rate of that resource for a certain, limited amount of time, i.e. $C(t) < \frac{dR}{dT}, l < t < u$, C being consumption, R being the resource and *l* and *u* being the lower and upper bounds of the time interval. For details, see section 2.2.

the year 1992 in Rio de Janeiro, where, among other resolutions, the UN member states decided on the United Nations Framework Convention on Climate Change (UNFCCC). The reduction of greenhouse gas emissions has played an important role in the arena of international politics since then. The European Union has shown strong commitment to climate change mitigation by agreeing on binding emission reducing targets and the 20/20/20 goals. A transition from fossil fuels to renewable ones is argued to be necessary due to limited capacities of the atmosphere to accommodate further greenhouse gas emissions, and due to limited fossil resources. Additionally, an increase in the security of supply by decreasing imports of fossil fuels (Barreto and Turton, 2007), and prospects of green growth that allow the creation of jobs in the energy sector are frequently used as arguments to support the transition from fossil fuels to renewable energies (Wei et al., 2010).

Strong public support in the form of subsidies has allowed a significant increase in renewable capacities in the last decade, in particular in some European countries, the US, and China (British Petrol, 2015). The technical feasibility of renewables has been proven – and costs have decreased to levels that are making them competitive with fossil fuels in some world regions (Bolinger and Weaver, 2014). The rapid uptake of those technologies has however also created opposition against them, as costs and benefits of the energy conversion process have been redistributed. Those conflicts may arise on a local level fueled by negative impacts of renewables on the environment and the population (Wüstenhagen et al., 2007), they may exist on national levels due to increasing costs for subsidies and for integrating renewables in the current energy systems, and due to distributional issues of renewable energy policies (Grösche and Schröder, 2014). Additionally, conflicts evolve on a global level where oil and gas producing countries may be facing difficult economic conditions due to low carbon policies (Johansson et al., 2009) and bioenergy policies may increase deforestation in world regions which are unrelated to the direct bioenergy supply chain (Searchinger et al., 2008).

Shedding light on the *big* questions – such as total resource availability and global impacts of energy technologies – is an important task. However, the transition of our energy system to a low-carbon one is also in need of addressing technical, economic, regulatory, social, and ecological questions (Cochran et al., 2014). The transition affects many different systems, from biophysical and ecosystems over the technical conversion systems to the systems that allocate resources to producers and consumers in an economy. Normative issues of how systems should be designed are mingled together with positive questions of how systems work. To adequately address the important questions that arise in the transformation from a fossil to a renewable energy system, theoretical considerations therefore have to be combined with empirical data on system behavior and with perspectives of stakeholders. Integrated Assessment and Modelling (IAM) is a methodological approach that aims at addressing these research challenges by means of integrating models from different disciplines that operate on different temporal and spatial scales with knowledge, values, and perspectives from stakeholders (Parker et al., 2002). I consider my own research contributions to be part of a specific subfield of integrated assessment modelling with a particular focus on applying bottom-up modelling approaches to renewable energy systems. In this treatise, I will therefore first introduce the basics of my main field of research, that I tentatively call Integrated Bottom-up modelling of Renewable Energy systeMs (IBREM) in chapter 2. I will discuss the concept of IBREM, will point at challenges of integrating different disciplines, and will address transdisciplinarity, i.e. the integration of stakeholders in the research process. In chapter 3, I will present the different disciplinary subsystems and how they are linked in IBREM, before classifying my own work within the IBREM framework and showing my own contribution to the field in chapter 4. In chapter 5, I give an outlook on future research potentials in the field.

"But they are useless. They can only give you answers."
Pablo Picasso on Computers (Fitfield, 1967)

2. Fundamentals of Integrated Bottom-Up Modelling of Renewable Energy Systems

Within this chapter, I aim at defining Integrated Bottom-up modelling of Renewable Energy Modelling systeMs (IBREM). IBREM have to be understood in the context of Integrated Assessment and Modelling (IAM) (Parker et al., 2002). This is a field of research that has a strong tradition in the environmental research community, where studying natural systems (such as ecosystems) and the impact of human interventions on those system has been in the focus of research for a long time. Different disciplines (natural and social sciences) meet knowledge, perceptions, and interests of stakeholders, i.e. of organizations and people who are directly and indirectly affected by a particular (environmental) problem they want to approach. Disciplinary, scientific interests therefore not mainly drive research into IAM, but research requirements are often derived from particular real-world problems. Ideally, research needs are therefore defined according to the nature of that problem (Kragt et al., 2013; Parker et al., 2002)[14]. IBREM are a subset of IAM approaches: they evolve around a particular, socially highly relevant subject, the transformation of our energy system to a renewable one, and aim at inter- and transdisciplinary integration of knowledge, perceptions, and values with the help of computer models. The term Integrated Assessment Model is, however, ambiguous: large scale, multi-sector, mainly global or continental, economic models with representations of greenhouse gas emissions used to assess climate change policy are also called Integrated Assessment Models (Ackerman et al., 2009). While IBREM can also be used in the framework of IAM (for example, for specifying a highly renewable electrical sector in detail), I do not focus on that particular use of IAM in this treatise.

In this chapter, I first present a tentative architecture of IBREM. At the core of IBREM are integrative efforts: i.e. integrating different perceptions of a problem setting to create new knowledge. This integration has to struggle with integration barriers along the lines of model and data types, disciplines, epistemologies, and the role of normative and positive approaches in research (Kragt et al., 2013). I therefore discuss those fundamental properties of IBREM, which are later on, in chapter 4, used to categorize my own work and put it into the broader context of IBREM.

2.1. A tentative architecture of IBREM

I define IBREM as models of renewable energy systems that (a) draw a consistent picture of current and possible future states of renewable energy systems, (b) consider a wide range of systemic relations and impacts from different systems, such as the bio-physical system, the technical system, or the socio-economic system, (c) are able to provide answers to requests from users outside of the research community and including those users into the model building process, (d) and use a bottom-up modelling approach. Figure 1 shows a basic architecture of an

[14] IAM can be considered to be part of the transition of the scientific system to Mode 2: Nowotny et al. (2003) acknowledged that research realities had been changing in the second half of the twentieth century, generating "a new paradigm of knowledge production ('Mode 2'), which was socially distributed, application-oriented, trans-disciplinary, and subject to multiple accountabilities".

IBREM. There are four supporting subsystems that provide data to the main integrating model, the energy allocation system model. The four supporting subsystems are mainly considered from a users' perspective by IBREM modelers, i.e. they use data or apply models from those fields, but main model development is occurring in the energy allocation system model. The transdisciplinary process, i.e. the integration of stakeholders into the modelling process, is linked to all five submodels. Only in rare cases IBREM consist of all elements and a clear distinction between the subsystems may not always be possible, e.g. the representation of the technical conversion system and the energy allocation system are often strongly integrated into one model. I consider any model which at least partly fits into the scheme as part of the IBREM family.

IBREM mainly deal with renewable energies (although fossil or nuclear energy are partly represented in the models). Renewable energy system models are different from traditional energy system models, which have put a strong focus on fossil fuels. Section 2.2. discusses the definition of renewable energies, and why their treatment in the context of modelling is different from fossil fuel energy systems.

From a methodological point of view, IBREM are based on system modelling with the help of computers. I therefore introduce computer modelling and why it may be considered to be useful in terms of integrating different perspectives, as required by interdisciplinary and transdisciplinary approaches, in section 2.3. Different modelling approaches, and in particular the bottom-up approach, which is a constituting element of IBREM, are also discussed to show the range of possible data-theory interactions in the field of computer modelling.

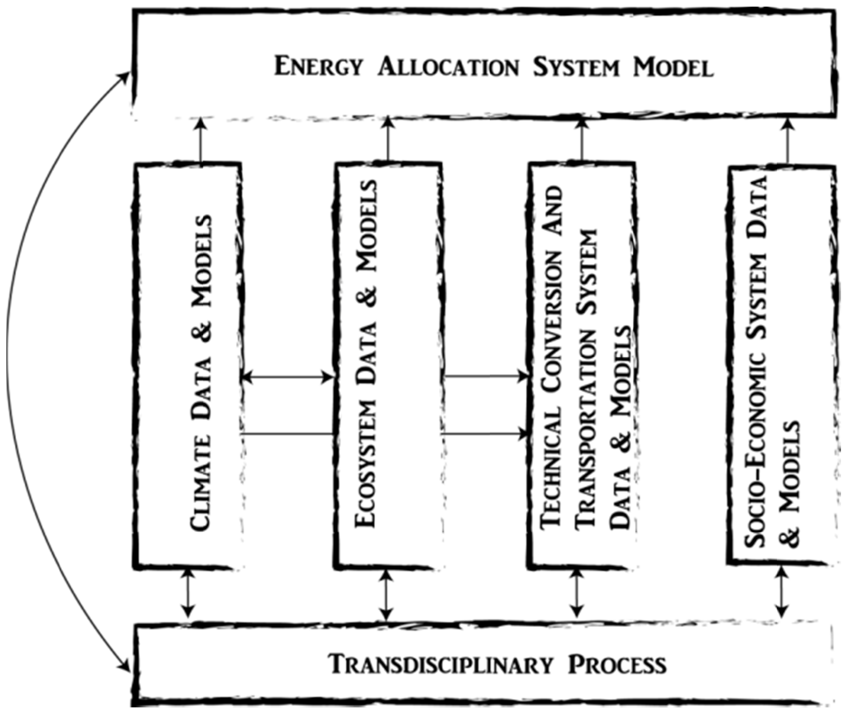

Figure 1: A basic architecture of an IBREM.

IBREM consist of disciplinary submodels, representing subsystems of an overall system. A detailed discussion of the subsystems is given in chapter 3, while the challenge of interdisciplinary integration is discussed in 2.4. For the moment, it is important to observe that there may be a model for each of the subsystems and that output of models may be used in other models. The energy allocation system model integrates these outputs directly or via an intermediate model, e.g. climate data passes through the technical conversion and transportation system model before ending up in the energy allocation system model. The arrows between the systems shown in Figure 1 therefore do not relate to known functional relationships between the real systems, but to the model interfaces that are primarily implemented in IBREM (see chapter 3 for details).

The transdisciplinary process which handles the integration of stakeholders into the research process, i.e. which crosses the border of the research land and reaches out to the application of the models to practical problems as posed by e.g. policy makers, citizens, interest groups, or the like, may have a link to any of the submodels. Stakeholders may co-develop parameters as well as structural relationships of any of them. Section 2.5 discusses transdisciplinary research processes and different forms of transdisciplinary interactions relating to IBREM.

The different submodels in IBREM are differently related to positive or normative science: they show *how systems work* (positive), or *what should be done to achieve some societal goal* (normative). In many cases, positive and normative applications of the models are mingled together in a fuzzy way. I therefore discuss positive and normative components in IBREM, and in particular in the energy allocation system in section 2.6.

IBREM are used to depict future system states. Depending on the epistemological point of view, models may be considered to be tools generating predictions, or scenarios, or simply tools that are used to trigger discussions among stakeholders on how the future is perceived and how these perceptions may shape today's decisions. The epistemological position prevailing in a research project may change the modelling practice, and in particular the communication of the methodology and of results to the scientific community and the general public. Different epistemological positions taken in IBREM are therefore discussed in section 2.7.

2.2. Renewable Energy Models

The optimal installation and operation of renewable energy technologies, the associated economic and policy challenges, and positive and negative environmental externalities are frequently addressed by IBREM. Renewability of primary energy resources links to the sustainability concept as it suggests that, if renewable sources of energy are used, the prevailing consumption patterns can be sustained for a very long time[15]. At the same moment, colloquially renewable energies contribute to climate change mitigation as they emit low amounts of CO_2 in the conversion process[16]. A pragmatic definition of renewability therefore links consumption to natural reproduction of the resource, such as $C(t) < \frac{dR}{dT}, l < t < u$, *C(t)* being consumption at time *t*, *R* being the resource and *l* and *u* being the lower and upper bounds of the time interval. In that sense, humans probably used fossil fuels in a renewable manner in e.g. the period 100-200 A.C. when consumption was most likely lower than natural reproduction. Solar energy is, under this definition, not renewable, if *u* is set to some billion years in the future, when the sun ceases to exist.

[15] The possibility of a warm death universe prevents using the term "infinite" here.

[16] Which is contested for some renewable energy technologies, in particular those that use biomass as source of primary energy due to emissions from direct and indirect land-use change (Fargione et al., 2008; Havlík et al., 2011; Searchinger et al., 2008).

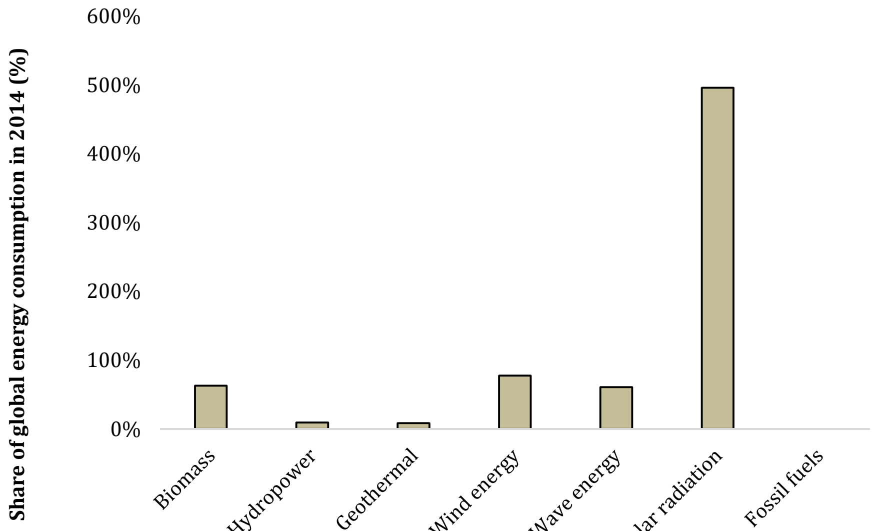

Figure 2: Global technical, renewable potential of primary energy sources as a share of total global energy consumption in 2014 (British Petrol, 2015; Hoogwijk and Graus, 2008). Observation: The renewable potential of fossil fuels is very close to 0 and thus not visible on the chosen scale.

For myopic choices of the parameters, i.e. $C(t) = C(2014)$, $l = 2015, u = 2114$, the amount of primary energy that can be provided renewably by different sources of primary energy is shown in Figure 2. Combined technical potentials of renewables and even solar radiation alone are sufficient to cover current and a possible future growth in demand in a renewable manner (de Vries et al., 2007). However, fossil fuel consumption is renewable only at very low consumption rates (at around 10.000^{-1} of current global energy consumption[17]) due to the slow natural process that build those resources. Stocks of fuel for Deuterium based nuclear fusion would theoretically allow covering current world demand for "virtually unlimited" years (Hoffert et al., 2002), thus being a practically infinite fuel on any human time-scale. However, Deuterium is not generated naturally on earth and is therefore not renewable. My definition of renewable energies seems to be of theoretical use only: still, those sources of energy which have significant renewable potential under the above definition are also considered to be "renewable" colloquially[18].

The characteristics of *new* renewable energy systems, i.e. of energy systems with very high shares of renewables, are very different from traditional energy systems in terms of technical, socio-economic, and bio-physical aspects. E.g. land use issues are of minor interest when mainly dealing with fossil fuels but are highly important when assessing bioenergy options (Havlík et al., 2011; Searchinger et al., 2008). Bioenergy resources are sourced from agricultural and forestry markets which are fundamentally different from markets for fossil resources and also trigger different controversies such as the food vs. fuel debate (Rathmann et al., 2010) or the "Food, energy, and environment trilemma" (Tilman et al., 2009).

[17] Taking into account that fossil fuels started to build around 550 Million years ago (Berner, 2003) and that all known oil, gas and coal resources are just a hundredth of all existing fossil resources.

[18] I.e. wind, solar, and hydro energy, bioenergy, geo-thermal energy, wave energy

Table 1: Comparison of important characteristics of renewable and fossil fuel energy system models

	Fossil fuels only	Renewable energies only
Biophysical characteristics		
Climate	Impact on demand side	Important for both, demand and supply side
Type of resources	Mainly stocks	Mainly flows
Spatial variability of resources	High	High / Mid (Biomass, solar)
Temporal variability of resources	Almost none	High / Low (Biomass)
Temporal and spatial concentration of resources	High	Low / Mid (Wind, geo-thermal)
Techno-economic characteristics		
Storage	Cheap	Expensive (Exemption biomass)
Transportation costs	Low (Oil) Mid (Coal, Gas)	Mid (Biomass) High (Electricity)
Dynamics of technological innovation	Low (for conversion technologies), High (for resource extraction technologies, e.g. shale gas)	Low (e.g. Biomass), High (e.g. solar, wind, storage)
Markets		
Land markets	Low land use -> low coupling	High land use–> high coupling
Markets for products from agriculture and forestry	Low: Limited coupling through land-use of fossil fuel extraction	High: Coupling through land-use and products (biomass)
Global coupling of markets	High	High (biomass) / Low (flow based renewables)
Strategic behavior	Highly important due to resource concentration	Less important, depending on particular markets
Marginal pricing	Low investment costs – high variable costs: marginal pricing works rather well	High investment costs – very low variable costs: marginal pricing in markets may not work well (Exemption: biomass)
Environmental impacts		
Greenhouse gas emissions	High impact, mainly direct through fossil fuel combustion	Low (Wind, Solar)/ Mid (Biomass), mainly indirect impact
Biodiversity	Highly complex direct and indirect impacts	Highly complex direct and indirect impacts

Solar and wind power are distributed, intermittent sources of electricity which pose different challenges to the operation of the electricity grid than the historical model of centralized power generation in thermal and hydro-power plants, as frequency and magnitude of variability and the degree of uncertainty differ from traditional power generation technologies (Hart et al., 2012). Similarly to how the current technical, institutional, and economic framework is struggling in accommodating new sources of renewable energies, traditional energy models are therefore also facing challenges when modelling possible future energy systems with high shares of renewables (Connolly et al., 2010). More traditional energy sector models, such as TIMES (Giannakidis et al., 2015; Thiel et al., 2016) or MESSAGE (Sullivan et al., 2013), consider many different sectors and they play a fundamental role in understanding how different sectors and their interactions may play a role in renewable energy systems. Also, those models can be adapted to better represent renewables (Sullivan et al., 2013). However, due to their coverage of many sectors and consequently, their computational complexity, they are not able to fully depict renewable energy systems. I argue that building an energy system with high shares of renewables is therefore also in need of an underlying modelling infrastructure, which is able to represent this kind of systems. For that reason, I deal with *renewable* energy system models in this treatise. Anyhow, it is possible coupling them with large-scale energy sector modelling approaches to refine the representation of renewables in the later.

Table 1 shows the most important differences between the modelling of traditional, fossil fuel dominated energy systems and renewable energy systems. This is a highly simplified table as complexity varies between renewables (e.g. there is a large difference between biomass based and PV power generation). Still, the table indicates that for many subsystems, modelling renewable energy systems is more complex than modelling fossil fuel systems. One of the main reasons is the spatially and temporally highly variable resource availability without simple options for storage. The technological dynamics at work also create more complexity with respect to renewable energy systems: most fossil fuels systems are in a mature state of development and future cost reductions and efficiency increases can therefore be expected to be of minor magnitude, although technological dynamics play an important role in terms of primary resource extraction (e.g. shale gas extraction). For renewable energy systems, technological dynamics are still very high as some of the technologies did not travel down the learning curve very far yet which increases uncertainties in models. Another important difference between fossil and renewable models is that land use is higher for renewable energies, at least at locations in proximity of consumption[19]. This implies an integration of renewable energies into land markets and, in particular when regarding bioenergy, into agricultural commodity markets, making modelling complex. The modelling of impacts of energy technologies on biodiversity (e.g. impact in remote off-shore regions with low data availability (Dale et al., 2015)), strategic behavior of agents (due to high resource concentration, in particular of oil), and the high coupling of international markets (as fossil fuels are, in general, a globally traded commodity) are areas where fossil fuel models may be more complex than renewable models.

2.3. Computer modelling in the context of IBREM

Computer modelling interlinks "the traditional methods of scientific knowledge production—theory, experiment, observation, and measurement—in new ways" (Gramelsberger, 2011, p. 1). It is neither purely theoretical nor empirical only, but provides a link between theory – which provides the structural, causal framework for a model – and data – which provides the link to measured phenomena, and boundaries for the range of model parameters: it is a numerical derivation of results from a set of causal relationships and a set of input data. In natural science, where the first computer models were developed, they are used for prediction of future system states (Gramelsberger, 2011). Computer modelling is in many cases the only possible form of

[19] Land use of fossil fuel systems can be located very distant from consumption, while transportation costs of renewables often puts geographical limits on the outsourcing of production activities.

scientific prediction[20], as it is often impossible to build and "run" a second, identical system to predict the observed system's future state[21]. Models may also be used for the exploration of the parameter space, for testing scenarios, and for generating new hypothesis on the behavior of systems. Computer models are able to consistently translate knowledge from different perspectives into one unique framework. Language alone may often be too ambiguous to allow for a full, logically consistent specification and application of a theory to an empirical case (Schnell, 1990)[22]. Those properties make computer models a possible methodological candidate for integrating inter- and transdisciplinary perspectives (Nicolson et al., 2002): a framework can be set up that allows for a consistent definition of causal relationships between the involved variables and systems. In theory, any single participant of the research project can examine and change those relationships – and the used input data. Additionally, those system models can be "run" and consequences for the systems under study can subsequently be studied.

As the answer that we receive from models is completely predetermined by the structural equations of a model and the associated parametrization[23], it is of importance to always understand the theoretical assumptions embodied in the computer models we use. In this context Picasso's observation that computers "*can only give answers*" may be extended to "*but modelers can ask the right questions*". Professional computer modelers therefore seek to ask the right questions and, subsequently, derive a consistent description of the system under study that will allow gaining new insights from answering the questions with the developed model. In that sense, modelling is much less about deriving model results than about developing relevant research questions and using a consistent approach based on theories and empirical data to explore possible answers. The role of data and of given structure (i.e. theories) in computer modelling are different, depending on the applied modelling approach. A brief typology is therefore given next.

The role of pre-defined structure and data in computer models

Computer models can be differentiated by the role of data and pre-defined causal relationships in the modelling approach. Although there is no clear distinction, as most models use both, there are two large model families called black- and white-box modelling (Kleijnen, 1995). Black Box models are not assuming any particular internal causal relationships of a specific system, but rather observe inputs and outputs and use either statistical tools such as regression and time-series analysis (Hamilton, 1994) or computational tools such as artificial neural networks (Bishop, 1996) to explain the relation of inputs and outputs. For instance, a pure time-series model may take into account trends, seasonality, and auto-correlation of the data without any prior assumptions on the type of process. White Box models do explicitly assume causal relationships between different subsystems, e.g. a White Box simulation of the power market may explicitly account for behavior of market participants and for physical limitations of the electricity system.

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[20] It is important at this point that computers not necessarily are machines. Actually, before electronic devices were available, computers were all human (Oxford English Dictionary, 1989).

[21] Even if it was possible to build an identical system, "running" the duplicated system would take the same time as observing the real system.

[22] However, that does not mean that natural language is unnecessary, or as Hinkel (n.d.) puts it: "The advantage of ordinary language over the mathematical one is that in mathematical language one cannot express everything that can be expressed in ordinary language. The advantage of mathematical language is that once one has arrived at the point of being able to express what's at stake in mathematics, then unambiguous further exploration is possible in a way that is not achievable in ordinary language".

[23] In the end, any computer model is a turing machine that deterministically operates on a set of input symbols (Turing, 1937). Even if randomness is introduced to computer models (by e.g. drawing numbers from random generators which are seeded by "real-world" randomness such as the current time or the hard disk activity), they still are fully deterministic and a given set of results can be completely explained by the chosen set of input parameters.

In many cases no clear line between white- and black-box approaches can be drawn: e.g. regression models often do assume structural relationships between variables derived from theory, while White Box models at some point have to use Black Box estimates of model parameters. On one extreme of the spectrum, big data enthusiasts propose that models based on data are sufficient because relations between the data can be derived from data only, without proposing any prior relationships (not even functional ones, such as in non-parametric time series analysis (Fan and Yao, 2005)). The other extreme of the spectrum are e.g. agent-based models (Epstein, 2012), which in many cases are based on the assumption of a very high number of causal relationships within the system.

Black Box models in general reproduce observed data very well and the short-term quality of forecasts is high if the system is in a stable region of operation, i.e. if it is well represented by the historical, observed data. Lucas (1976) however criticizes this approach if it is used for deriving economic policy recommendations from the exploration of past observations: as most variables are endogenous, a change in policy will make the system behave differently. Those adaptation effects however cannot be addressed with Black Box models if they have not been observed before.

IBREM apply a White Box approach. In contrast to Black Box models, they are better able to assess structural breaks which have not been observed yet in the data (or at a very low frequency so that no statistical inference is possible). Those models do not compare that well to historical, observed data[24], and forecast quality is generally low. They are therefore frequently used in the context of scenario analysis.

Although all of my own work presented in this treatise is mainly related to Bottom-Up and therefore White Box modelling, I also applied mixed approaches in some of the research projects. I therefore categorize my own work with respect to the relation to White-Box and Black-Box modelling in chapter 4.

2.4. Interdisciplinarity in IBREM

Following Figure 1, IBREM integrate models of subsystems stemming from different disciplines. The climate layer and the ecosystem layer, positioned on the left of the figure, are directly associated with disciplines from natural sciences (i.e. meteorology and ecology), while the socio-economic system and the energy allocation system can be associated with economics and other social sciences. The technical conversion and transportation system is in-between those two classes: it is based on engineering knowledge, but also has a strong component that is linked to social sciences. The subsystems are discussed in detail in chapter 3, and I associate my own work to the subsystems in chapter 4.

Some consider interdisciplinary modeling that crosses epistemological paradigms to be impossible due to incommensurable basic assumptions about the world. A less strong position would rather emphasize that a combination of different research approaches, although not simple to integrate, would allow for different views on the same problem setting. Finally, problems in integrating different epistemological positions can also be simply ignored by naïve approaches (Yearworth and White, 2013).

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[24] However, there are procedures available that allow calibrating bottom-up models in a way that exactly reproduce observed outputs (Schmid and Sinabell, 2005).

However, even though diverse disciplines are associated with the layers in Figure 1, they share, in principle, the same epistemological background. Both, the layers associated with natural sciences as well as the layers associated with economics and social sciences follow positivistic epistemologies in most modeling practice. The later are strongly influenced by neo-classical economics, which has a positivistic epistemology[25]. Positivistic epistemologies make natural and social sciences analogous (Furlong and Marsh, 2002), and the scientific practice of encoding theory in structural equations and numeric data is present in any one of the disciplines. Although I argue in section 2.7 that epistemologies of IBREM are not necessarily fully positivistic, in particular due to how input parameters are derived and how results are communicated, the models have their roots in positivistic disciplines and therefore allow, on a practical level, for an integration of knowledge using computer models.

While in principle, the integration of the different models is therefore possible, conceptual differences may make the practical coupling or integration of models complex, even within one discipline. Differences in the basic approach to White or Black box modelling, in how data is aggregated and in how system boundaries are defined often make integration hard to achieve, e.g. when bottom-up and top down models are coupled. Also, different factors are endogenous in different models, and finding the right system boundaries for all involved models may therefore be a complex task. In particular, if a detailed model of a subsystem has to be integrated in a more general purpose model, i.e. if the modelled systems have a large overlap, a mismatch in data sources, time and spatial scales, structural assumptions, and consideration of endogenous factors makes integration highly complicated. To face those challenges, intensive communication within the project team, rapid prototyping, and a detailed idea of the actual research problem facilitate integration (Nicolson et al., 2002).

2.5. Transdisciplinarity: involving stakeholders into the research process

IBREM are applied to develop socially robust knowledge and to solve real-world problems, i.e. they are used in a context which is not purely driven by research interests, but also strongly driven by actors and societal needs from outside of the research community, such as policy makers, interest organizations, citizens, and companies (Pfenninger et al., 2014). One of the starting points of trying to strengthen the link between the research community and society in general was the perception that new technologies and ways of organizing the society proved to be not strictly welfare improving. Modernization of societies is considered to be an ever more complex field of engagement, and more holistic assessments of future development options are therefore necessary (Hadorn et al., 2008). Research approaches are required that (I) are able to integrate knowledge from increasingly specialized disciplines and from stakeholders and (II) increase the relevance of scientific results to society, in particular if "knowledge about a societally relevant problem field is ambiguous, when the concrete nature of problems is disputed, and when there is a great deal at stake for those concerned by problems and involved in dealing with them" (Hadorn et al., 2008, p. 37). Transdisciplinary research approaches therefore aim at treating social, environmental, and economic challenges encountered by practitioners. For that reason, practitioners, stakeholders, or citizens are part of the research process starting at the beginning, when problems are framed, and throughout the whole research process.

[25] Neo-classical economic theorist Walras, the inventor of general equilibrium theory, was even inspired by a theoretical view developed in natural sciences: Newtonian mechanics. *"Walras, having also been guided by the precedent of Newtonian celestial mechanics, used his 'rareté' as the connecting common principle in the construction of his general equilibrium model. One of León Walras's last publications, 'Économique et mécanique' (1909), published the year before he died, was a reaffirmation of his reliance on the pattern of Newtonian mechanics to inform his conception of catallactic mechanics."* (Jaffé and Walker, 1983, p. 102)

Additional rationales behind integrating stakeholders into the research process, besides defining the initial research problem, are diverse. Bauer and Pregernig (2013) developed a classification of those rationales for technology assessment and foresight studies. This is a broad field and methodologically not necessarily related to modelling or, in particular, to IBREM. However, the rationales fit well to IBREM as both, technology assessment and foresight studies and IBREM, do address perceptions of the future. Bauer and Pregernig differentiate between three rationales for integrating stakeholders into research projects: a *cognitive*, a *constructive* and a *political* rationale. Within the *cognitive* rationale, the main purpose of integrating stakeholders is gathering knowledge from stakeholders to increase the quality, usability and reliability of results. Researchers, according to the rationale, are able to learn more about a particular system by interacting with their partners from outside of the research community than if they stayed within the community only. Stakeholders are considered to be an additional, important source of knowledge, that would not be available otherwise. In the *constructive* rationale the focus is put on triggering learning and coordination processes among researchers and stakeholders. The rationale suggests that future pathways of socio-economic development are shaped by the actors involved in the respective decision making processes (i.e. future does not *occur* to actors, but they themselves take decisions which co-constructs their future). In this context, IBREM are used to coordinate actors based on a common system understanding and to support actors in constructing a common future pathway with respect to the energy system. As Bauer (2015, p. 198) puts it, "the expectation is that participatory processes induce reflection, communication, and networking that, in the long term, contribute to the realization of shared goals and visions". Participation of non-scientists in the *political* rationale is a way of democratically legitimizing research processes and results. It is expected that common visions of the future energy system can be generated in a participatory process. Those visions are thought to be socially robust in comparison to ones which are derived by scientists alone: after all, they are supported by the stakeholders or citizens. Within the constructive as well as the political rationale, a consensus between participating transdisciplinary partners is a desired outcome. However, if the group of stakeholders is not homogenous in views and believes about the modelled subject, consensus may be hardly achieved, and learning may be very restricted (Wiek, 2007). Also, participatory processes are not free of power relations and may even maintain "existing power relationships, though masking this power behind the rhetoric and techniques of participation" (Christens and Speer, 2006). Thus, consensus may not be reached on important project parameters that integrate non-scientists: in that case, there is at least the possibility to show how differences in values and beliefs of the participants play out on the level of model results.

Mostly, the discussed rationales for engaging stakeholders are applied implicitly in most research projects. Still, they result in different ways of how researchers are integrated and result in different project outcomes. A categorization of my own work with respect to the three rationales of transdisciplinary research is therefore given in chapter 4.

2.6. IBREM and the normative and positive scientific approach

Normative research approaches aim at examining preferred system states, i.e. they are interested in *what should happen*. Positive approaches, on the other hand, examine *what happens*. Natural sciences are mostly positive in the sense that they investigate how things work[26]. In social sciences and economics, the normative component may be much stronger. As IBREM are thought to address real-world social, environmental, and political problems, they have a strong normative character, because objectives are very much depending on values and preferences of

[26] Georgescu-Roegen argues that thermodynamics is an exemption, as it introduces the normative notion of „useful" energy to physics (Georgescu-Roegen, 1971).

actors. This mixture of normative and positive components within an IBREM in particular is important at the energy allocation layer: the question of how resources *should be* allocated is often mingled together with the question of how they *are really* allocated.

The normative approach is for instance found in optimization models. They are applied to find efficient allocations of resources that maximize or minimize some objective, subject to restrictions in the modelled system. The planner assumes the variables in the model controllable, i.e. the model supports the decision maker in finding *optimal* outcomes according to the objective function, technical coefficients, and constraints. For example, Schmidt et al. (2010a) assess efficient allocations of biomass resources to conversion technologies with the aim of minimizing costs of greenhouse gas emission mitigation. The modeler defines the objective, i.e. the cost minimization, with the background of balancing political climate change mitigation goals with policy costs. Instead of deriving objectives from policy goals, a participatory modelling process may allow stakeholders or citizens to define their own objectives in a normative modelling exercise (Höltinger et al., 2016).

IBREM with a strong focus on the analysis of markets are mostly based on neo-classical economic theory. The distinction between the normative and the positive application of such a model is often not clearly drawn in this context. As Thaler (1980, p. 1) puts it, "although the theory is normatively based (it describes what rational consumers should do) economists argue that it also serves well as a descriptive theory (it predicts what consumers in fact do)". An example is the theory of efficient markets. It shows that, given a set of basic assumptions on institutional settings and behavior, efficient markets clear at marginal utility and marginal cost, and that pareto-efficient allocations are achieved if goods are traded on those markets. Total welfare is maximized in that case (Arrow, 1951)[27,28]. Although those assumptions are not met in many real markets, those models are used positively in the sense that their outcome is described as a projection or prediction of system behavior, instead of normatively prescribing how economic agents should behave to achieve a certain goal. One example is one of my papers on the design of cost-effective policies for reducing greenhouse gas emissions (Schmidt et al., 2011b), which states that "the model results indicate that a carbon tax on all fossil fuels is cost-effective with regard to both policy targets". What the model results actually do indicate is that market participants would minimize their costs of energy supply when they behave according to model prescriptions under the different policy schemes. In any case, while implicitly the differentiation between *normative* and *positive* models may be clear to researchers, they often not explicitly communicate the difference to users of research results outside of the community. I therefore classify my own work with respect to their relation to *normativity* and *positivity* in chapter 4.

[27] Welfare maximization is, obviously, also a normative goal (Kronman, 1980).

[28] It is well known that most, if not all, of the basic assumptions are not met on real markets, e.g. there is a limited number of market participants (although the theory requires a large or even infinite number of market participants), and market participants do not act fully rationally (which is a theoretical requirement). Often, it is assumed that those irrational market participants leave markets eventually as rational traders will take their share of the market. It has however been shown that this is not necessarily the case (Thaler, 2000). Most of those issues can be dealt with in standard economics, or with extensions that go beyond neoclassical economics. Those extensions make models more complex and computationally expensive. Therefore, simpler versions of models that ignore the violation of basic assumptions are often applied in the contet of IBREM.

2.7. Epistemological modes of future production in IBREM

IBREMs are applied to assess or construct future system states. The basic epistemology of how future is perceived by researchers and stakeholders in IBREM projects can make a fundamental difference in the setup of the project and in the communication of project results. Bauer (2015) develops a categorization of epistemological paradigms for future studies, which are also useful in the context of IBREMs. She differentiates between the positivist-prognostic paradigm, the critical-realist paradigm, the evolutionary paradigm, the interpretive-constructivist paradigm, and the critical-deconstructionist paradigm (see Table 2). One important difference between the paradigms is the mode of how futures in the context of modelling are framed: the models may be believed to produce *probable* futures (positivist-prognostic), i.e. models are believed to give clear indications on how the future is going to be. The produced futures may be perceived to be *possible* (critical-realist, evolutionary), i.e. models are at least able to limit the futures to ones that seem to be feasible points of development. Futures may also be perceived to be *preferable* (interpretive-constructionist), i.e. models are used to develop preferences about future system states. Finally, the critical-deconstructionist paradigm questions all forms of future production. As it is not relevant to IBREM, it is not further discussed here.

The *positivist-prognostic* paradigm is very much associated with the belief that the future is predictable, controllable – and that there is a continuous link between the present and the future. The *critical-realist* approach emphasizes that predictability may not be given completely, but that a logically coherent approach gives the opportunity of external evaluation. The *evolutionary* paradigm questions predictability very much, as (social) developments are assumed to be a mixture of linear (predictable) developments and unpredictable bifurcations. In the *interpretive-constructivist* approach, futures are believed to be multiple due to different values and beliefs about them. Futures should therefore be jointly constructed. Depending on the epistemological presuppositions in modelling projects, different actor groups are involved. While modelling exercises following a positivist or critical realist paradigm largely rely on experts/scientists only, models based on evolutionary and interpretative-constructionist paradigms additionally involve stakeholders and citizens respectively to a larger extent.

The disciplines mainly involved in IBREM, from meteorology, biology to economics, have deep roots in the positivist-prognostic paradigm. IBREMs may therefore be regarded to be of a positivist-prognostic nature. At the same moment, however, IBREM are very much influenced by the critical-realist, evolutionary and interpretive-constructivist approaches. Critical-realist future studies focus on possible instead of probable futures. Today, the integrated modelling community very much emphasizes the role of uncertainty (Asselt and Rotmans, 2002; Refsgaard et al., 2007). Neither scenarios nor ranges for uncertain parameters can be associated with probabilities and they therefore depict possible futures. Evolutionary future studies add another element to uncertainty: developments occur linearly in a predictable way for some periods, but they are disturbed by large-scale evolutionary, unpredictable shifts in others. This is very much in line with the approach of complexity sciences which is gaining importance in the modelling of energy systems (Bale et al., 2015): here it is emphasized that complex systems are prone to develop to a wide range of different future states, depending on initial conditions of parameters. Small differences in initial conditions can lead to a series of widespread outcomes, similar as observed in chaotic systems (e.g. logistic maps) (May, 1976). In the interpretive-constructivist approach the focus lies very much on preferable futures, i.e. on the derivation of futures which are desired by a particular group of people. IBREM that involve citizens and stakeholders into the research process to discuss a vision of a future that is not considered to be pre-determined - but rather co-constructed – may be linked to this epistemology. In IBREM, participatory research designs are important, as discussed above in section 2.5. Models are often used as boundary objects (Bergmann et al., 2010, p. 106), "which are both plastic enough to adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites" (Star and Griesemer, 1989). This line of research is increasingly visible in the modelling community (Voinov and Bousquet, 2010), in particular in research projects that apply participatory modelling approaches, such as Höltinger et al. (2016).

I argue that the roots of computer modelling can be found in the positivistic epistemological approach, but that IBREM partly also apply critical-realist, evolutionary or interpretative-constructivist approaches, in particular as they aim at integrating knowledge from different disciplines and different actor groups. A classification of my own work in terms of its relation to the epistemological paradigms is therefore given in chapter 4.

Table 2: Classification of epistemological approaches in future studies (Bauer, 2015)

	Positivist-prognostic	**Critical-realist**	**Evolutionary**	**Interpretative-Constructionist**	**Critical-deconstructionist**
Futures	*Probable*	*Possible*	*Possible*	*Preferable*	*Questions all futures*
Prediction	*Possible*	*To some extent*	*Predictable (stable) and unpredictable (bifurcations) trajectories*	*Multiple futures, no a-priori discovery possible*	*Rejects prediction*
Actors in modeling	*Scientists*	*Scientists, Experts*	*Scientists, Experts and stakeholders*	*Scientists, Experts, stakeholders, citizens*	*Not applicable*

"It is sheer nonsense to expect that any human being has yet been able to attain such insight into the problems of society that he can really identify the central problems and determine how they should be solved. The systems in which we live are far too complicated as yet for our intellectual powers and technology to understand."
C. West Churchman (Churchman, 1968, p. x)

3. Subsystems in the integrated approach

In this chapter, the implementation of the most important subsystems in state of the art IBREM is discussed. The five subsections are related to Figure 1, where the subsystems, their interfaces, and their hierarchy is shown. For most of the subsystems, IBREM modelers take a user perspective: the subsystems are not modelled in detail within IBREM, but output from other models is used or adapted and integrated into the IBREM, where the energy allocation layer, as depicted in Figure 1, forms the integrative concept. Still, it is of importance to understand the fundamentals of those systems and how they are represented in IBREM. I therefore first discuss the disciplinary background, important data sources and modelling approaches for each subsystem, including an overview of previous work. The interfaces implemented between subsystems in IBREM are also presented. Finally, I differentiate between the exogenous or endogenous role of different variables in the subsystems. Endogenous variables can be adjusted according to the change of other variables during a run of the model. Exogenous variables – or parameters – are fixed within one model run and therefore do not dynamically adapt to changes in other variables.

3.1. The climatic system

Models of renewable energy systems depend on the provision of climate data, as climatic processes are either the direct source of primary energy in renewable energy conversion chains (e.g. solar, wind, or hydro power) or as they are fundamental to determine productivity of agricultural and forestry systems (i.e. biomass for bioenergy). The climate also has a strong influence on energy demand for heating and cooling processes and human behavior as result of changes in meteorological variables such as precipitation or temperature (Mirasgedis et al., 2006). Additionally, there is a feedback effect between the energy and the global climate system due to e.g. greenhouse gas emissions, carbon sequestration (e.g. biomass), and the albedo effect. Access to climatic data and an understanding of the climate system is therefore of importance for the development of integrated renewable energy modelling frameworks.

Disciplinary Background, Data and Previous Work

The data and models used in this subsystem are strongly associated with natural sciences: meteorological models are based on theoretical relations between variables as defined by theories from physics, in particular from mechanics (Gramelsberger, 2011). In renewable energy models, the climate system is represented by some variables important to determine energy conversion and demand. Those variables consist mainly of temperature, solar irradiation, precipitation, and wind speeds (although other variables may be relevant too). Renewable energy modelers in most cases do not generate climate data from climate models themselves but resort to gathering data from existing model runs or meteorological observations. Long time-series of historical observations exist and a series of models is used to derive homogenous historical time series for important meteorological variables for the whole globe (e.g. European Centre for Medium-Range Weather Forecasts, 2014; Rienecker et al., 2011). Similarly, a range of models that projects future climate states, taking into account changes in the accumulation of greenhouse gas emissions, is continuously being developed (Sillmann et al., 2013). Model and data inter-comparison and thus addressing of uncertainty from meteorological data in IBREM is therefore possible and recommended (Schmidt et al., 2016b). Nevertheless, data availability is quite different for different world regions – a fact which has to be taken into account when planning research projects[29].

The temporal and spatial resolution of climatic data has to be high in renewable energy models in comparison to fossil based energy models, where climatic data is mainly used on the demand side. Flow based renewables such as wind and solar energy have high temporal variability – and the resource availability, in particular wind, also varies significantly between different locations. Those energy sources are currently not storable at low cost and renewable energy models therefore have to depict the underlying meteorological processes at high temporal (i.e. hourly or sub-hourly) and spatial resolution such as shown in Schmidt et al. (2013). Hydropower is another important source of renewable energy. Similar to wind and solar energy, it is dependent on the (dis)continuous flow of river runoff, with much lower short-term variability than wind or solar radiation[30]. Different from those sources, though, storage is simple – a reservoir is sufficient. A temporally very highly resolved resource assessment is therefore not necessary in many cases. Still, the determination of electricity generation potentials is complex, as, depending on the type of hydropower plant, at least monthly or daily water flows in certain river basins have to be known – and as inventories of rivers have to be built to determine the potential of hydropower in a certain region. Bioenergy is a different case: the modelling of biomass production is not in need of temporally highly resolved climate data as hourly or even sub hourly data does not increase the quality of biomass growth models tremendously[31]. However, the spatial resolution of resource assessments is important due to high transportation costs as the energy density of biomass is lower than the density of most fossil fuels (Schmidt et al., 2011b). If climatic conditions for growing biomass do vary significantly in the area of interest, the use of spatially highly resolved climatic data may therefore be necessary.

Static assessments of resource potentials show that climatic and biophysical conditions allow for a fully renewable global energy supply (Hoogwijk and Graus, 2008; IPCC, 2011; Jacobson and Delucchi, 2011), even with increasing levels of energy demand. Currently, the focus of research therefore shifts from statically assessing resource potentials to dynamic assessments of optimal portfolios of renewables. For that reasons, and also to be able to include climate change impacts, reliable climate data on high spatial and temporal resolution has to be used. Increasingly, global reanalysis data[32] is applied in that context (Andresen et al., 2015; Juruš et al., 2013; Schmidt et al., 2016a, 2016b; Staffell and Green, 2014) as the data sets allow deriving long-term, consistent time-series for the whole globe. The reanalysis data is available with refined temporal resolutions of down to one hour, which is sufficient for long-term studies. Wind data has been used and

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29 The official Austrian meteorological service has access to data from 250 automatic weather stations for a country size of around 83,000 km^2. Brazil has less than double, i.e. 480 automatic weather stations, for a country around 100 times the size of Austria (~8,515,000 km^2). Obviously, the number of necessary stations also depends on the heterogeneity of the terrain.

30 Long-term variability of river flows may be of higher magnitude than that of wind and solar radiation, though (Schmidt et al., 2016a).

31 Although very short extreme events may be responsible for a large share of damage to crops (Klik and Eitzinger, 2010).

32 Reanalyis data sets take historical observations of climate parameters, assilimiate them using climate models, and provide them on a global grid with different spatial and temporal resolutions.

validated for several world regions such as Denmark (Andresen et al., 2014), the United Kingdom (Cannon et al., 2015; Staffell and Green, 2014), Hungary (Kiss et al., 2009) and Brazil (Schmidt et al., 2016a). For solar radiation data, similar analysis have been conducted for the whole of Europe (Boilley and Wald, 2015), the Czech Republic (Juruš et al., 2013), and Brazil (Schmidt et al., 2016a). Results are promising, i.e. at least on daily temporal resolutions or if data is aggregated over larger regions simulations of renewable energy generation from reanalysis data and real, measured generation data are highly similar. Recent research (MacDonald et al., 2016) applies localized climate models to derive spatially and temporally highly resolved climate data for energy system analysis. While this allows for a better representation of climate processes at the local levels, computational efforts are very high and the simulation of timeseries is limited to short periods. Also, the models have to be calibrated to the respective region, while reanalysis data is readily available globally.

There is little consensus about the impact of climate change on future potentials of renewables. There is at least one global study on the impact of climate change on hydro- and thermal power generation (van Vliet et al., 2016), which shows that the majority of power generation will be negatively affected by climate change. Regional case studies point in opposite directions due to regionally different impacts of climate change (de Lucena et al., 2009; Pryor and Barthelmie, 2011, 2010).

Interfaces between Submodels

Climatic data is primarily used as input to the modelling of ecosystem productivity (e.g. Schmidt et al., (2012)) and as input to the modelling of the technical conversion and transportation system. Additionally, the modelling of the energy allocation system may require climatic data for an improved description of human behavior changes due to climate conditions in the energy allocation system. The main variables that are passed to the other submodels include precipitation, temperature, wind, and solar radiation. Timeseries for several years in different temporal and spatial resolutions may be provided to the models to account for diurnal, seasonal, and inter-annual variability and extreme events in weather conditions.

Endogeneity

Although the climatic system may be considered to be independent of human activities in the short term, those activities do generate greenhouse gas emissions and therefore have an impact on the future state of the global climatic system (Smith et al., 2009). Additionally, human activities, in particular in the energy sector, may change local climate systems in a much shorter time period due to deforestation e.g. caused by hydropower projects (e.g. Stickler et al., 2013). While for some models of renewable energy systems the climate may be considered an exogenous variable and historical data may reasonably well describe the system, for others this assumption may introduce a significant source of uncertainty. Stickler et al. (2013) have shown for example that there is a negative feedback loop between the construction of hydropower dams and local precipitation in the Amazon region. Others (Jacobson et al., 2015; Miller et al., 2015) have shown that the large scale deployment of wind turbines reduces the local wind potential.

On a longer time scale, climate change has to be taken into account. However, an integrated modelling of climate change in combination with IBREM only is consistent, if a global analysis is performed. As IBREM, currently, are mostly regionally limited and as a link between climate models and IBREM is complex to implement, it has not been conducted yet. Instead, the impact of different carbon-dioxide emission scenarios (mainly, but not exclusively, driven by energy conversion processes) on the climate system (e.g. Riahi and Roehrl, 2000; Solomon et al., 2009) and the impact of different climate scenarios on the energy system (de Lucena et al., 2009; Schaeffer et al., 2012) have been evaluated separately.

3.2. The ecosystem

Ecosystems provide biomass as energy resource and many energy conversion technologies have a strong impact on ecosystems due to emissions, mechanical inference, and barrier functions. For that reason, ecosystems are modelled in many renewable energy models. In particular bioenergy assessments (Schmidt et al., 2012; Stürmer et al., 2013) do explicitly model biomass productivity and, in rare cases (Kirchner et al., 2015), associated impacts on ecosystems services in the production areas. Due to the complex interaction of energy conversion technologies with ecosystems and due to many particularities of ecosystems and technologies – e.g. a wind turbine in an area of intensive agricultural production has a completely different ecological impact than a large hydro-power dam – assessments of the impact of energy conversion technologies on ecosystems are often limited to case studies (Hastik et al., 2015).

Disciplinary Background, Data and Previous Work

The theories describing biomass growth at particular sites stem from rather well understood processes studied in biology and agronomy. Human interventions with respect to biomass productivity can thus be reasonably well modelled; in particular as observational data on the productivity of biomass growth in many ecosystems and areas is available. Inter-comparison of modelled and observed data is therefore possible (e.g. Balkovič et al., 2013), as well as an inter-comparison of different modelling exercises – even under climate change (Rosenzweig et al., 2014). Spatially explicit variables on biomass productivity (e.g. crop yield/region) are often used as input variables to the models and as such represent a particular part of the agro-ecosystem. Still, the assessment of impacts of human activities on a wider range of indicators for ecosystems, besides biomass production, has to rely on insights from ecology and is less well understood (Zhang et al., 2007). The spatial variability of ecosystem services is high. Provision of biomass on large areas of intensively cultivated agricultural land may not vary drastically on a local level (i.e. hundreds of meters), but differences in soil conditions and climate may have a considerable impact on a regional level (i.e. kilometers). Biodiversity may be even much more spatially diverse[33]. The modelling of the ecosystem and associated services is therefore highly complex.

A common anthropocentric approach of framing the interaction between human societies and ecosystems is the concept of ecosystem services, which suggests that ecosystems provide a series of services to humans which directly and indirectly contribute to human well-being (TEEB, 2010). It is frequently used to assess the impact of human activities on ecosystems. However, as the framework does not define the indicator sets to be applied, a wide range of different indicators may be used to quantify impacts on services such as naturalness (Rüdisser et al., 2012), or landscape esthetics (Kirchner et al., 2015). Although data collection on indicators for ecosystem services and biodiversity is continuously improving globally[34] (e.g. Butchart et al., 2010; Jenkins et al., 2013; Sala et al., 2000) and regionally (e.g. Kirchner et al., 2015; Tasser et al., 2008), there is still uncertainty about what to measure[35]. Researchers have for example looked

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[33] A rather obvious example is the high difference in number of species between an intensively managed agricultural area and a neighbouring, unmanaged hedge (Caporali, 2010). However, even undisturbed ecosystems show a locally highly variable distribution of species, such as confirmed by research on snail populations in Malaysia (Schilthuizen et al., 2003) and France (Aubry et al., 2005).

[34] See http://biodiversitymapping.org or http://www.iucnredlist.org/ for an example.

[35] Although there are international efforts to homogenize the indicators such as the "Common International Classification of Ecosystem Services" (http://cices.eu).

into impacts of renewables on ecosystems in case studies and have found (I) increasing bird mortality due to the operation of wind turbines (de Lucas et al., 2012; Drewitt and Langston, 2006), (II) decreasing biodiversity at PV installations (Evans et al., 2009), (III) toxic emissions to the environment from the production of renewable technologies (Pehnt, 2006), (IV) water use of renewable energy technologies (Fthenakis and Kim, 2010), and (V) for the case of bioenergy, all of the environmental externalities that are associated with (intensive) agriculture and forestry production (Kirchner et al., 2015). The overall scale of these impacts and if emerging technologies (e.g. bird detecting radars for wind turbines) can mitigate those are less understood.

A very different, but still anthropocentric, approach (Steffen et al., 2015) aims at defining safe limits for the most important global biophysical processes and, consequently, assessing if those limits have been surpassed by human activities already: in contrast to the ecosystem services concept that aims at showing trade-offs between different uses of ecosystems (e.g. providing large amounts of biomass vs. providing biodiversity), the concept of a safe operating space defines absolute limits: the concept allows an exploration of trade-offs to a certain extent but emphasizes that passing the limits may have "detrimental or even catastrophic" consequences to humanity (Steffen et al., 2015). An associated set of indicators informing about the state of the most important biophysical systems is constantly developed and updated to inform about the most urgent needs for environmental action (Rockström et al., 2009; Steffen et al., 2015). Up to the current moment, this approach has not been coupled with IBREM though.

In general, there is a weak representation of impacts of energy systems on ecosystems and the environment in IBREM, in particular with respect to a representation of the ecosystem services or the safe operating space approaches. One way how impacts are assessed is life cycle analysis. Berrill et al. (2016) have e.g. investigated the impact of renewable energy expansion scenarios in Europe on different indicators such as greenhouse gas emissions, freshwater eutrophication, or freshwater ecotoxicity, by coupling a life cycle analysis model with an energy system model. They show that renewables have a positive impact on most indicators in comparison to fossil fuel systems. However, metal depletion and land occupation may increase, depending on the type of the chosen renewable energy mix. Lima et al. (2015) couple the energy system model MESSAGE with a life-cycle analysis to show similar results. In particular land-use of a renewable energy system, in comparison to a fossil system, may increase significantly if large shares of biomass are used. Greenhouse gas emissions are estimated to be lower, however, without taking into account emissions from land use change.

Interfaces between Submodels

The ecosystem submodel delivers data to the conversion system submodel and the submodel of the energy allocation system, in particular biomass productivity data, i.e. biomass production levels on different locations under different management options. The ecosystem submodel however may also be able to report on indicators for ecosystems (such as indicators for ecosystem services) apart from biomass productivity: e.g. the siting decisions of wind turbines and hydro power plants has impacts on bird or fish populations (Hastik et al., 2015), and a backlink from the energy allocation layer to the ecosystem model can provide the opportunity to assess those impacts in detail – and incorporate them in the analysis of e.g. tradeoffs in ecosystem services or of the safe operating space of earth concept.

Endogeneity

The influence of ecosystems on human activities and well-being is strong – and, likewise, human activities have a strong impact on ecosystems: the development of indicators for ecosystems and human decisions for managing those systems are therefore highly linked. The indicators are inherently endogenous, i.e. the installation of hydropower dams may reduce fish populations, which can cause the exodus of fisher communities from large rivers to cities (Berchin et al., 2015), which in turn may have an impact on fish populations in the river. There is also a strong relationship of the ecosystem with the climate: ecosystems are heavily influenced by the climate (e.g. Hoegh-Guldberg and Bruno, 2010) – but ecosystems also regulate the climate globally through functions such as carbon sequestration (West et al., 2010), water evaporation, or albedo. However, the endogeneity of ecosystems with respect to the climate and the energy allocation system is hardly realized fully in IBREM due to the sheer complexity. An exogenous approach, i.e. the determination of indicators for ecosystem services derived from different scenarios of energy supply, is used more frequently (Kirchner et al., 2015). Very recently, a large-scale project started that assesses possible integration pathways of energy and ecosystem modelling for the UK[36].

3.3. The technical conversion and transportation system

The conversion and transportation system addresses the transformation of physically available quantities of primary energy into secondary energy and energy services such as the use of land to produce biomass which is consequently fed into a cooking stove to heat water - or the integration of a big wind park into the national grid to provide electricity. Also, it deals with the transportation (or transmission) of energy between different geographical locations.

Disciplinary Background, Data, and Previous Work

This submodel is based on engineering knowledge about the transformation of natural resources into energy services and about their transportation. Within this submodel, basic economic parameters such as investment and operation & maintenance costs are determined. The basic causal relationships for modelling conversion of energy resources are driven by laws of e.g. thermodynamics (thermal conversion), or mechanics (wind and hydro power). Transportation of electricity, i.e. transmission, is based on the principles of electrical engineering. However, in integrated modelling approaches, these relationships are often simplified and technologies are represented on a much lower level of detail. Thus linear functional relationships between variables are frequently assumed, e.g. the transformation of biomass into heat is in many cases represented by a single conversion factor (e.g. Schmidt et al., 2012). Other models may be more complex: the effective electricity generation of hydropower plants with reservoirs depends on the non-linear combination of a series of factors such as the inflows into the reservoir, the current water level of the reservoir, and the installed turbines (Labadie, 2004). There is a vast amount of literature that estimates relationships between inputs, outputs and costs of conversion processes (e.g. Hamelinck et al., 2005; Höltinger et al., 2013; Macrelli et al., 2012; Piccolo and Bezzo, 2009; van Vliet et al., 2010). This information can be used for a thorough uncertainty analysis with respect to conversion processes (e.g. Schmidt et al. (2010a)).

The transportation of primary resources such as biomass is well represented in recent IBREM (Leduc et al., 2015; Schmidt et al., 2010a; Wetterlund et al., 2012). Dealing with the transmission of electricity along power lines is more complex and simple linear relationships are not able to describe non-linear behavior of the transmission system, such as loop flows (Lumbreras and Ramos, 2016). In recent large scale, continental analysis, transmission therefore either was not regarded at all or is regarded by simple transportation or DC load flow models that do not fully cover the real complexities of the transmission system (e.g. Becker et al., 2014; Rodriguez et al.,

[36] http://www.ukerc.ac.uk/programmes/challenges/advent.html

2015; Schmidt et al., 2016a). In comparison to climate data, the spatial and temporal resolution of conversion technology data can be kept low in the models. Differences in the spatial availability of technologies derive mainly from institutional settings, e.g. Austria has banned nuclear energy and Brazil has high tariffs on imported technology. The temporal resolution may also be low, i.e. annual data is sufficient in most cases. However, the treatment of existing infrastructure in IBREM is often a time consuming process due to data availability. It is, nevertheless, important as long delays in the turnover of energy infrastructure causes the need for incorporating it into IBREM. The available data is, in many cases, of minor quality or lacking completely. Collaborative efforts to collect and provide data, such as carma.org or the open energy modelling initiative[37], are therefore of high importance for modelling of this subsystem.

One could assume that models of this subsystem show low uncertainties – as they are based on well understood *engineering* concepts, which themselves are based on well understood laws of physics. However, innovation and the evolution of technology play a fundamental role in this subsystem (Group, 2004). Currently unknown technologies – and even physical principles – constantly change the underlying assumptions in the models: while we may very well know how *existing* technologies work (and how much they cost), technological development is highly dynamic. Future states of the system are therefore hardly predictable. How technology develops, how innovations emerge, and if the industrial system is able to continuously innovate products that better serve a certain purpose (e.g. cheaper PV cells), is much less understood than the underlying physical laws - but is highly important for the purpose of (renewable) energy modelling (Gritsevskyi and Nakićenovi, 2000). Future resource availability, the cost-effectiveness of particular technologies, and even policy mechanisms may depend on the availability of respective conversion technologies. However, at least for some technologies, theoretical efficiencies and the current technological status-quo can be determined (e.g. Polman et al., 2016) and used as benchmark in a model analysis. Some technologies, such as PV (Bolinger and Weaver, 2014) and batteries (Nykvist and Nilsson, 2015), have shown very large cost reductions in very short periods. An endogenous representation of those dynamics should be part of any IBREM that assesses long-term competitiveness of energy technologies.

Interfaces between Submodels

This submodel mainly delivers data to the energy allocation submodel. There, the techno-economic data is integrated into the respective decision models, as it forms one of the most important decision factors for picking a certain technology in the decision making process. Frequently, conversion efficiencies of technologies, investment, fixed, variable and, external costs are provided to the models to choose the set of technologies which best satisfy a particular objective. Additionally, the technical conversion and transportation subsystem may provide data on expected learning effects with respect to a set of technologies to the energy allocation submodel. Thus, an endogenization of learning can be achieved.

Endogeneity

The conversion system is a techno-economic system which is subject to rapid developments through innovation. Characteristics and costs of conversion and transportation technologies may change rapidly over time through learning. Those learning effects are very much endogenous, i.e. technologies that are deployed at an accelerated pace will experience larger learning effects than

[37] http://www.openmod-initiative.org/

technologies that are not being used at all[38]. A standard way of dealing with technologies in integrated renewable energy models is therefore to assume that future learning effects depend on the future capacity to be deployed – i.e. technologies that are growing rapidly will experience much quicker decreases in costs and increases in efficiency (Yelle, 1979). This is the so called learning curve approach and historical data on the development of existing technologies are used to determine the learning rates present in technological systems (McDonald and Schrattenholzer, 2001).

3.4. Socio-economic boundary systems

A renewable energy system model aims at depicting the state of a particular subsector of the socio-economic system. Therefore, a set of boundary conditions does apply, i.e. assumptions on the state of the residual socio-economic system have to be assumed within the models. Typical variables of interest are energy demand, in many cases derived from GDP growth, demand elasticities, policies, capital availability, and prices of input goods (such as biomass or oil). In many cases, scenarios for future states of those variables have to be developed as most integrated renewable models deal with the future state of the energy system. Within IBREM, those variables are mostly exogenous and existing scenarios or scenarios developed with stakeholders are therefore used.

Disciplinary Background, Data, and Previous Work

Disciplinary background and data applied in the context of socio-economic boundary conditions are very diverse. Socio-economic data used in IBREM include energy demand and prices. E.g., Schmidt et al. (2012) use projections from the Austrian national Energy Efficiency plan and downscale them to the case study region. GDP and population growth are also frequently used parameters, e.g. Zeyringer et al. (2015) apply projections on GDP and population growth, as provided by government institutions, in combination with a regression model to forecast electricity demand on regional level. Other data is much more specific, such as car driving behavior, which is used by Eser et al. (2016) to derive scenarios for the impact of electric mobility on the European power grid. Simões et al. (2015) assess the uncertainty of assumptions on exogenous parameters in their modelling approach and find that socio-economic parameters have the strongest influence, while technological development is of lower importance.

The historical data basis for some of these variables such as demand, prices, GDP, and population are available in good quality for most world regions, as they are collected by national statistical offices. Other data – such as behavioral data on the adoption and usage of appliances or cars – is mostly not available on national level and modelers have to resort to using and up- or downscaling data from case studies. Also, local versions of national data sets are often not available. Therefore, proxy values (such as inhabitants, floor space, or others) have to be taken to downscale national data to the regional or local level (e.g. Schmidt et al., 2010b; Zeyringer et al., 2014).

Projections of future states of the system are associated with high uncertainties which derive from the hard to predict complex dynamics of social systems, a thorough uncertainty analysis on these parameters is therefore of outmost importance. In many cases, IBREM use projections by official institutions that are based on other models quantifying projections of socio-economic

[38] The growth rate of renewable energy technologies depends, among others, on the relative costs in relation to natural resources and on policy decisions. The learning rates for renewable energies are therefore very much interlinked with many other variables in the model of the energy allocation system.

boundary conditions. Those models can be of any type outlined in section 2.3 (i.e. Black Box and White Box and Bottom-Up and Top-Down models) and have, in many cases, a strong focus on modelling economic processes (e.g. Andrle et al., 2015; Cripps et al., 2010). In general, they depict a much more complete picture of the whole economy than energy-only models, i.e. they include feedbacks between all sectors, but lack in sectoral detail. In addition to modelling, scenario processes are often used to describe future system states. Models may consequently be applied to derive quantitative values for system variables. The storylines for the shared socio-economic pathways which are used in the IPCC climate change assessments are, for instance, an outcome of a scenario building process that involves expert elicitation, group consensus, and quantitative modelling (O'Neill et al., 2013).

Interfaces between Submodels

This submodel delivers data to the submodel of the energy allocation system, in particular energy demand derived from macro variables such as GDP and population growth, and regulatory changes (such as environmental and trade policies). The basic assumptions are often co-developed with stakeholders. Therefore, a bi-directional flow of data between stakeholders and this submodel may take place. Consistency between socio-economic and climate (change) scenarios may be necessary and should be addressed.

Endogeneity

Most of the variables in these models are highly endogenous: on the one hand, GDP growth depends on the costs and supply of energy (Berk and Yetkiner, 2014). The future availability of technological options, on the other hand, may depend on the development of these macro-variables. Nevertheless, most renewable energy system modelling approaches assume scenarios for socio-economic variables and introduce them as exogenous, fixed parameters into the models. Endogenously modelling the interactions is possible if either CGE models are part of a IBREM, or if the technological subsystem is depicted with greater detail within a CGE. This has proven to be possible however always at the cost of losing technical detail (Fortes et al., 2013). It very much depends on the concrete research problem and on the time horizon of the analysis if a research project should aim at achieving such a coupling.

3.5. The energy allocation system

The fifth subsystem deals with the allocation of resources to conversion processes and of conversion products to end services to satisfy human demand for energy services. In the hierarchy of IBREM, it is on the top as it integrates the outputs of all other submodels. Also, it is this model where most of actual model developments take place, while IBREM modelers approach the other subsystems from the perspective of users of models and data. On this layer, the allocations of primary resources to conversion processes and consumption are determined. It is therefore also the subsystem where positive and normative approaches are most strongly mingled together (see section 2.6).

Disciplinary Background and Data

The aim of this submodel is to find feasible, efficient, or optimal allocations of energy resources to conversion systems and consumers in the energy system and draws mostly on economic theory. Feasible allocations describe allocations that are *possible* from the point of view of the lower layers, e.g. they do not violate physical or ecological restrictions. Additionally to the feasibility of a certain allocation, the efficiency concept also assesses how the resources should be allocated to minimize inputs and maximize outputs. This concept can be applied if resource prices are uncertain (e.g. in the case of future costs of photovoltaic production) or cannot be observed at all (e.g. in the case of ecosystem services). In general, a large set of (non-dominating) efficient allocations exists and they can be derived by means of multi-objective approaches (e.g. Bilil et al., 2014). If resource prices are known, models can be used to derive *optimal* solutions. Optimality, obviously, depends on a set of assumptions: in particular, prices of resources have to represent full production costs and the willingness to pay of consumers, and some objective function that either determines the total welfare in an economy or a subsystem or just costs of a particular solution has to be found. Many IBREM are cost minimization models, in that case there is no explicit assumption of a welfare function but only the costs of supplying a particular good (such as electricity) are taken into account.

In many cases, optimization models of static or dynamic character are applied in IBREM. They can optimize either just the supply or the demand side by allocating resources to uses, or they can integrate supply and demand in partial-equilibrium models. IBREM do not model the interactions with other economic sectors and are therefore not of the general equilibrium type of models. The role of risk in the allocation process can be addressed by applying approaches that do not assume perfect foresight but that consider the inherent variability in the processes underlying economic allocations. Those may stem e.g. from natural variations in the climate or in the economic system. Optimal decisions under existence of stochastic processes can be treated by applying e.g. options theory (Markowitz, 1952). Depending on the particular kind of problem, multi-stage stochastic programming may be necessary to derive optimal actions under intertemporal portfolio optimization problems (Pflug and Pichler, 2014). If optimization is computationally infeasible, heuristics such as genetic programming or simulated annealing are useful to find near-optimal solutions of the problems.

Apart from the optimization approach, simulation models can be applied in a positive context if utility optimization is not considered being a feasible description of the behavior of economic agents. Agent based modelling (ABM) is applied in economics and in particular in the context of IBREM to better understand systems with imperfect markets, bounded rationality of agents, and network effects of influence (Battiston et al., 2016). ABM is also increasingly used when stakeholder interaction is importance, as different views on agent behavior can be integrated into ABM transparently (Gaube et al., 2009).

The application of IBREM in energy allocation is manifold. Cost estimates of renewable energy systems in cost-minimization scenarios compared to fossil-fuel baseline scenarios reach from negative costs (Ćosić et al., 2012; Lund and Mathiesen, 2009; MacDonald et al., 2016) due to fuel savings to an increase by about 10%. External costs of conventional technologies however are estimated to be higher than additional market costs of renewables (Delucchi and Jacobson, 2011). Local, regional, national, and global studies have been performed to assess the optimal technological mix of renewables for providing low carbon electricity supply (Becker et al., 2015; Brancucci Martínez-Anido et al., 2013; e.g. Ćosić et al., 2012; Jacobson and Delucchi, 2011; Lund and Mathiesen, 2009; MacDonald et al., 2016; Schmidt et al., 2016a). They have reached high technological, temporal, and spatial detail and have assessed a series of options for integration. In principle, a fully renewable electricity supply seems to be possible, even with a high share of intermittent resources, if a large scale expansion in transmission capacities is assumed. Storage plays a rather limited role, however, the optimal size of storage is very much influenced by the availability of transmission (Becker et al., 2014), and by regulatory restrictions in the distribution grid (Schmidt et al., 2016c).

A different line of IBREM looks into the role of renewables in energy markets and the interplay with current regulation. Decreasing spot market prices due to the expansion of renewables are causing preoccupations about security of supply as investments into thermal backup or other flexible capacities may decline. Capacity mechanisms are therefore increasingly implemented to increase security of supply, and models are used to assess consequences (Assili et al., 2008). The future regulatory support for renewables is also in the interest of IBREM modelers. They e.g. assess the design of effective support policies under consideration of technological and resource diversity (May, 2015; Schmidt et al., 2013) and address the issue of declining market values of renewables with increased penetration (Hirth, 2013).

Interfaces between Submodels

This submodel receives data from all other submodels, as it integrates most of the model output of lower subsystems into one single model. Data may be reduced or simplified before being used in the model. It may also be converted to an economic context by assigning costs or utilities to activities. Results of this submodel are important – and sometimes final – results of the IBREM. They can be used in the transdisciplinary process, where economic variables are of high importance when evaluating different (policy) options. Also, stakeholders can have a strong influence on the normative objectives applied in the models. Results of the model are often used to inform policy makers about the cost-efficiency of possible solutions and about the larger consequences in terms of economic impacts.

Endogeneity

Within this submodel, feasible, efficient, or optimal allocations of resources are determined. Depending on which parameters are provided by the lower submodels, the model may endogenize most of the submodels discussed in the previous sections – or it may be very simplistic and use exogenous parameters for most variables instead. With respect to the economic system, partial-equilibrium models do focus on single sectors or even subsectors and do not usually address model interactions with all other economic sectors, such as the impact of higher or lower energy prices on the output of the overall economy.

"*Your assumptions are your windows on the world. Scrub them off every once in a while, or the light won't come in.*"
Alan Alda (Alda, 2008)

4. My own contributions to IBREM: a classification

Within this chapter, I present my own contributions to IBREM, and classify my research according to the criteria developed in chapter 2. The published articles (see Table 3) are grouped according to the models they are based on: COPA, a large-scale, temporally explicit optimization model for the deployment of renewable electricity generation technologies, EnHouseOpt, a family of models to assess the deployment of distributed generation in households, WTWB (Where The Wind Blows), a spatially and temporally explicit optimization model for wind power deployment, and BeWhere, a spatially explicit biomass conversion system model. For each of these modelling approaches, I discuss what they are intended to do, if they follow a White or a Black Box approach, which of the disciplinary subsystems they mainly consider, which transdisciplinary rationale they follow, if they can be considered being normative or positive, and which epistemological paradigm of future production is mainly applied. I also show my contributions to the development of IBREM and the understanding of renewable energy systems. I conclude the chapter by giving an authorship statement for all of my papers.

4.1. Climate based Optimization of renewable Power Allocation

COPA (Climate based Optimization of renewable Power Allocation) is a temporally explicit model for optimizing the deployment of renewable electricity generation technologies, in particular wind, solar PV, and hydro power. It was developed for the case of Brazil. Due to the use of globally available reanalysis data, it can however be easily adapted to other world regions. Instead of assessing short-term integration issues with renewables (such as storage requirements for shifting solar PV from day to night), the model takes a long-term perspective of several decades and assesses the reliability of different portfolios of electricity systems with very high shares of renewables. The reanalysis data was validated against ground measurements from meteorological stations, statistical characteristics of the time series were derived, and optimal portfolios of different generation technologies at different locations were assessed.

Paper I addresses the question how reliability in the Brazilian hydro-thermal system can be increased by adding different portfolios of wind, solar PV, and hydro power to the current system. In particular, it assesses the effect of placing generation technologies at different locations on the overall system performance. Paper II validates wind speed data from the reanalysis data set against meteorological measurements on the ground, develops a methodology to simulate consistent wind power production from wind speeds, and assesses how wind and hydropower are correlated in the long-term. Paper III optimizes the portfolio in the Brazilian system in a long-term perspective. Additionally, uncertainty in the operation of the system is assessed by comparing the costs of a perfect foresight operational model with a model without any foresight.

COPA uses a white box approach with respect to the modelling of the supply-demand balance. The climate data is taken from existing reanalysis projects and can therefore be considered to be in black box mode in the model. Paper II uses a statistical, black box approach for data validation and for assessing the correlation of hydro and wind power production.

The model puts a very strong focus on the climate and the technical conversion system. The energy allocation system is represented by the optimization of the electricity supply portfolio. However, the optimization is not based on economic variables, but on the minimization of fossil thermal power production only, thus emphasizing the role of carbon mitigation. Integration of the different systems is straight-forward, as they are represented in one single model. All of the representations of the systems follow a strongly positivistic-prognostic approach, which also facilities integration of subsystems. In particular, the focus on data validation (comparison of reanalysis data with ground measurements) and the analysis of (past) climate data to estimate likely behavior of an electricity system with high shares of intermittent renewables emphasizes the role of this epistemology. Applying the concept of validity to data sets and performing statistical analysis on the data to derive conclusions about the likely behavior of a system assumes the possibility of the – although limited - discovery of the true state of the world.

The model has positive character as it examines *how* climate systems behave, e.g. by assessing the variability of climatic processes and the correlation between the different processes. It however also has a normative component, as the optimization model is used to discover sources of electricity (and locations of generation) which minimize thermal power production and limit the risk of loss of load. The model does not rely on any particular assumptions about markets, as prices of resources are not considered.

The papers contribute to literature in various ways. First, for the first time long-term reanalysis data sets for wind power and solar PV were developed and applied for the case of Brazil. Also, the reanalysis data sets were validated with respect to their suitability in electricity system models and we found significant differences between different reanalysis products. This is a major, important finding for future integration studies. Also, we have developed an approach that is able to measure the value of high quality weather predictions by showing the gap between a perfect foresight model and a simple simulation model without any projections on future behavior of the system. The results indicate that wind power and solar power do not necessarily have a complementary structure to hydro power in the long-term, but that both sources still very much decrease the long-term risk in the system. Inter-annual and intra-annual variability of solar PV is lowest, it therefore contributes most to a stable output of the system (if hourly and sub-hourly variability can be handled with short-term storage). The optimal portfolio that minimizes thermal power production is different from other world regions due to the high amount of hydro-power production and the temporal particularities of Brazilian winds.

4.2. EnHouseOpt

The optimization models applied in papers IV and V are used to assess the economic incentives for investing into distributed generation and storage on the level of households. Both papers investigate the role of PV and battery storage in reducing revenue streams for Distributed System Operators (DSOs). Paper V is applied to the case of South-Africa and assesses the impact of lower PV and battery costs on the DSO revenue streams. It proposes partly changing the variable consumption fee to a fixed fee to overcome revenue losses. The case of Austria is in the focus of Paper IV and additionally to assessing the adaptation of households to changing electricity and grid tariffs and PV/battery cost structures, the consequences of household adaptation on the combined load on the grid are examined.

Both models are optimization models that follow a white box approach. However, electricity demand in the households is fixed and taken from measured load profiles. They can be considered a black box component therefore. The focus of both papers is on the energy allocation system. The climate system delivers important input data (i.e. solar radiation), while the technical conversion system is also explicitly modelled: switching technologies is an option for households to adapt to different policy environments. The long-term development of costs is exogenously modelled in both papers. Integration of the different system models is easily achieved, as they are based on the same epistemological position (i.e. positivistic-prognostic), and the same modelling approach (white box). In none of the research projects related to the papers, a transdisciplinary process was applied and both papers can be considered to be positivist-prognostic: they assume a clear relationship between household behavior and cost-structure and do not emphasize the role of uncertainty or scenarios.

Both models are normative, as optimization of profits of households is in the focus of modelling. They are used for supporting policy making: adaptation of households to changing policy environments are therefore assumed to take place under the assumption of profit maximization, which may be understood as a positive application of the models, e.g. the abstract of Paper V contains the following sentence: "The budget gap can be reduced by replacing the energy-based tariff with a revenue-neutral fixed network-connection fee implementation of which is particularly effective in reducing incentives to invest in storage."

Paper IV and Paper V use a straight-forward approach to assess policy impacts on household adaptation procedures. Their innovation lies in the application of temporally highly resolved time series and in the exploration of the problem setting: distributed generation is a fairly new issue, in particular in South Africa, and the discussed revenue problems for DSOs will only become highly relevant in future years when PV costs decrease further and deployment of distributed PV (and possibly battery storage) therefore increases significantly. Paper IV additionally models how adaptation of households to changed grid-fees affects their load profiles – and the joint load profile on the distribution grid. We show that incentives for lowering peak grid load for single households not necessarily incentivize an overall low peak load on the grid, as changes in the correlation of household load profiles have to be expected.

4.3. Where the Wind Blows

With the help of the Where the Wind Blows (WTWB) model, we assess the optimal placement of wind turbines in Austria, based on GIS analysis and optimization tools. The model builds on work by Gass et al. (2013), who first developed a GIS model to define suitable areas for wind turbine deployment and, based on the climatic modelling of wind speeds in Austria from the Austrian wind atlas, estimates the economic potential for wind power in Austria. In Paper VI, this approach was enhanced by determining suitable areas together with stakeholders in a participatory modelling process and deriving supply curves for wind power from different scenarios for potential construction areas. In Paper VII, the focus is on electricity markets and the role of subsidy policies in defining incentives for wind turbine developers. We enhanced WTWB by generating timeseries of wind power production, based on meteorological data, and using this data to estimate the value of wind power on electricity spot markets. A fixed feed-in tariff subsidy scheme was subsequently compared to a premium feed-in tariff scheme.

The model follows a white box approach. In Paper VII, we mixed it with a black box approach: an econometric model is used to estimate the influence of wind power production on market prices in the German-Austrian market zone. This parameter is subsequently introduced to the white box optimization model approach. In Paper VI, we apply a strong white box approach, opening the modelling box largely to the stakeholders in the participatory research process.

Papers VI and VII have both components related to the climate and the technical conversion system. Paper VII puts a strong focus on the energy allocation system, assessing incentives for wind turbine developers. Paper VI also addresses the socio-economic system to some extent by using exogenous scenarios on electricity supply. The energy allocation layer is not built on an economic optimization model only, but integrates the views of stakeholders when defining suitable zones for the deployment of wind turbines. Still, supply curves for wind energy are derived from different scenarios of land use: the efficient allocation of turbines to land depending on wind speeds is therefore embedded in the framework of land assessment by stakeholders. Integration of the different systems is easy in paper VII, where white box models are used in a positivist-prognostic way. In Paper VI, integration is more complex as different epistemological paradigms play a role. Integration is achieved by defining an interface between the stakeholder process in the form of land use categories which are judged as suitable or non-suitable by stakeholders. Based on those stated preferences, scenarios are derived on top of the land use categories by means of economic optimization.

Paper VI is based on a research project where an intensive integration of stakeholders was applied. For Paper VI, we used a strong form of interaction to participatively model potentials of wind energy in Austria, following a cognitive and constructive rationale. The views of different groups from public administration, from the electricity sector, from wind turbine investors, environmentalists, and political interest groups on the expansion of wind power in Austria served as an important input to the modelling process and should help to make the final scenarios more robust. In particular, stakeholders defined scenarios for the suitability of areas for the deployment of wind turbines. Within the project a co-learning process was enabled that allowed participants to better understand views of the involved actors. We did not aim at establishing consensus about the final scenarios, the political rationale was therefore less present within the project. The project showed that some of the stakeholders used more time resources in different phases of the project. Therefore, they may have influenced results more than others. In addition, even though consensus positions were not enforced, one stakeholder left the project, as he perceived the project to be a threat to the position of his organization. Projects with a participative component therefore have to deal with new demands and challenges, while creating new structural relationships that do not guarantee power-free negotiations of stakes. No transdisciplinary process was applied in the development of Paper VII.

Paper VII follows clearly a positivist-prognostic approach: we apply optimization to show optimal profits under the implementation of different subsidy schemes. The role of uncertainty is addressed by a sensitivity analysis, but it is not put into the focus of the analysis and the critical realist component is therefore minor. In contrast, Paper VI mixes different epistemologies: the basic wind resource assessment model emphasizes the role of data validation and therefore has a positivist-prognostic character. The range of uncertainty in the results of the economic analysis relates to the critical-realist position. The approach to derive scenarios of land use also has critical-realist aspects, as one of the scenarios (med) is built based on expert opinion and criteria from literature. But there is also an interpretative-constructivist component: the minimum and maximum scenario were developed together with stakeholders, emphasizing the communication between them, and triggering learning effects within the group. Thus it can be considered to be a co-production and construction of knowledge of stakeholders and scientists.

Paper VI is strongly normative: both, the economic supply curve approach as well as the derivation of scenarios together with stakeholders have normative character. The first approach simply minimizes the costs of wind turbine deployment, while the second approach explicitly addresses the normative position of stakeholders with respect to wind energy deployment: they were asked about their personal and organizational preferences with respect to the deployment of wind turbines on different land categories. We aggregated the respective responses and developed the scenarios by grouping of preferences in the min and max scenario. There is a minor positive component related to the estimation of wind energy productivity at different locations. Paper VII also applies a normative approach, i.e. optimization of profits of wind turbine developers. However, it is also used to derive policy conclusions such as:

> *"The numerical results show that under a PFIT scheme, (1) spatial diversification is incentivized, (2) the covariance of wind power production with marginal electricity production costs increases, and (3) the variances of the wind power output and of residual load decrease if wind power deployment attains 10% of total national electricity consumption." (From the abstract of Paper VII)*

Here, the reader may understand results in a positive way, i.e. as the prediction of behavior under different policy schemes. However, the results rely on the profit maximizing optimization models which should not per-se be understood as predicting human behavior. There are other clearly positive components in the paper, e.g. the derivation and validation of wind power production data from meteorological time series.

The main contribution of paper VI lies in advancing how wind energy potentials are derived on the national level. Previous assessments of wind energy potentials for Austria and other regions are mainly based on applying technical and legal criteria from literature and expert opinions to exclude land as potentially useable for wind power production. In contrast, we developed a participatory modelling approach to derive scenarios of land use. In our study, we clearly show that stakeholders on national level have highly different preferences, which cause highly diverging views on potentials for wind energy. This is in contrast to many studies, which assume that mainly actors on the local level build up resistance against wind turbines and that a consensus between actors on the macro level is established easily. Paper VII shows for the first time that the type of chosen subsidy policies creates different economic incentives for different wind locations: remuneration schemes that are partly based on market prices can foster spatial diversification of wind turbines. An analytical model develops the argument. A mixture of black and white box modelling approaches to test the empirical relevance of the effect complements the analytical model.

4.4. BeWhere

Papers VIII and IX are based on BeWhere (Leduc et al., 2015; Schmidt et al., 2012, 2011a, 2011b, 2010a, 2010b), which is a static, spatially explicit model to optimize biomass supply chains in the context of bioenergy applications. There are versions for several countries and regions (e.g. Khatiwada et al., 2016; Natarajan et al., 2014; Wetterlund et al., 2012) however our model runs for the case of Austria and smaller Austrian subregions. The intention is to look into the competition for biomass from agriculture and forestry in the context of increasing the use of biomass for renewable energies. For that reason, the model is integrated with an agricultural land use model and a simplified representation of the forestry sector (Schmidt et al., 2012, 2011b) to be able to estimate consequences of increased uses of biomass in the sectors of primary biomass production. The model was also used in a larger modelling framework (Kirchner et al., 2015) to assess the consequences of climate and policy change on the Austrian agricultural and forestry sectors. Paper VIII examines the impacts of climate and policy change on Austrian agriculture and forestry with a large set of indicators for eco- and economic systems. We use BeWhere to examine different scenarios for bioenergy conversion. Paper IX assesses the consequences of using biomass and other renewables to achieve regional autarky in the electricity and heating sector, i.e. by replacing imports of primary energy by electricity and heat production within the region.

The BeWhere model has a strong White Box modelling approach, as biomass resources in the agricultural and forestry sector, logistics, conversion processes, and demand are explicitly depicted, based on biophysical simulations. However, it also relies on black box estimates of the economic supply functions in the forestry sector by using estimated price elasticities in a reduced coupling approach (as outlined in Schmidt et al. (2011b)). The supply curves from agriculture are based on a White Box modelling approach of the Austrian agricultural sector (Kirchner et al., 2016).

Both, papers VIII and IX, cover all subsystems. Paper VIII reports the results of a very extensive integration effort. All five subsystems are regarded, indicators on the impacts of management choices on the ecosystem are generated and reported, and a macro-economic model evaluates the macro-economic implications. While the integration of disciplinary data along the modelling chain was straight forward for most interfaces, linking the inherently dynamic forestry sector to the static models applied in the other sectors was tricky and not fully achieved. Here, the problem was not a fundamental difference in the epistemological position, but the fact that a static optimization cannot account for the dynamic development of biomass growth in forests, contrary to agriculture where mostly yearly time horizons apply.

While Paper IX does not report on a project with a relevant stakeholder process, in the research process that led to paper VIII stakeholders from public administration were included. They assessed which options are politically realizable, but they also legitimized the research project and results. Elements of the cognitive and the political rationale therefore were strongest in the project. In particular, we discussed with stakeholders from the Ministry of Agriculture, Forestry, Environment and Water Management possible outcomes of the Common Agricultural Policy (CAP) Reform and implemented results of this discussion process into the model. Alternatives to the CAP were developed by the research team, but were acknowledged to be "realistic" by the stakeholders from the ministry. Power relations between researchers and stakeholders were relevant: the ministry is also a funding institution and important collaboration partner for the involved researchers. At one point this relation was used by the ministry to exclude a certain set of scenarios (e.g. carbon capture and storage as mitigation option) from the project. Those relations were reflected within the research group, but were not openly discussed in the final project publication. The example shows that transdisciplinary processes are not necessarily a way of resolving conflicts but that conflicts and power relations between stakeholders and between stakeholders and researchers are reproduced within the research process.

The BeWhere model family applies mainly a positivist-prognostic approach. However, elements of the critical-realist approach are also visible in both papers. First, scenarios play an important role in both papers. Stakeholders well understood results of the models as possible scenarios of future developments and not as predictions of future system states. In paper VIII, we report on the stakeholder process - and how stakeholders influenced the scenario parameters. This gives them an important role in the development of the research, placing them next to researchers. Such an approach cannot be considered to be purely positivist-prognostic.

The models are normative since they apply a cost minimizing approach. However, they are also used to some extent in a positive way, as autonomous adaption to policy interventions and to climate change are assumed to be modelled by cost minimization.

The BeWhere papers contribute to research methodology by integrating White-box and Black-box approaches in an extensive, spatially explicit framework. Econometrically estimated supply curves are calibrated with spatially explicit bottom-up data. BeWhere also contributed to the large modelling compound developed in paper VIII, which is able to depict a series of impacts of policy interventions and climate change on indicators for the economic and the ecosystem. Results consistently show that biofuel production is not a cost-competitive solution in comparison to other uses of biomass for energy conversion. Also, if agricultural land is used for growing biomass for bioenergy applications, woody biomass such as short rotation coppice is economically the most viable source. Additionally, woody biomass on agricultural land has benefits for ecosystems and landscape diversity. At the same moment, paper IX indicates that biomass potentials are quite limited, even for rural regions with low population densities. Autarky in the heating and in the electricity sector is costly and causes a significant substitution of food and feed production, thus reducing food and feed exports to other regions.

4.5. Authorship statement

I classify my contributions to the articles in the five categories Design (DE), Data Preparation (DP), Analysis (AN), Manuscript Draft (DR), and Discussion (DI) (see Table 3). A category is included, if I perceive my contribution to be larger than 33%. I am first author of papers I, II, III, IV, VII, and IX. For those papers, I am mainly responsible for everything from design over data preparation, analysis, draft to discussion. Papers V, VI, and VIII were mainly developed and written by the respective first authors. The model used in paper V was initially designed in a collaboration between the first author Dieter Mayr and me, while the model used in paper VI was initially developed by Viktoria Gass and me. In both cases, I also contributed to the design of the analysis and extensively discussed various versions of the article. Paper VIII is the outcome of a large collaborative project that I managed. I helped designing the study, I actively modelled energy conversion scenarios which were linked to other model outputs, and I extensively discussed various versions of the draft with the first author.

4.6. Final remarks

The comparison of my research papers clearly shows that significant differences exist in basic assumptions about the world in different research projects, even if the very same models are applied. This may make the research process and in particular the communication of results complex. Nevertheless, these differences also allow drawing a richer picture of a particular research problem. Making them explicit to the readers of the research reports and papers, but also to the researchers in the research process is of high relevance to allow for a reflective research process and dissemination. Perceived small shifts in some parameter settings may cause a major shift in the underlying assumptions of the modelling framework: as papers VIII and IX and papers VI and VII show, similar models may be used in a very different context, generating different kinds of results in the research process. This, at least, should be communicated transparently in any integrated modelling exercise.

	Publication	*Model*	*White vs. Black box*	*Subsystems involved*	*Trans-disciplinary rationale*	*Positive / normative approach*	*Epistemological approach*	*Authorship Statement*
I	The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal electricity system *Schmidt, J., Cancella, R., Pereira Jr., A.O.*	*COPA*	*White Box*	*Climate, Technical conversion (minor), Energy allocation*	-	*Normative*	*Positivist-prognostic*	DE, DP, AN, DR, DI
II	The effect of windpower on long-term variability of combined hydro-wind resources: the case of Brazil. *Schmidt, J., Cancella, R., Pereira Jr., A.O.*	*COPA*	*Black Box*	*Climate, Technical conversion (minor)*	-	*Positive*	*Positivist-prognostic*	DE, DP, AN, DR, DI
III	An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil. *Schmidt, J., Cancella, R., Pereira Jr., A.O.*	*COPA*	*White Box*	*Climate, Technical conversion (minor), Energy allocation*	-	*Normative*	*Positivist-prognostic*	DE, DP, AN, DR, DI
IV	A reduction of distribution grid fees by combined PV and battery systems under different regulatory schemes *Schmidt, J., Wehrle, S., Rezania, R.*	*EnHouseOpt*	*White Box*	*Climate, Technical conversion, Energy allocation*	-	*Normative*	*Positivist-prognostic*	DE, DP, AN, DR, DI
V	The impact of residential photovoltaic power on electricity sales revenues in Cape Town, South Africa. *Mayr, D., Schmid, E., Trollip, H., Zeyringer, M., Schmidt, J.*	*EnHouseOpt*	*White Box*	*Climate, Technical conversion, Energy allocation*	-	*Normative*	*Positivist-prognostic*	DE, AN, DI
VI	Assessing scenarios of socially acceptable wind energy potentials for Austria - a participatory modelling approach. *Höltinger, S., Salak, B., Schauppenlehner, T., Scherhaufer, P., Schmidt, J.*	*WTWB*	*White Box*	*Climate, Ecosystem (minor), Technical conversion (minor), Socio-economic, Energy allocation*	*Cognitive Constructive*	*Normative*	*Interpretative-constructivist*	DE, AN, DI
VII	Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines. *Schmidt, J., Lehecka, G., Gass, V. and Schmid, E.*	*WTWB*	*White Box/ Black Box*	*Climate, Technical conversion (minor), Energy allocation*	-	*Positive*	*Positivist-prognostic*	DE, DP, AN, DR, DI
VIII	Ecosystem services and economic development in Austrian agricultural landscapes - The impact of policy and climate change scenarios on trade-offs and synergies. *Kirchner, M., Schmidt, J., et al.*	*BeWhere*	*White Box*	*Climate, Ecosystem, Technical conversion, Socio-economic, Energy allocation*	*Cognitive Political*	*Normative*	*Critical-Realist*	DE, AN, DI
IX	Regional energy autarky: potentials, costs and consequences for an Austrian region. *Schmidt, J., Schönhart, M., Biberacher, M., Guggenberger, T., Hausl, S., Kalt, G., Leduc, S., Schardinger, I., Schmid, E.*	*BeWhere*	*White Box*	*Climate, Ecosystem, Technical conversion, Socio-economic, Energy allocation*	-	*Normative*	*Positive-prognostic*	DE, DP, AN, DR, DI

Table 3: A classification of a selection of my own research articles. Papers with the same shading are based on the same modelling family.

"You can't control the past. You can't control the future. You can't control the present. You can only control the TV. Remotely."
God @TheTweetOfGod (9th of July, 2012)

5. A renewable energy future: a research agenda

After classifying my own research, I close this treatise by identifying important open research problems in the field of IBREM. They are loosely related to the subsystems discussed in chapter 3: in the climate layer, the assessment of extremes in energy systems with high shares of renewables is currently at a starting point. However, when discussing future fully renewable energy systems, those events are of major importance as they define the need for long-term backup capacities. At the ecosystem layer, the integration of the concept of ecosystem services or the safe operating space concept into IBREM is a huge methodological challenge that should be considered a highly important line of research, as the impact of renewables on ecosystems is often neglected in modelling studies. At the technical conversion & transportation layer, the uncertainty in future technological development makes definition of robust technological portfolios complex. However, identifying the main drivers of those portfolios and defining portfolios based on robust knowledge is of importance. At the energy allocation layer, the representation of human behavior is simplified in most renewable energy models. The impact of different behavioral representations on the outcome of IBREM is a highly interesting and relevant line of research. Integrating knowledge of different disciplines and actor perspectives is an increasingly important requirement for IBREM as discussed in chapter 2. Addressing the challenges of knowledge integration is therefore another interesting line of future research.

Assessing extreme production events in energy systems with high shares of renewables

A renewable energy system with high shares of intermittent electricity production from wind power, PV and hydro power relies heavily on underlying meteorological processes. The climatic dynamics and how they relate to an energy system with high shares of renewables have been extensively researched in the last years, e.g. for Brazil (Schmidt et al., 2016a, 2016b), Europe (Rodriguez et al., 2015), China (Huber and Weissbart, 2015), the US (Becker et al., 2014), Western US (Mileva et al., 2013), Denmark (Andresen et al., 2015), Australia (Elliston et al., 2012), and New Zealand (Mason et al., 2010) indicating optimal mixes of PV and wind and optimal extensions of storage systems and the electricity grid. From these studies it is well understood that short-term variability (e.g. the day-night shift in PV) can be handled by limited amounts of energy storage capacity, curtailing, and spatial and technological diversification[39].

Up to the moment, however, there is very limited research on the role of extreme events in the climate system which pose serious risks to energy systems with high shares of renewables (Jensen and Greiner, 2014). In particular, studies explicitly exclude the long tails of distributions (focusing on the 0.99 quantile of events, e.g. Rodriguez et al. (2015)) or focus on single or a few years only (Elliston et al., 2012) to be better able to handle the complexity of the studied systems. However, extended periods of combined low wind, low irradiation, and low precipitation in periods of high demand impose very high risks of uncovered load on those systems, if sufficient backup capacities or storage systems are not available (Bollen and Hassan, 2011). As those events may be rare, the study of long periods of climatic data is necessary.

[39] Demand side management and fossil fuel backup may additionally contribute to stabilizing the grid.

Extreme events in the meteorological system have been investigated independently of renewable energy production (e.g. (Larsén and Mann, 2009)). However, the focus is on different types of events (such as very high wind speeds instead of extended periods of low winds), and they do not include an assessment of the interrelation of variables (such as precipitation, wind, and irradiation). Energy researchers have lately focused on assessing extreme events of particular meteorological variables, such as low and high wind periods for GB (Cannon et al., 2015), and low and high solar radiation for Australia (Elliston et al., 2015). Again, there is a lack of research into the role of interdependency of meteorological processes over different time and spatial scales (François et al., 2014), with the exception of some studies that assess the relation of wind and hydro power (Denault et al., 2009; Schmidt et al., 2016b). Extreme events can be handled by spatial and technological diversification of production technologies: as solar radiation, wind speeds, and hydropower are not perfectly correlated, a smoothening of extreme events occurs. Additionally, large backup or energy storage capacities can be used for mitigating the risks of low production events. In particular the role of biomass within a renewable energy framework can be significant, as it is not an intermittent source of renewable energy and hence it can help to buffer extreme events of low generation by other renewables such as wind-, hydropower and PV. An assessment of the frequency, length, and importance of low-production events in energy systems with high shares of wind-, hydropower, and PV, the variability in biomass production, and the role of long-term backup technologies such as biomass is therefore of high importance and is suggested as future line of research.

Representing ecosystem impacts in IBREM

IBREM mostly do not focus on assessing indicators of renewable energy impact on ecosystems apart from greenhouse gas emissions and other air emissions. Little is therefore known about the ecological impacts of a large scale deployment of non-biomass renewable energy technologies on the system level[40]. While the global land demand in 100% renewable scenarios is estimated to be in-between 1% and 2% of global land area (Jacobson and Delucchi, 2011), the land may be located in highly sensitive areas. Integrated modelling exercises in agriculture and forestry have a much longer tradition in assessing those impacts (e.g. Schönhart et al. (2011), Leclère et al. (2013), Kirchner et al. (2015)), and the impacts of using bioenergy on ecosystems is therefore better understood. Applying those methods to IBREM may be of high interest, although some of the pre-conditions (i.e. long-term field studies on the impact of technologies on ecosystem indicators) may not be fulfilled to allow for an exhaustive assessment. A mixture of case studies that link measurements of renewable energy technologies on ecosystem indicators in field studies with modelling exercises (such as in Kirchner et al. (2015) for agriculture) and of the exploration of large, existing databases e.g. on species richness in combination with land use, may therefore be a way forward to better understand the relationship between energy systems and the ecosystem. Research along the lines of either ecosystem services or the safe operating space approaches is recommended to align IBREM results with those of other sectoral modelling approaches.

Deriving robust technological portfolios

Incorporating the role of technological change in IBREM is of high importance. Some technologies, such as PV (Bolinger and Weaver, 2014) and batteries (Nykvist and Nilsson, 2015), have shown very large cost reductions in very short periods. An endogenous representation of those dynamics should be part of any IBREM that assesses long-term competitiveness of energy

[40] For individual technologies, in particular hydropower and windpower, case studie evaluations are available, e.g. Anderson et al. (2006) and de Lucas et al. (2012).

technologies. Anyhow, future technological developments remain highly uncertain – major game changers such as nuclear fusion are still no technical alternative but may become so in the coming 50 years (Kite and Richardson, 2015), while the future of PV which experienced significant cost reductions in recent years is highly uncertain and future cost estimates show high variations, putting PV in the range of the cheapest to the most expensive of all major power generation technologies in 2050 (Curtright et al., 2008; Mayer et al., 2015; Verdolini et al., 2015). Those uncertainties are only going to be reduced down the road, but explicitly addressing them and showing the sensitivity of models to assumptions on technical parameters seems to be of highest importance in renewable energy models. A different approach of addressing the uncertainties may be to determine pareto-efficient frontiers between different technologies, under consideration of production conditions such as climate, and estimate optimal portfolios of technologies based on these pareto-efficient frontiers. Thus, stable parameter regions can be identified where changes in the costs of technologies are not going to change the overall optimal portfolio. Future research should assess how to reduce complexity of deriving the efficient frontiers for the assessment of a large set of different technological combinations.

IBREM and complex systems

Research in behavioral economics has shown that the assumption that only fully rational, utility maximizing market participants populate markets may be invalid (Thaler, 2000). Extensions to the standard model that handle complex human behavior are difficult to integrate methodologically in the optimization models applied in the field. Additionally, the concept of equilibria, such as the equilibrium of a market that clears at marginal costs and benefit, is questioned. Equilibria were introduced as a simplification necessary to derive analytical (and computational) results for the models introduced in neo-classical economics but are not necessarily a valid description of real world dynamics (Arthur, 1999). A newly forming field in economics therefore uses a different approach: the notion of complexity theory is introduced into the economic discipline. Within this paradigm, the economy is understood as a computational tool instead of being a system that continuously converges to equilibrium states (Arthur, 2013, 1999). Uncertainty and associated heuristics in decision making instead of optimal behavior of agents and the role of technology in an evolving economy are at the core of this theoretical approach. Agent based modelling is one possible methodological option that allows to deal with the complex systems approach and is increasingly applied in the field of energy system modelling (Bale et al., 2015). Incorporating the theory of complexity systems and the methodological tool of agented based modelling into IBREMs may allow answering important questions with respect to the evolution of the renewable energy system. For instance, technology adoption and diffusion, lock-in effects of technological choices, booms and busts in the deployment of new technologies, and the effect of market power on electricity markets may be studied with IBREMs that switch from pure optimization and the associated neo-classical paradigm to complex system theory.

Integrating knowledge

IBREM are a tool for integrating knowledge – from different disciplines and different perspectives, including ones from outside of the research world. Enhancing the integration tools on a technical level, i.e. increasing inter-operability of the applied quantitative models is one important line of future research. This may involve adopting open source procedures for developing software by sharing models and data with the community, to improve verification and validation of the models. A better understanding of the different nature of knowledge within IBREM is also of high importance to better achieving integration. Knowledge integration has to be made possible by the organization of inter- and transdisciplinary research: technical tools, and data standards can facilitate the interaction of researchers and stakeholders, and a better theoretical understanding of the relation of different disciplines to each other can help to outline potential conflict lines. Knowledge integration among disciplines and stakeholders however is principally made possible by iterative learning processes, which repeatedly allow the communication between all involved actors (Kragt et al., 2013). The traditional institutional setting of research, i.e. along institutes, departments, and disciplinary research funding, therefore has to shift to organizational forms that allow for an increased collaboration between disciplines and actors from outside of research. Knowledge integration is therefore a concept that needs more than researchers: researchers, administration of research facilities, and the users of research results have to be involved in the update of the research infrastructure to better allow for knowledge integration.

Significant research has to be conducted in the field of renewable energies and IBREM have to keep pace with rapidly evolving technologies, policies, and environmental and social boundary conditions. The question if the world should go renewable is going to be a highly controversial one for the coming decades. The possibility of achieving such a future is there – and there is a lot we have to learn to be able to construct it.

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Part B: Appended Papers

Article I

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The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal electricity system.

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The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal power system

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A B S T R A C T

Brazilian electricity production is subject to considerable hydrological risks due to a large share of hydropower production. A long drought has caused a crisis in the electricity system in 2014 implying high operational costs and a high amount of carbon-intensive power production. A further expansion of the Brazilian electricity system is therefore necessary to guarantee security of supply, in particular when considering the projected growth in demand. We assess how high shares of renewable electricity production can be maintained in the Brazilian system, while reducing hydrological risks. We focus on a long-term perspective and simulate 36 years of renewable power production from meteorological data, assessing the statistical characteristics of different portfolios and, using an optimization model, balancing monthly supply and demand in different technological portfolios. The uncertainty in the operation of that portfolio is compared to a hydro-only scenario. Results indicate that adding both, solar PV and wind to the system, will decrease the need for thermal power backup and the risk of loss of load, as total variability of renewable supply decreases significantly in comparison to a scenario that adds only hydropower to the system. Solar PV has a slight advantage over wind power in decreasing supply risks.

1. Introduction

Brazilian electricity production is subject to considerable hydrological risks due to a large share of production from hydropower plants [1]. The variability of hydrological resources, which has been related to the El Niño Southern Oscillation, is high, in particular in the Northeast of Brazil [2]. Droughts have been one of the causes of a crisis in the electricity system in 2001 and as recently as in 2014[1]: hydropower production fell to 90% of the average 2011–2013 production in 2014, although hydro reservoir levels in December 2014 have even fallen to 45% of the average of the Decembers in 2011–2013 [4]. As a consequence, more than double of thermal power generation had to be dispatched in 2014 compared to the average of 2011–2013 [4], implying high operational costs and high greenhouse gas emissions. A further expansion of the Brazilian electricity system is therefore necessary, in particular when considering a significant growth in projected future demand [5]. Brazil has a wide range of options for renewable energies, ranging from wind energy with highly productive locations in the North–East of the country to hydropower production in the North of Brazil, and solar PV all over the country. All of these sources cannot be dispatched on demand. This is also the case for hydropower production in the North of Brazil, where new reservoirs are not going to be built due to environmental and social restrictions [6]. They are operated as run-of-the-river plants therefore.

The purpose of our study is to assess how those different resource potentials can be optimally combined to maintain high shares of renewable electricity production in the Brazilian system, while, at the same moment, reducing hydrological risks – and thus the risk of high operational costs and high greenhouse gas emissions. We therefore focus on the long-term dynamic behaviour of a combined hydro-wind-solar system, and less on the technical details of the system. For that purpose, we simulate long-time timeseries of solar PV, wind, and hydropower production, using data from global reanalysis projects and local observations on water run-off at the most important hydropower plants. We assess how

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[1] It is stressed in the literature that the crisis in 2001 is wrongly attributed to the low rainfalls, and that the real reason were failures in regulation, as droughts were foreseeable [3]. Still, the planning of the operation of any electricity system dominated by hydropower is more complex when facing high hydrological variability.

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the long-term flexibility of the system evolves when considering different forms of renewable electricity sources, in particular we look into how different shares of renewable electricity sources affect hydrological risks in the system. We do so by generating 100 climatic scenarios for a period of 36 years and running a perfect foresight optimization model and a second „dumb“ simulation model to assess the range of uncertainty implied by (1) uncertain climatic conditions and (2) planning and operational tools used.

For the case of Brazil, a related study has been conducted using daily simulated timeseries data from the same data source [7]. While the approach is similar, the applied simulation of timeseries lacks for controlling for auto-correlation, which may make the distribution of extreme events in the generated timeseries less reliable, and there is no comparison of scenarios of different shares of renewables, thus not allowing understanding which technologies affect system availability most. Becker et al. [8] have applied a similar methodological approach as we do, i.e. they simulated renewable energies from long-term reanalysis data and used those data-sets in stripped down energy system models for the case of the United States. They assessed integration of wind and solar PV into the US system and showed that a mix of 80% windpower and 20% PV would minimize backup capacities. Huber and Weissbart [9] have assessed the future potential of renewables for the case of China, also applying reanalysis data. They use an hourly model and show that the optimal mix of wind and PV is about 70:30. However, both China and the US generation portfolio do not rely on such extensive hydropower capacities as Brazil and large-scale long-term water storage is therefore not available. Also, the time profile of renewable generation in China and the US are different from the Brazilian one. Our analysis is therefore the first to extensively assess the role of different shares of wind and PV power in a (sub)-tropical country with high shares of hydropower production.

We first put our long-term modelling approach in the context of renewable integration studies in the following section, explain our modelling approach and data subsequently in Section 3 and present results in Section 4. The paper closes with a discussion of results and some major conclusions drawn from the modelling exercise in Section 5.

2. Time horizons for the modelling of renewable integration

The integration of renewables is studied, in many cases, with high resolution hourly datasets – even if longer time periods are assessed. However, such an approach has two serious drawbacks: first, computational complexity of modelling increases and second and more importantly, a true understanding of the long-term behaviour of underlying energy generating (i.e. meteorological) processes may not be reached by those approaches. For the operation of a complex hydropowered system with extreme drought events which is buffered by hydrostorage, however, the long-term perspective is of high importance as the operation of the storage is complex and extreme events on the horizon of two or three years in the future should be considered in today's decision making [10]. We argue that in such a case, i.e. integration of intermittent renewables into a large hydrothermal system with large storage, an approach that separates the short and long-term perspective may be useful to better understand the characteristics and the value of different renewables to the system. Expensive flexibility options such as bidirectional storage (in contrast to hydrostorage) and demand side management can only provide flexibility on the very short-term due to economics: as Rathgeber et al. [11] have shown, the number of cycles of a storage device determines its costs to the system. Annual cycles of only 1 or 2 increase costs by a factor of up to 500 in comparison to a device that is used almost daily. Similar conclusions can be drawn for capital based demand side management options or integration options beyond the electricity sector [12] which are frequently proposed to lower integration costs. The installation of those flexibility options can be studied for typical situations and days throughout the seasonal cycle of resource availability, as there are economically no feasible option to deal with rare extreme events. Long lasting extreme events with periods of low rainfall, low windpower generation, and low solar radiation, however, pose a serious threat to energy systems with large shares of renewables. Determining the likeliness of those events can be better addressed with a modelling approach that focuses on modelling long-term data with less focus on the hourly or daily variations. For the case of Brazil, managing those extreme events is possible due to the availability of large, cheap hydro-storage, which is an economically feasible option for balancing extreme events even if it is used only rarely.

Obviously, short-term and long-term optimization of the system may come to different conclusions in terms of optimal portfolios. However, the two perspectives can be brought together if sets of economically similar solutions are produced (which is possible due to low computational complexity), and fit together.

3. Data & methods

Between 69% and 84% of total electricity production came from hydropower plants in the period 2004–2013 in Brazil. Huge reservoirs are used to balance seasonal and inter-annual variability of precipitation. Therefore, the planning of operation of hydropower plants needs a long-term approach to define the levels of reservoirs, as an overuse of reservoir water would increase the risk of loss of load in the future, while underusing reservoirs would increase the probability of not using future water supplies [10]. In Brazil, the long-term planning of operation of the electrical system is achieved with the dynamic stochastic optimization model NEWAVE that operates on a monthly basis for the four Brazilian subsystems SE (South–East), S (South), NE (North–East) and N (North) [13]. The model looks ahead up to 5 years. The monthly dispatch schedule derived by NEWAVE is disaggregated by other models to derive feasible hourly dispatch.

The model minimizes expected operational costs, i.e. fuel costs of thermal power production. Cascading hydropower production in combination with huge reservoirs – a total storage volume of 212 TWh is available in Brazil – is represented by an equivalent reservoir approach for each subsystem. NEWAVE uses a timeseries model for representing hydrological resources, generated from past observations of inflows into hydropower plants.

Instead of NEWAVE, we developed our own modelling approach for several reasons: first, NEWAVE is a very complex and time consuming model that does not allow to be run for several scenarios and very long periods of simulation time. Also, it does not consider electricity production from new renewables, i.e. wind and PV. In NEWAVE, wind production is currently deterministically included by calculating the residual load, i.e. demand minus wind production, for one scenario of wind power production. We, however, aim at including the uncertainty associated with wind and solar PV production explicitly in our model and thus create our own timeseries model that takes into account hydro inflows, wind speeds and solar radiation. A second reason is that we do not apply a particular stochastic model as computational complexity is huge. We rather show the range of possible results of operational models: for that purpose, operation in the system is calculated with a perfect-foresight optimization model, i.e. the best possible case, and with a „dumb“ simulation model that uses simple operational rules for operating the storage, i.e. the worst possible case with no forecast of future meteorological conditions at all. We further simplify the NEWAVE approach by aggregating the four subsystems into one, effectively not taking into account transmission limits between the systems.

3.1. Input data

The most important input data to our operational models consists of simulated data of wind power, solar PV and hydropower production. Wind power is simulated for the four most promising wind power producing states in Brazil, Bahia (BAw), Ceará (CEw), Rio Grande do Norte (RNw), and Rio Grande do Sul (RSw). Schmidt et al. [14] describes in detail how the long-term timeseries of wind speeds for the four states are generated. We use data from the ECMWF reanalysis project [15] and validate the data against ground measurements of wind speeds [14] provided by the Brazilian meteorological office INMET [16]. A similar approach is used to produce solar radiation timeseries for all Brazilian states with the exception of Acre, Alagoas and Sergipe as no ground measurements were available for them. The solar locations are named by an abbreviation of the respective federal state they are located in. A detailed list of all stations including their abbreviations and a comparison of the solar irradiation data with ground observations is shown in the appendix in Table A1. In that way, a consistent timeseries of four daily measurements for the two variables wind speed and solar irradiation can be constructed for the period 1979–2014. The meteorological data is subsequently used in technical models of wind turbines and PV models to estimate power output and is afterwards aggregated to monthly data.

Monthly data of average inflows into different hydropower dams are available at [17] for the period 1931–2014. In a simple technical model, we produce timeseries of hydropower production as if the hydropower resources were used in run-of-the-river plants, using technical details of the hydro dams installed in Brazil. We aggregate production of all existing hydropower plants in Brazil (BR), and also calculate hydropower production for the NO (North region only), as future expansion of hydroelectricity is going to be almost exclusively taking place there. All locations are shown in a map in Fig. 1.

As we aim at assessing uncertainty of results, the single set of timeseries that we derive from historical observations is not sufficient. To be able to generate plausible renewable production data from past meteorological observations, we therefore created a timeseries model that simulates the availability of wind power resources, i.e. wind speeds, solar PV resources, i.e. solar radiation, and inflows into hydro power plants taking into account the correlation between those resources and between different regions.

In total, we therefore deal with 30 timeseries (2 for hydropower production, 4 for windpower and 24 for solar PV) of monthly temporal resolution (index m) and 36 years, i.e. 432 months, length. For each timeseries (index i), we estimate the following timeseries model:

$$x_{m,i} = \sum_{j=1}^{12} \alpha_j dum_{j,m} + \beta x_{m-1,i} + r_{m,i}$$

The model adjusts for seasonal differences using dummy variables and additionally considers auto-correlation in the residuals of the seasonal adjustment by including a lagged variable. The residuals are stored in the matrix R with dimension (432, 30). The residuals of the timeseries of total hydropower production and hydropower production in the North are strongly positively correlated, while residuals of total hydropower production and solar radiation is slightly negatively correlated for some of the 24 states, and the residuals are not correlated for other combinations. These correlations should be maintained in future simulations of the timeseries.

For the simulation of timeseries, we therefore bootstrap one row of the matrix R, corresponding to the respective simulated month. i.e. for simulating a January, a random row from all rows in R corresponding to a January is drawn. This results in a matrix R_new of dimension (432, 30). Afterwards, we use R_new and the coefficients of the timeseries models for simulation:

$$\begin{aligned} &if (m < 12): && x_{m,i} = \alpha_{m \ mod \ 12} + \beta x_{m-1,i} \\ &if (m > 12 \ and \ m \leq 444: && x_{m,i} = \alpha_{m \ mod \ 12} + \beta x_{m-1,i} + R\_new_{m,i} \end{aligned}$$

Subsequently, we discard the 12 first elements of $x_{m,i}$ as they are only used to seed the timeseries simulation. We do not estimate a trend as no consistent relationship between linear trends and the timeseries could be found, i.e. some timeseries had statistically significant positive trends, others had statistically significant negative-trends and some timeseries had no significant trend at all. Statistically significant trends were however of no practical relevance, i.e. increases or decreases over years were very low.

3.2. Operational models

We derive two different models for planning of storage and dispatch of power plants: first, a perfect-foresight optimization model that optimizes storage operation under full information, i.e. we assume that meteorological conditions are known for the whole planning period. This is the best possible case, no other dispatch schedule can achieve a lower combination of thermal power dispatch and loss-of-load events. Additionally, a simulation model is used to assess a situation without any foresight: storage operation is only based on the current storage-level and on current meteorological conditions. This is the worst possible case. Any real planning and operational model will achieve results in-between those two options. Our results therefore inform on how much planning tools can contribute in decreasing long-term operational costs.

3.3. Optimization model

We have developed an optimization model that manages the hydro reservoirs, and thermal dispatch, considering the given timeseries of renewable energy production. The model uses the monthly timeseries of power production (as described in the previous section) and minimizes the production in thermal power plants and the loss-of-load events. Demand is considered to be doubled from the level of 2013. We optimize the system for a period of 36 years with different meteorological conditions in each year, maintaining demand constant.

The objective function is the simple sum of thermal power production x_t^t during the whole time period and the loss of load which is valued at 10 times the cost of thermal power production (the officially used estimate of 3.150R$ (around 820US$) [18] is around 10–15 times thermal generation cost, depending on the considered marginal thermal technology):

$$\min \sum_t x_t^t + 10 \sum_t x_t^{lol} \quad (1)$$

The optimization program is restricted by an equation balancing demand d_t with the immediate use of inflows for production in existing hydropower plants with reservoirs x_t^{hr}, of wind and pv power production at all available locations $\sum_l (w_{l,t} + p_{l,t})$, of run-of-the-river hydropower production at new locations h_t^{h-new}, of thermal power production x_t^t, of hydropower production using

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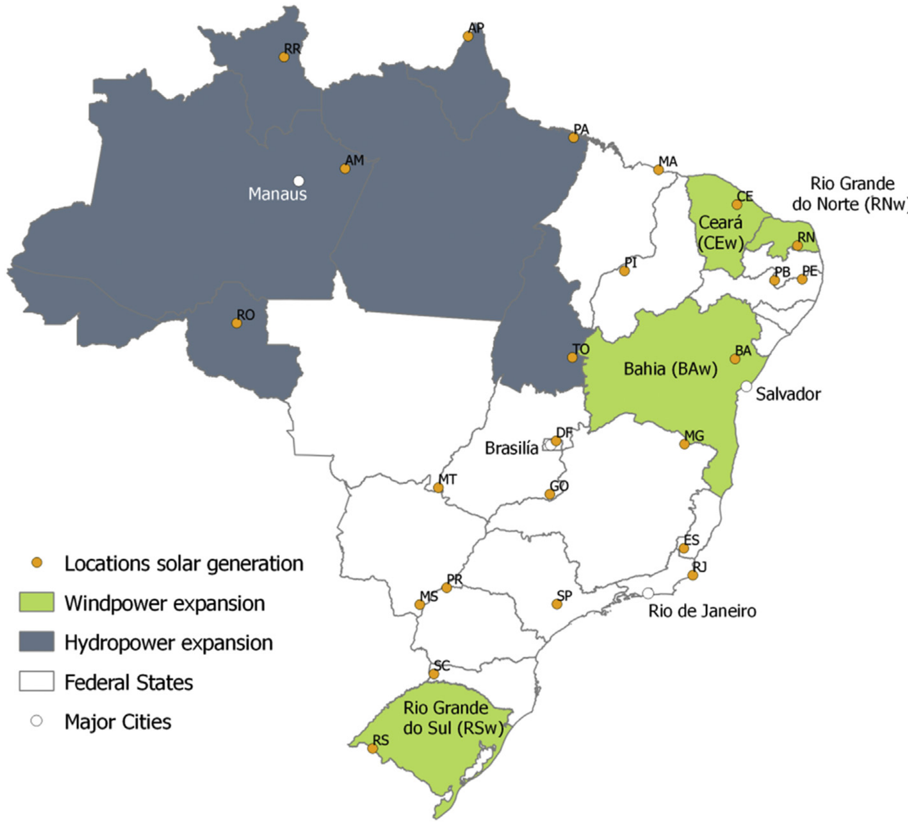

Fig. 1. Locations of expansion of renewable power generation.

water stored in reservoirs x_t^{st-}, of curtailing of power production x_t^{cur}, which occurs if renewable power production is too high to be used or stored x_t^{cur}, and of loss-of-load events x_t^{lol}:

$$d_t = x_t^{hr} + \sum_l \left(w_{l,t} + p_{l,t}\right) + h_t^{h\_new} + x_t^t + x_t^{st-} - x_t^{cur} + x_t^{lol}, \ \forall t \tag{2}$$

Hydropower production from plants with reservoir x_t^{hr} and water withhold in reservoirs x_t^{st+} have to be equal to the availability of inflows into the reservoirs h_t^r at that moment:

$$x_t^{hr} + x_t^{st+} = h_t^r, \ \forall t \tag{3}$$

New hydropower production is assumed to have no storage capacities. The level of reservoirs of hydropower plants $x_{t+1}^{st\_lev}$ is determined by the level in the previous period $x_t^{st\_lev}$, by inflows into the storage x_t^{st+} times storage efficiency ρ and by outflows from storage x_t^{st-}:

$$x_{t+1}^{st\_lev} = x_t^{st\_lev} + \rho x_t^{st+} - x_t^{st-}, \ \forall t \tag{4}$$

The storage level is restricted by the maximum amount of installed storage in the system s^{max}:

$$x_t^{st\_lev} \le s^{max} \tag{5}$$

Thermal dispatch is limited by the maximum of the installed capacity t^{max} which is a predefined parameter:

$$x_t^t \le t^{max} \tag{6}$$

3.4. Simulation model

The simulation model gives an upper bound estimate for thermal power production and loss-of-load in the real system. It does not feature any foresight capability and uses the stored water only taking into account current levels of storage and current meteorological conditions. There is one parameter, the *threshold* level, that indicates at which state of the reservoirs thermal power production is dispatched. The lower *threshold*, the higher the risk of loss of load. We assume a value of 60%.

The simulation model first compares availability of renewable resources (hydropower h_t^r with reservoirs and hydropower without reservoirs h_t, wind power $w_{l,t}$, and PV $p_{l,t}$) with demand d_t. The current surplus s_t is calculated by the following equation:

$$s_t = d_t - \left(h_t^r + h_t + \sum_l \left(w_{l,t} + p_{l,t}\right)\right) \tag{7}$$

The five most important cases are shown in Fig. 2. In case 1, storage is either completely full or almost full, i.e. if $>s^{max} - x_t^{st\_lev}$, $\rho\min(s^{max} - x_t^{st_{lev}}, h_t^r)$ is stored and $s_t - \min(s^{max} - x_t^{st_{lev}}, h_t^r)$ is curtailed. In case 2, $s_t>0$, $s_t<h_t^r$ and $s_t < s^{max} - x_t^{st\_lev}$. Therefore the storage level is changed to $x_{t+1}^{st\_lev} = x_t^{st\_lev} + s_t$, i.e the hydro-reservoir, is increased by ρs_t.

If $s_t<0$, there is a lack of intermittent production capacities. In case 3, $x_t^{st\_lev} > threshold$, and hydro-reservoirs are therefore used for production $x_t^{st-} = -1 * s_t$. The storage level is decreased by s_t, i.e. $x_{t+1}^{st\_lev} = x_t^{st\_lev} + s_t$. In case 4, $x_t^{st\_lev} < threshold$. Thermal power plants are therefore dispatched. In case 5, thermal power plant capacities are not sufficient to cover demand, therefore a LOL (loss-

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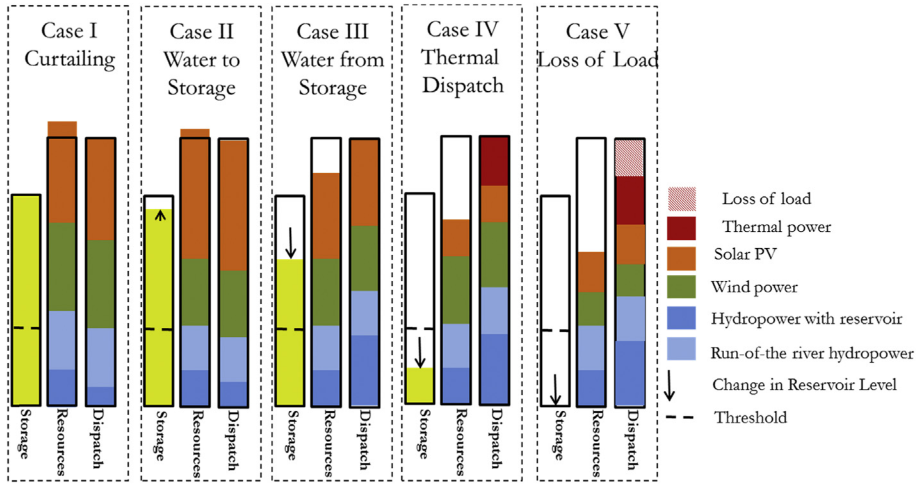

Fig. 2. A scheme of the five possible cases in the simulation model.

of-load event) occurs to match the difference of $LOL = s_t - x_t^t - x_t^{st-}$.

3.5. Scenarios

The monthly load on the public grid is calculated from hourly load data in the year 2013, thus containing losses from electricity transmission and distribution [19]. We double the load, which will occur around 2030 if demand grows at 4.2% annually, which is estimated in the official government expansion plan from the year 2013 [5]. In total, we simulate a period of 36 years to account for different annual climate meteorological conditions. However, demand is kept constant between the years as we are interested in the effect of meteorological events on stable operation of the system – and not into optimizing the expansion plan for renewables.

We assume that the currently installed hydro and thermal power capacity is available throughout the whole simulation period. Hydropower reservoirs are also kept constant, i.e. the storage capacity in the system does not increase. This is a realistic assumption, as most of the additional hydropower potential is located in North Brazil where installing reservoirs is impossible due to social and environmental restrictions [1]. The additional renewable capacities (i.e. hydropower in North Brazil, wind and PV) that are assumed to be installed are chosen so that total power output matches demand when summing up over the whole period. Due to differences in the temporal profile in the different renewable energy sources, however, backup production from thermal power production and hydropower is still necessary and loss of load events may occur. The sum of thermal power production and loss of load events is, due to the equivalence of additional demand and renewable supply, equal to the sum of curtailed renewable energy production. To determine the impact of different sources of renewable electricity – and of different locations – on the long-term performance of the system, we generate 35 scenarios. 29 of the scenarios assess the individual performance of technologies at all locations, i.e. we assume that the complete additional demand is supplied by wind power in 4 different federal states (W1–W4), solar PV at 24 locations (S1–S24), and hydropower in the North region H1 (see Table 1 and Fig. 1 for details on locations). We also generate a scenario, where windpower in all 4 regions equally contributes to power output (M1), one scenario where solar PV at all 24 locations equally contributes to power output (M2), one scenario where 50% of wind and solar PV are mixed (M3), and two scenarios where wind and solar PV are mixed with a 50% share of hydro, respectively. In scenario M6, wind, solar PV, and hydropower equally contribute to power output.

To assess the performance of the different technological mixes in different climate conditions, we first simulate 100 scenarios of wind, PV, and hydropower timeseries with a length of 432 months from the statistical model explained in Section 3.1. Each of the technological scenarios shown in Table 1 is subsequently run with all 100 different timeseries. All 3500 scenarios (i.e. 35 technological mixes times 100 climate scenarios) are assessed with both, the optimization as well as the simulation model (see Section 3.2 for details). In the results section, we are therefore able to show an uncertainty range for our results, depending on the meteorological scenario.

4. Results

4.1. Statistical and temporal characteristics of renewable energy sources

We first show the boxplots of renewable energy sources as derived from the original 432 months of reanalysis data at all locations that were normalized by dividing through the mean (see Fig. 3). Existing hydropower and in particular hydropower at new locations in the North of Brazil (i.e. BR and NO) show a much larger variance than the other renewable sources, and solar PV shows the lowest. Extreme values in the hydropower distribution are far off the mean. Variance of windpower production is quite different between the four states. Rio Grande do Sul shows the smallest variance of all locations (RSw). There is considerable difference in variance between PV locations, however, PV locations with highest variance are still comparable to the variance of wind in Rio Grande do Sul. The highest variance of PV locations can be found in Quarai (RS) in the federal state of Rio Grande do Sul. This is the most Southern location and therefore the distance to the equator is highest – thus the high variance can be explained by the difference in day and night length over the year. The lowest variance in PV production is found in Alto Taquari (MT), in the federal state Mato Grosso. This is not the location closest to the equator, but differences in rainfall over the year are less pronounced than at locations closer to the equator.

The variance of the timeseries consists of seasonal variation and of deviations from the monthly means. The seasonal component of the timeseries at all modelled locations and the interannual variation are therefore shown in Fig. 4 and Fig. 5. Hydropower has, by

Table 1
Scenarios of mixes of technologies and locations.

Technology (% of additional production)	Location (% of participation)	Scenario name
Wind (100%)	Bahia (100%)	W1
Wind (100%)	Ceará (100%)	W2
Wind (100%)	Rio Grande do Norte (100%)	W3
Wind (100%)	Rio Grande do Sul (100%)	W4
Solar PV (100%)	1 Scenario for each federal state, with the exception of Acre, Alagoas, and Sergipe (100%)	S1–S24
Hydropower (100%)	North of Brazil (Amazonas Region)	H1
Wind (100%)	All locations equally (25% of total additional production)	M1
Solar PV (100%)	All locations equally (1/24)	M2
Wind (1/2), Solar PV (1/2)	All locations equally (i.e. 1/8 for wind power and 1/48 for solar PV)	M3
Wind (1/2), Hydro (1/2)	All locations equally (i.e. 1/8 for wind power and ½ for hydropower)	M4
Solar (1/2), Hydro (1/2)	All locations equally (i.e. 1/48 for solar PV and ½ for hydropower)	M5
Wind (1/3), Solar PV (1/3), Hydropower (1/3)	All locations equally (i.e. 1/12 for wind power, 1/72 for solar PV, and 1/3 for hydropower)	M6

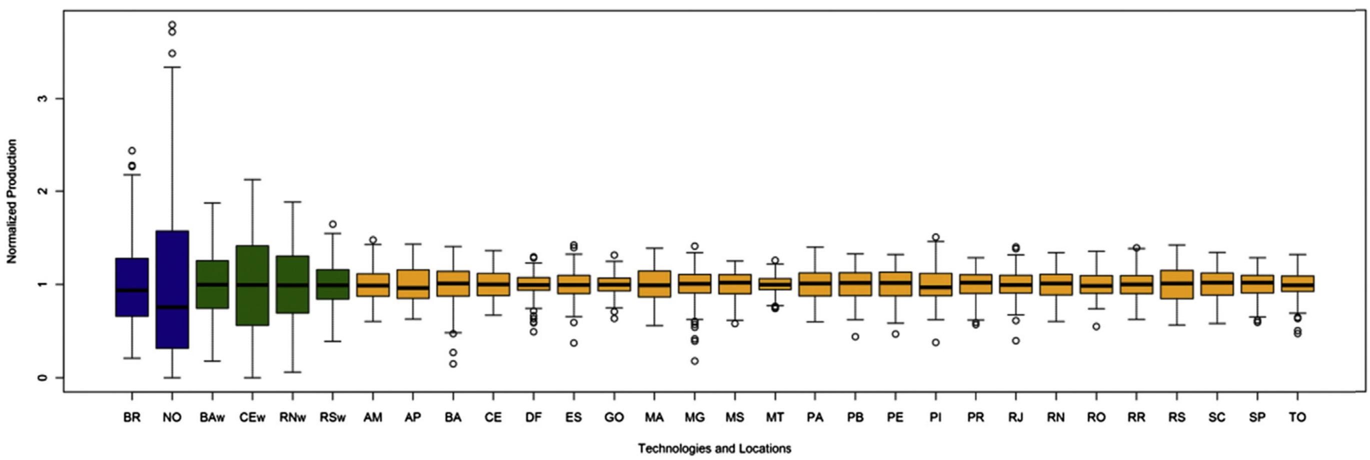

Fig. 3. Boxplots of monthly modelled production data of all renewable energy sources: existing hydropower (first blue boxplot, BR), new hydropower from the North (second blue boxplot, NO), windpower (green), and solar PV (yellow barplots) at all modelled locations. Observation: The small circles show outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

far, the highest seasonal variability with high resource availability in the Brazilian summer and autumn (January to June) and very low availability in winter and spring (July–December). In contrast, windpower has complementary seasonality, however, to a lower extent: windpower production is lower in the first half of the year than in the second half. Finally, solar PV shows the lowest seasonal differences with some complementarity with hydropower generation. This is due to the fact that Brazil is located close to the

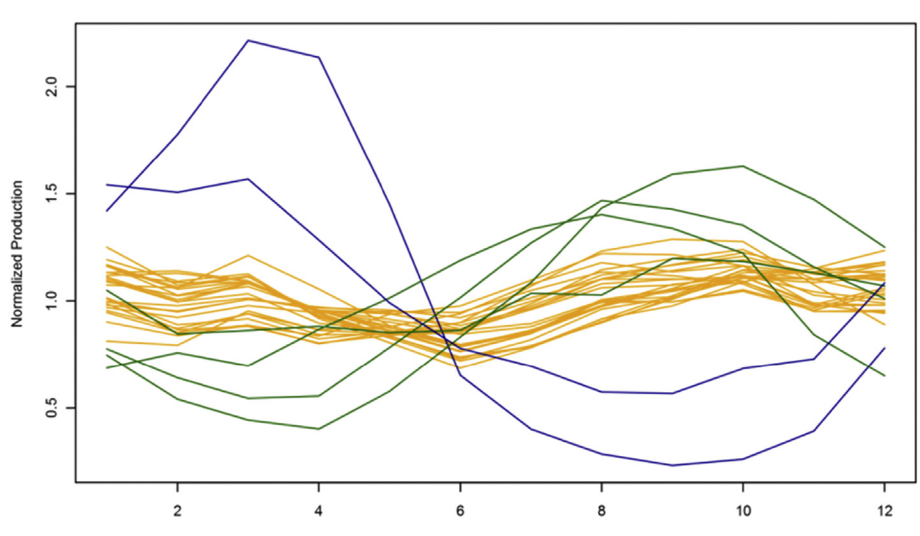

Fig. 4. Normalized average of monthly renewable energy generation at all locations over 36 years: hydropower (blue), windpower (green), and solar PV (yellow) at all locations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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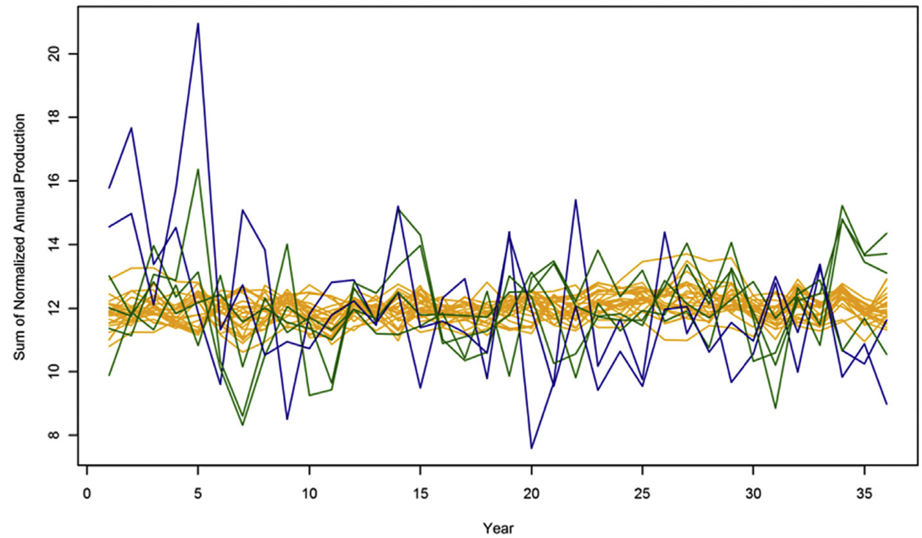

Fig. 5. Normalized annual renewable energy generation at all locations: hydropower (blue), windpower (green), and solar PV (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

equator. Seasonal differences with respect to solar radiation are therefore low in comparison to e.g. Europe. Solar PV also has the lowest inter-annual variability (with some exceptions), as shown by Fig. 5. Differences between years are highest for hydropower, and second highest for windpower – with the exception of wind in Rio Grande do Sul which generates quite stable output on an inter-annual level.

4.2. Thermal power production & loss of load

Fig. 6 shows boxplots of combined, overall thermal power production and loss of load in both methodological approaches, i.e. simulation and optimization, for all technological scenarios. The variation in each technological mix is generated by the 100 different climate scenarios. First, it can be observed that the hydropower-only scenario (H1) is by far the scenario with the highest mean and widest spread of results: this is a consequence of the much higher variance of hydropower compared to wind power and solar PV. On average, the system is less able to cope with the high variation in renewable resources when only hydropower is used, even though Brazil has significant amounts of hydrostorage installed. Differences in the climate scenarios cause significantly different outcomes, indicating that the operational uncertainty in the system is much higher than when using the other renewable energies. This also has a huge impact on the operation of the system: the optimal operation with full knowledge of future conditions (yellow boxplots) performs significantly better than the simulation without any foresight.

Windpower generation at single locations, i.e. scenarios W1–W4, has the second highest mean and variability in the results.

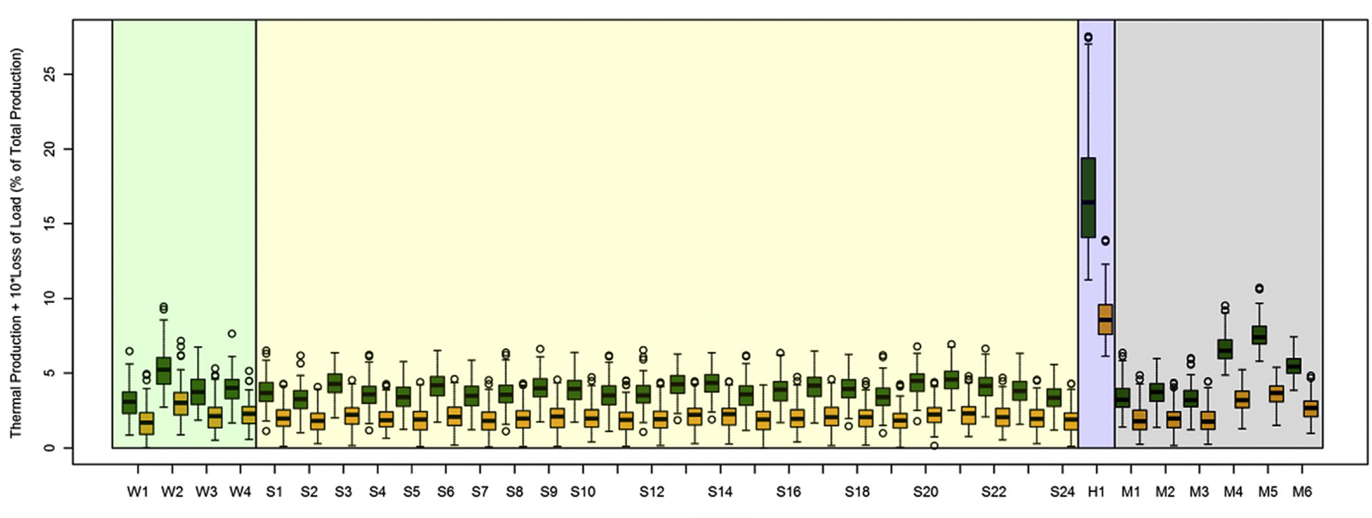

Fig. 6. Boxplots of thermal production +10*Loss of Load (i.e. the objective of the optimization model) for all technological scenarios. The barplots indicate the variance due to the 100 climate scenarios within one technological scenario. Boxplots in green show results of the simulation model, those in yellow results of the optimization model. The scenarios highlighted in light green are wind-expansion scenarios, the ones in light yellow solar PV, the blue one is hydropower expansion, and the grey ones are the scenarios with technological mixes. Observation: see Table 1 for details on the scenarios and their names. The small circles show outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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In particular the scenario with wind from Ceará (W2) shows higher resulting thermal power production and loss of load than the other wind locations and solar PV, which may be a result of its higher correlation with existing hydropower production, as confirmed by Schmidt et al. [14]. However, variability is far below the one of hydropower. Third, solar PV at all locations has the lowest mean and variance in terms of costs of thermal power production and loss of load compared to wind and hydro power. Fourth, a mix of locations and/or technologies reduces variability in comparison to hydropower production considerably. We show in-depth results of scenarios M1–M6 later. Observe that a reduced overall variability also reduces the gap between the optimal and the simulation results: therefore, operation of the system is less complex if the new intermittent sources are added to the system, as uncertainty about future resource availability is lower.

A detailed zoom into the technological mix scenarios M1–M6 is shown in Fig. 7. The difference in thermal power production between the wind M1, the solar PV M2, and the mixed wind and solar PV scenarios M3 is very low. At the same moment, there is quite some difference with respect to loss of load between the scenarios M1–M3: in the solar PV scenario M2, loss of load is lowest while it is higher in the scenarios with wind, i.e. M1 and M3. This is a result of the higher seasonality and higher inter-annual variance of wind power in comparison to solar PV.

When adding hydropower to the mix (M4–M6), thermal power production increases significantly. A mix of wind and hydropower production needs less thermal power than a mix of solar PV and hydropower, probably due to the seasonal complementarity of hydro and wind resources. The lowest thermal power production in the three scenarios is observed in M6, where all three sources are mixed. The loss of load in M4–M6 is significantly higher than in M1–M3 in the simulation model, but comparable to M2 and M3 and lower than in M1 in the optimization model.

A clear conclusion is that adding wind or solar PV to the production mix will decrease overall production variance a lot. In terms of extreme events which trigger loss of load, solar PV performs slightly better than wind. This is also confirmed by the plots of annual production sums (Fig. 5).

5. Discussion & conclusions

Our results indicate that, in case short-term storage for a large-scale integration of renewables is available, adding windpower as well as solar PV will stabilize the overall output of the system. Results indicate that the current flexibility in the system, as provided by hydropower storage, is enough to allow for the long-term balancing of renewable energy supply and demand. Obviously, our results only can give indications on the monthly demand and supply balance. The large-scale integration of wind and PV, however, will need additional short-term storage capacity to accommodate submonthly variations of renewables (e.g. shifting PV production from day to night) and is not considered here. Also, perfect regional integration of renewable supply through the electrical grid is assumed, as we do not consider grid restrictions. The expansion of the grid, new hydro pumped storage projects [20], the installation of pumped storage units in existing reservoirs, or batteries may be, among others, feasible solutions for integrating larger amounts of intermittent renewables into the system.

Adding hydropower from the North of Brazil, in contrast, will create the need for additional thermal backup capacities to be prepared for longer droughts. Solar PV delivers the most stable seasonal and inter-annual supply of electricity in Brazil and therefore makes the operation of portfolios with high shares of PV less complex than systems with high shares of wind. This result is in contrast to results in other world regions (e.g. Becker et al. for the US [8] and Huber et al. for China [9]), where optimal portfolios in terms of reducing necessary backup capacities contain only up to 20–30% of solar PV capacities. Those studies, however, do not assume full short-term storage availability for solar PV and they recognize that increasing short-term storage will shift the portfolio from wind to PV.

The current ten years government plan for the expansion of the electrical system [6] sees a significantly growing role for wind power in the Brazilian system. However, solar generation is still not considered as major source of power generation up to the year 2023 in the government plan. Our study shows that, in particular at the currently very low rates of penetration, solar generation can play a highly useful role in the Brazilian system as it stabilizes overall output. Costs for PV have also been decreasing significantly in recent years. The future role of solar PV should therefore be reassessed in the long-term government plans.

In our modelling approach, installation costs of the different technologies are not taken into account. Currently, the levelized costs of electricity are around 1:1.3:2 for hydropower, wind, and solar PV, respectively, according to the auctions of new capacities in Brazil [21]. This means that from a pure economical point of view, PV is currently not competitive in terms of utility scale operation, even though the temporal profile may stabilize the

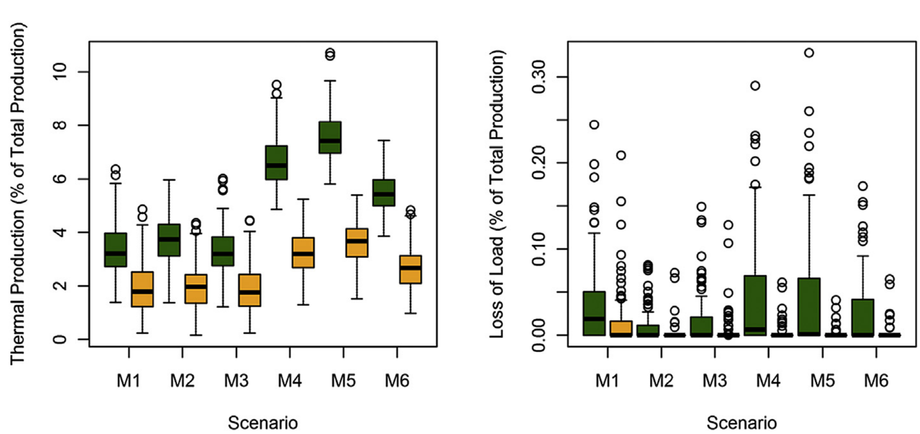

Fig. 7. Thermal Power Production (Left) and Loss of Load (Right) in the mix scenarios for the simulation (green) and the optimization (yellow) model. The scenarios from left to right are wind at all locations (M1), solar PV at all locations (M2), wind and solar PV (M3), wind and hydropower (M4), solar PV and hydropower (M5) and all three sources (M6). Observation: see Table 1 for scenario details. The small circles show outliers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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output. However, grid parity will be reached soon for distributed generation [22], or may have been already reached due to recent increases in household electricity prices. Distributed generation from PV may therefore deliver additional balancing benefits to the system, besides reducing household electricity costs. We therefore highly recommend adopting policies that further boost the deployment of distributed PV production, and increase the share of windpower. A further expansion of hydropower in the North of Brazil is, however, not recommend from the point of view of system stability.

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Appendix. Generation of solar PV data.

The generation and validation of the windpower data is presented in detail in Schmidt et al. [14]. Here, we show how the solar PV data was generated and compared to ground observations. We used the ECMWF interim reanalysis dataset [15] as primary data source, as ground observations for solar radiation are only available for a short period of time and as data quality is partly poor. The parameter SSR (surface solar radiation – net solar radiation at surface) was used as indicator for solar radiation available to solar PV production. We compared reanalysis data to ground measurements to gain confidence in the reanalysis dataset. Ground measurement data was taken from INMET [16], which provides a dataset of hourly solar radiation measurements for 484 stations for the whole of Brazil. Earliest measurements started in 2001. For each of the ground measurement stations, we calculated the closest point in the ECWMF (European Centre for Medium-Range Weather Forecasts) reanalysis dataset and compared the respective data, calculating Pearson correlation, Pearson correlation of deseasonalized data, and the ratio of the means of the monthly aggregated values of the two datasets. We calculated the Pearson correlation of deaseasonalized data to see if deviations from the seasonal mean were captured by reanalysis data. We had to remove three states (Acre, Alagoas, and Sergipe) from further calculations as there were no INMET stations with a sufficiently high number of observations available. We chose those points in the reanalysis dataset as reference points for a federal state that had the highest correlation with the closest INMET ground observation. The results for those stations are shown in Table A1. For most stations, correlation of observations and reanalysis data is above 0.90 (with the exception of MT, RO, RR, and TO). For deseasonalized data, correlation is above 0.70 for most states (with the exception of AP, CE, MT, PA, PI, RN, and RO). Reanalysis data underestimates solar radiation for almost all locations with the exception of CE. The mean is off by as much as 35% for PB, however other stations are closer and show deviations of 6% only. Please observe that the number of observations in the INMET dataset is low and in particular the coefficient of correlation of deseasonalized data may therefore be significantly distorted.

Table A1
Comparison of monthly sums of irradiation data from ground measurement (INMET) and reanalysis data.

Federal State (Abbreviation)	Selected ground measurement station	Correlation	Correlation of deseasonalized data	Calibration Factor (Mean(Observation)/Mean (Reanalysis))	Number of INMET observations
AM	Urucara	0.91	0.72	1.19	75
AP	Oiapoque	0.94	0.55	1.05	54
BA	Serrinha	0.96	0.7	1.21	74
CE	Guaramiranga	0.92	0.67	0.86	81
DF	Aguas Emendadas	0.91	0.78	1.1	70
ES	Alegre	0.96	0.91	1.28	87
GO	Catalão	0.93	0.84	1.06	80
MA	Farol Preguiças	0.93	0.75	1.26	65
MG	Águas Vermelhas	0.95	0.86	1.14	82
MS	Itaquirai	0.98	0.84	1.12	44
MT	Alto Taquari	0.82	0.67	1.06	77
PA	Bragança	0.91	0.5	1.23	68
PB	Monteiro	0.93	0.73	1.35	81
PE	Surubim	0.95	0.77	1.26	75
PI	Uruçui	0.94	0.67	1.26	77
PR	Diamante do Norte	0.98	0.83	1.14	66
RJ	São Tomé	0.94	0.83	1.33	73
RN	Santa Cruz	0.93	0.69	1.16	45
RO	Ariquemes	0.83	0.43	1.12	61
RR	Boa Vista	0.78	0.76	1.13	48
RS	Quarai	0.99	0.88	1.04	80
SC	São Miguel do Oeste	0.98	0.83	1.06	74
SP	Sorocaba	0.96	0.86	1.14	85
TO	Dianópolis	0.89	0.8	1.15	69

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Article II

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The effect of windpower on long-term variability of combined hydro-wind resources: The case of Brazil

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A high share of Brazilian power generation comes from hydropower sources and a further expansion of power generation is necessary due to high growth rates in electricity demand. As an alternative to the expansion of hydropower which shows high seasonal and annual variability with risks of load shedding due to droughts, windpower production may be increased. We assess the variability of potential windpower plants in the four most important windpower producing states Ceará (CE), Rio Grande do Norte (RN), Bahia (BA) and Rio Grande do Sul (RS) in comparison to adding new hydropower capacities in the North region. We assess seasonality and long-term deviations from seasonal production patterns. For that purpose, time series of windpower production from wind speeds derived from measurements and two global climate reanalysis models (NCAR and ECMWF) are generated and validated. Our results show that seasonal variability of windpower generation in the North-Eastern states is anticyclical to hydrological seasonality in the South-East, North-East, and North region of Brazil. Deviations of simulated windpower production from the monthly means are less correlated with current hydropower production than deviations of potential new hydropower projects. Adding windpower instead of hydropower to the system decreases significantly the risk of long periods of very low resource availability. The states Bahia and Rio Grande do Sul perform best with respect to that measure. Our validation procedure shows that ECMWF data may be the best source of long-term wind time series as it better reproduces ground measurements than NCAR.

Contents

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1. Introduction

Electricity consumption in Brazil has risen by around 4% annually in the decade 2004–2013 and is projected to increase continuously by around 4.7% annually, driven by population and economic growth [1]. Therefore an expansion of the Brazilian electricity generation capacity is of importance, even in case that rigorous energy efficiency measures will take place [1]. Historically, Brazil relies on a very high share of hydropower production: in the decade 2004–2013 between 69% and 84% of electricity production came from hydropower sources, depending on hydrological conditions [2]. Recently, windpower capacities have increased significantly, in particular in the North-East and South Region of the country. While a total of 20 GW of new hydropower capacity has been contracted and is partly under construction in the North of Brazil, a further expansion of 17 GW of hydropower is planned up to 2022. However, relying on power generation from hydro production increases operational complexity as seasonality of rainfall is very high in Brazil, and as most new projects in the North of Brazil will not include storage opportunities [1]. The risk of loss of load or the need for the expensive dispatching of backup thermal power plants would therefore increase. The electricity crisis in Brazil in the years 2014–2015, driven by rainfalls far below the average, shows that long-term variability is a serious issue. It not only causes high costs to the system due to the dispatch of thermal power capacities but may also eventually lead to load shedding.

An alternative to this expansion path is to focus on new, intermittent renewable sources of electricity. In particular windpower production has seen high growth rates in recent years due to good wind production conditions in several parts of the country and thus is able to economically compete with thermal power production [1]. Windpower may add a positive portfolio effect to the current hydropower dominated power regime, thus reducing the risk of loss of load. However, intermittent production obviously has drawbacks as it cannot be dispatched on demand and, unlike hydropower, lacks of any cheap storage possibilities. The very short-term intermittency in terms of minutely or hourly ramping in production due to changes in wind speed is the focus of most of the research that deals with integration of renewables [3–7]. This kind of intermittency causes problems in the transmission grid and increases the need for quickly ramping backup capacities. Nevertheless, there are also longer-term issues that have to be investigated: first, wind regimes may have the same or a different seasonality than hydropower inflows. Second, deviations from the long-term mean of windpower resources may be positively or negatively correlated with deviations of hydropower inflows. Third, as the time-profile of production regimes may vary significantly from location to location for windpower in a large country as Brazil, those effects may also vary significantly between the regions.

Research on these issues has been conducted in Brazil before, particularly on the seasonality of wind resources. Lopes and Borges [8] have shown that the electricity grid imposes significant restrictions on the amount of windpower that can be integrated into the system of the Southern Brazilian state of Rio Grande do Sul. Others, using simulated windpower production data, have shown that wind- and hydropower production are seasonally complementary, in particular hydropower production in the North and Southeast regions and windpower production in the North-East region is seasonally complementary [9–11,15–17]: While hydroinflows are higher in the first half of the year for most rivers in the North and North-East region, windpower production is higher in the second half of the year in the North-East region [9–11]. However, there is only weak evidence on how windpower production may be correlated with hydropower inflows when excluding seasonality. Chade Ricosti and Sauer [12]. used modelled time series of windpower production derived from the National Center of Atmospheric Research/National Centers for Environmental Protection reanalysis project (NCAR) reanalysis project [13]. to assess how wind from the North-East region and hydrological regimes in the North-East region are associated. They show that windpower production seems to be higher in years of low precipitation in the relevant river basins. However, the authors do not apply thorough statistical analyses for this purpose. Bezerra et al. [11]. use the same dataset to investigate inter-annual complementarity. They find no evidence for a systematic relationship between hydro inflows and availability of wind. They do not use statistical testing in their analysis and only assess annual sums of the respective variables. Additionally, globally modelled data-sets may not contain a very good representation of some of the estimated parameters, and validation of the data set is therefore of high importance. Data quality issues, however, were neither addressed by Chade Ricosti and Sauer [12], nor by Bezerra et al. [11].

The aim of this article is to assess the effect of adding windpower to the Brazilian production portfolio on the variability of joint wind- and hydropower resources. For that purpose, we combine different data sets from ground measurements, and globally modelled time series from two climate reanalysis projects – the NCAR reanalysis [13] and the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis [14]. We simulate time series of windpower production, as the timeseries of observed windpower production are too short to be used in statistical analysis. The data sets are compared with respect to their seasonality and residuals when removing seasonality. Also, the long-term correlation with hydropower production is derived. Additionally, we assess how the probabilities of very low combined resource availability of wind and hydropower evolve assuming different shares of windpower in the production matrix. We focus on the four most important windpower producing states in Brazil, i.e. Bahia (BA), Ceará (CE), Rio Grande do Norte (RN), and Rio Grande do Sul (RS).

In the following section, we present data sets being used for the simulation of windpower production and how these have been validated against each other. Furthermore, we discuss how they were used to assess the effect on long-term variability of joint output of hydropower and windpower system. Results, including the validation process, are presented in Section 3. We compare our results with other publications and discuss the limitations of our study in Section 4. Finally we conclude in the very last section of the paper.

2. Materials and methods

An overview over the methodological approach is shown in Fig. 1. We first model windpower timeseries on the basis of meteorological data from different geographical locations. By using a simple optimisation process we choose those locations that best fit observed windspeeds. We model monthly time series of windpower production for a multi-annual period to be able to calculate seasonality and deviations from seasonality for windpower sources. The simulation of synthetic time series is necessary as long-term data from real windpower production sites is not available. Official statistics report data on windpower generation since 2004. The data shows that annual production surpassed 100 GWh as recently as 2006 [2]. All data sets we use are publicly available for download and comprise either measured or modelled wind speeds.

Afterwards, we compare the timeseries derived from the different datasets and choose the dataset which shows the best fit

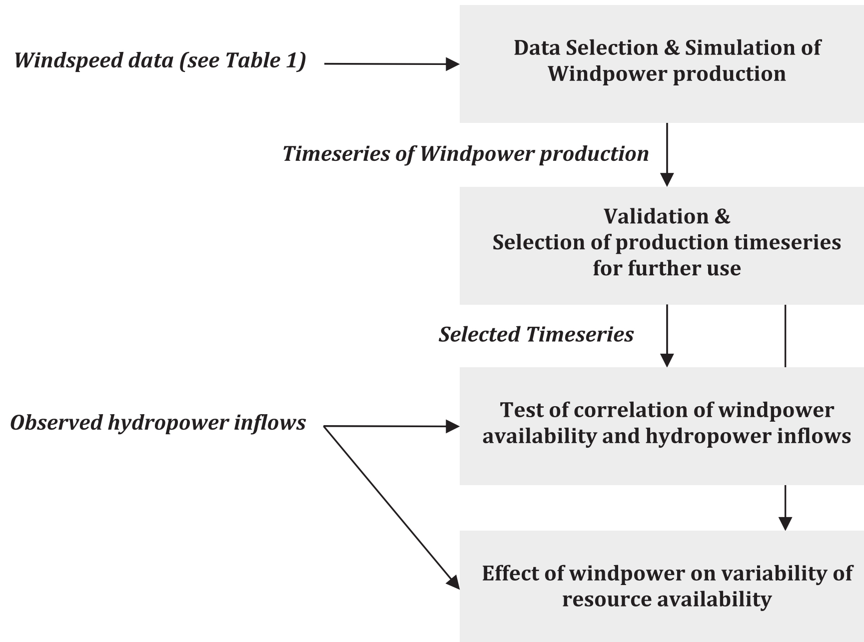

Fig. 1. Overview over the methodological approach.

Table 1
Data sources for simulation of windpower and hydropower production.

Data source	Period	Spatial resolution	Temporal resolution	Type
INMET manual stations [15]	1962–2013 (long periods of missing data)	292 Stations for the whole of Brazil	3 Observations/day (00:00, 12:00, 18:00)	Wind speed measurement from meteorological stations at 10 m height
AMA [16]	2012–2013 (no missing data)	One dataset for Bahia, Ceará, Rio Grande do Norte, Rio Grande do Sul	Monthly mean wind speed for each hour of day	Wind speed measurement at hub height of wind turbines
NCAR reanalysis [13]	1948–2013 (no missing data)	2.5×2.5 Degree Grid, globally	4 model outputs/day (00:00, 06:00, 12:00, 18:00)	Modelled wind speeds at different atmospheric pressure levels
ECMWF interim reanalysis [14]	1979–2013 (no missing data)	0.75×0.75 Degree Grid, globally	4 model outputs/day (00:00, 06:00, 12:00, 18:00)	Modelled wind speeds at different atmospheric pressure levels
CCEE [17]	1932–2013 (no missing data)	For all hydro power plants	Inflows (m^3/s) as monthly average	Water inflows into hydropower plants

with observed data. The chosen one is subsequently used to test the correlation between hydropower inflows and windpower production and to show how adding windpower to the production matrix affects the variability of resource availability.

2.1. Data sources

An overview of the used data sources is given in Table 1. Data from the Brazilian Instituto Nacional de Meteorologia (National Institute of Meteorology – INMET), from NCAR, and from ECMWF are used to simulate long-term windpower production. Data from Câmera de Comercialização de Energia (National Chamber for Commercialization of Energy – CCEE) is used for modelling hydropower production. INMET data is provided by the national meteorological office and comprises of wind speed measurements at a height of 10 m above ground. NCAR and ECMWF data are outputs of global meteorological models. Besides wind speeds, these models deliver other meteorological parameters as well at different atmospheric pressure levels. While outputs for several reanalysis projects by these organisations are available, we have chosen those datasets because they provide the highest frequency of model outputs and because they are continuously updated. Acompanhamento das Medições Anemométricas (accompanying anemometric measurements – AMA) data is collected by measuring wind speeds at hub height of wind turbines at real production locations and is provided by the official Brazilian energy planning institution. However, the data is made available only in an aggregated form for the four most important states of windpower production – Bahia, Ceará, Rio Grande do Norte, and Rio Grande do Sul – and only monthly mean wind speeds for each hour of a day are downloadable for the years 2012–2013. This data is therefore not used for simulation of windpower time series, but for the selection of measurement stations that are used subsequently for simulation. The temporal resolution is different between INMET (3 measurements a day) and NCAR and ECMWF that comprise of 4 simulations a day.

2.2. Data selection and simulation of wind power production

In our analysis, we focus on the four federal states for which reference measurements at the hub height of wind turbines are available in the AMA database (see Table 1): Bahia (BA), Ceará (CE), Rio Grande do Norte (RN), and Rio Grande do Sul (RS). Those states are also the ones which most recently have significantly increased their production capacities. We select locations from the three data sources INMET, NCAR, and ECMWF within the border of these states. While the NCAR and ECMWF data is complete and no further treatment of data is necessary, we select a subset of INMET data which has a sufficiently high number of observations available for the comparison period 2012–2013: the maximum number of missing data points is set to 100, i.e. 5% of the total time series. Missing data is interpolated between the two neighbouring data

Table 2
Number of NCAR and ECMWF modelled locations and INMET stations for the four states.

	NCAR	ECMWF	INMET	
	Total number of model locations		*Total number of measurement stations*	*Stations with less than 100 missing values in period 2012–2013*
Bahia	13	87	8	5
Ceará	3	22	6	5
Rio Grande do Norte	3[a]	8	5	5
Rio Grande do Sul	8	43	15	7

[a] There are no NCAR points within Rio Grande do Norte. We therefore chose the closest neighbouring points in the neighbouring states Pernambuco and Ceará.

points, allowing a maximum gap of 9 consecutive data points (i.e. 3 days of measurements). Table 2 shows the total number of locations per state and the number of stations containing sufficiently few data omissions for the INMET data.

To select the stations that best reproduce wind speeds at real production locations in the respective states, we calculated measures of fit between INMET, NCAR, and ECMWF data and reference data from AMA. INMET, NCAR and ECMWF data is not available on an hourly basis. We therefore calculate the average monthly wind speed for all data sources. However, INMET, NCAR, and ECMWF data are, depending on the chosen atmospheric pressure level for NCAR and ECMWF, not necessarily observations at the same height above ground compared to AMA which measures at hub height. As wind speeds change with the height above ground, we introduce a calibration factor which adjusts the mean wind speed of the three data sources INMET, NCAR, and ECMWF to the mean wind speed of the AMA dataset. The calibration factor is calculated as the simple proportion of the mean of the wind speed of the complete timeseries of the AMA data (i.e. the mean over the hourly wind speeds over all observed months) and the mean of wind speeds of the other three data sources INMET, NCAR, ECMWF.

For the selection of data locations which best represent AMA data, we calculate the mean squared error (MSE) and the Pearson correlation coefficient (COR) between INMET, NCAR, ECMWF and AMA data. We do so for the mean wind speeds of all possible sets of locations for each region and choose the set of measurement locations that minimise MSE. We also test correlations for significance by applying both tests for Spearman correlation (based on algorithm AS 89) [18] and standard tests for Pearson correlation [19]. Spearman test results are reported as for some of the involved distributions normality was rejected by the Shapiro–Wilk test and contrary to Pearson correlation, Spearman correlation does not rely on the assumption of normality.

When generating windpower time series for the period 1979–2013, we first have to address missing data in the INMET timeseries. For that purpose, we linearly interpolate up to one month of missing data and subsequently only use completed years for further analysis. Tests on the interpolation with different period lengths (between 10 and 100 days) showed no significant change of results.

A standard power curve for a typical Brazilian 2 MW wind turbine is assumed for the calculation of windpower production from windspeeds for each of the selected data points for each of the three data sources INMET, NCAR, and ECMWF [20]. Measured and modelled values for wind speeds are used as input to the power curve. As observation frequency differs between the different data sources, we assume that the respective observation is representative for the production of the subsequent period: for instance an ECMWF wind speed at 00:00 is assumed to be representative for the subsequent 6 hours. Subsequently, we aggregate the production from all data points within a certain state and aggregate the monthly data to come up with total windpower production for that state.

2.3. Data validation

The three datasets used to simulate windpower production comprise of ground measurements from INMET and of global climate models. We calibrate the mean production of NCAR and ECMWF to INMET data and then validate our modelled windpower production, comparing climate model based data with INMET measurements. We are mainly interested in two effects: first, the seasonality of the resource – we therefore calculate the average monthly production at each location by running a linear regression of monthly dummies on the data. Second, we assess the deviation from the average monthly production, which is considered to be of high importance: above/below average windpower production may or may not be associated with above/below average hydropower inflows. In the validation process, we therefore validate those deviations by calculating the residuals of the regression of monthly dummies on windpower production data and calculating correlations between the residuals of the different data sources. Wherever we report correlations between timeseries, we have also calculated the MSE. The two indicators, i.e. correlation and MSE, always point into the same direction, we omit them in the results section therefore. For further processing in subsequent steps, we chose the model dataset (i.e. NCAR or ECMWF) that shows the highest correlation with observed data from INMET.

We have also calculated regressions including a linear trend to test for trends in climate. Even though some datasets showed significant positive or negative trends for some states there was no consistent pattern for the trend. Furthermore in none of the datasets, the adjusted R^2 increased by more than 0.02 when including the trend variable. Results of subsequent sections did not alter significantly when using de-trended timeseries. We therefore do not report them here, they are however available upon request.

2.4. Test of correlation of windpower availability and hydropower inflows

We use historical values for hydro inflows into hydropower plants available for the period 1931–2013 [17] instead of hydropower production timeseries. Hydropower production is heavily influenced by storage while inflows are a good indicator for natural availability of hydrological resources, thus better enabling us to assess natural variability in total resource availability. We use those measurements which are associated with currently operating power plants to best cover the hydropower system currently in operation. We deseasonalize the hydropower data and compare the seasonality of windpower production with hydropower production. Finally, we assess if deviations from the mean monthly hydropower production in the dataset is correlated with windpower production. We compare the correlation of hydropower production from the North, i.e. the region where most new hydropower projects are planned, with the sum of inflows in all regions and the correlation of windpower production in the different states with the sum of inflows in all regions. This allows deciding which of the two sources do increase variability in the availability of renewable resources to a larger extent.

2.5. Effect of windpower on variability of resource availability

Finally, we show how variability of the availability of renewables is affected if either hydropower from the North region or windpower from all four federal states is added to the system. In particular, the assessment of extreme cases of joint renewable availability of wind and hydro resources is of interest. We therefore report how often the availability is below a certain threshold, and calculate the longest consecutive period of time that a certain timeseries is below a certain level. This gives an indication how non-availabilities may evolve in a system with different shares of renewables. We use timeseries of hydropower inflows and of simulated windpower production, normalised by dividing by the mean of the respective timeseries. We assume that shares of wind in the different states and hydropower from the North region are added, linearly scaling the timeseries. When analysing the variance reducing effect of windpower, we did not analyse inflows into hydropower plants at different rivers in detail, i.e. we assumed that adding new hydropower capacity in the North region will scale hydropower inflows according to the inflows observed at existing locations. This would imply a perfect correlation between new hydropower plants and existing capacities in the North region, which is a too strong assumption. A similar assumption is used for scaling windpower production. We therefore overestimate variance of both sources. The complete analysis was conducted using the statistical software R, version 3.10 [21].

3. Results

3.1. Site selection

Table 3 shows the results of the site selection procedure. Results indicate that the ECMWF model best reproduces AMA measurements, i.e. it has the highest correlation and the lowest MSE for all states – besides RS, where INMET data fits slightly better. The difference between ground level modelled wind speeds and speeds at 100 m is minor for ECMWF data – obviously, because the calibration factor decreases with increasing height. NCAR reproduces the data worse than the other two sources. In the case of NCAR, a significant difference between wind speeds at ground level and wind speeds at a higher height (i.e. data from atmospheric pressure level 2) with respect to the temporal match to AMA data can be observed. For NCAR, data on atmospheric pressure level 2 reproduces AMA measurements much better than the ground level data. The capability of INMET data of reproducing AMA data lies somewhere in between ECMWF and NCAR data. As an example, Fig. 2 shows how the ECMWF time series fits to AMA data. While the time-series in BA is almost perfectly reproduced after calibration, the data set shows larger deviations for RS.

For further calculations in this paper, we use the stations from the INMET data set, the NCAR atmospheric pressure level 2 grid points, and the ECMWF ground level grid points as they show the highest correlation and lowest MSE when compared to AMA data. The respective measurement sites chosen are shown in Fig. 3. Apparently the selected sites are more inland in BA and more on the coast in CE and RN which supports the validity of our approach as windpower production is indeed located inland in BA and on the coast in the other two states.

3.2. Data validation

Using the time series of wind speeds from the datasets chosen as described above, we modelled monthly time series of windpower production for the period 1979–2013. For this period, all three data sets provide data (although with significant amounts of missing data for the case of INMET). The factors for calibrating the mean production of NCAR and ECMWF data to INMET data are shown in Table 4 – these factors are calculated as the proportion of mean wind speed of the reanalysis datasets NCAR and ECMWF and of the mean wind speed of the INMET dataset over the whole period 1979–2013. For the state of BA, NCAR shows a much higher calibration factor than ECMWF, i.e. NCAR overestimates wind power production in comparison to the observed data. The seasonality, i.e. the monthly mean production, is shown in Fig. 4. There are strong deviations of the reanalysis models from the measured values in BA: the models show stronger seasonality than

Table 3
Performance indicators for comparing AMA data with INMET, NCAR and ECMWF data sets.

		Bahia	Ceará	Rio Grande do Norte	Rio Grande do Sul
INMET	*Correlation*	0.84***(***)	0.95*** (***)	0.88***(***)	0.92***(***)
	MSE	0.62	0.15	0.38	0.14
	Number of stations	2	2	2	2
	Calibration factor	3.73	2.90	2.19	2.04
NCAR/NCEP ground level	*Pearson*	0.57**(**)	0.25	0.63**(**)	0.61**(**)
	MSE	2.91	2.00	2.14	0.86
	Number of stations	1	3	2	1
	Calibration factor	2.06	10.08	7.97	1.71
NCAR/NCEP level 2	*Pearson*	0.83***(***)	0.58**(**)	0.89***(***)	0.66***(***)
	MSE	1.31	1.38	0.22	0.57
	Number of stations	1	1	1	1
	Calibration factor	1.37	0.99	0.87	0.99
ECMWF ground level	*Pearson*	0.98***(***)	0.96***(***)	0.97***(***)	0.87***(***)
	MSE	0.05	0.17	0.08	0.18
	Number of stations	3	2	1	3
	Calibration factor	1.96	1.71	1.45	2.
ECMWF 100 m	*Pearson*	0.99***(***)	0.96***(***)	0.97***(***)	0.81***(***)
	MSE	0.03	0.12	0.05	0.29
	Number of stations	4	2	1	1
	Calibration factor	1.31	1.31	1.01	1.23

*,**,*** Significance level of 0.05, 0.01, 0.001 of Pearson correlation, respectively and, in parentheses, of Spearman correlation calculated using AS 89 [18].

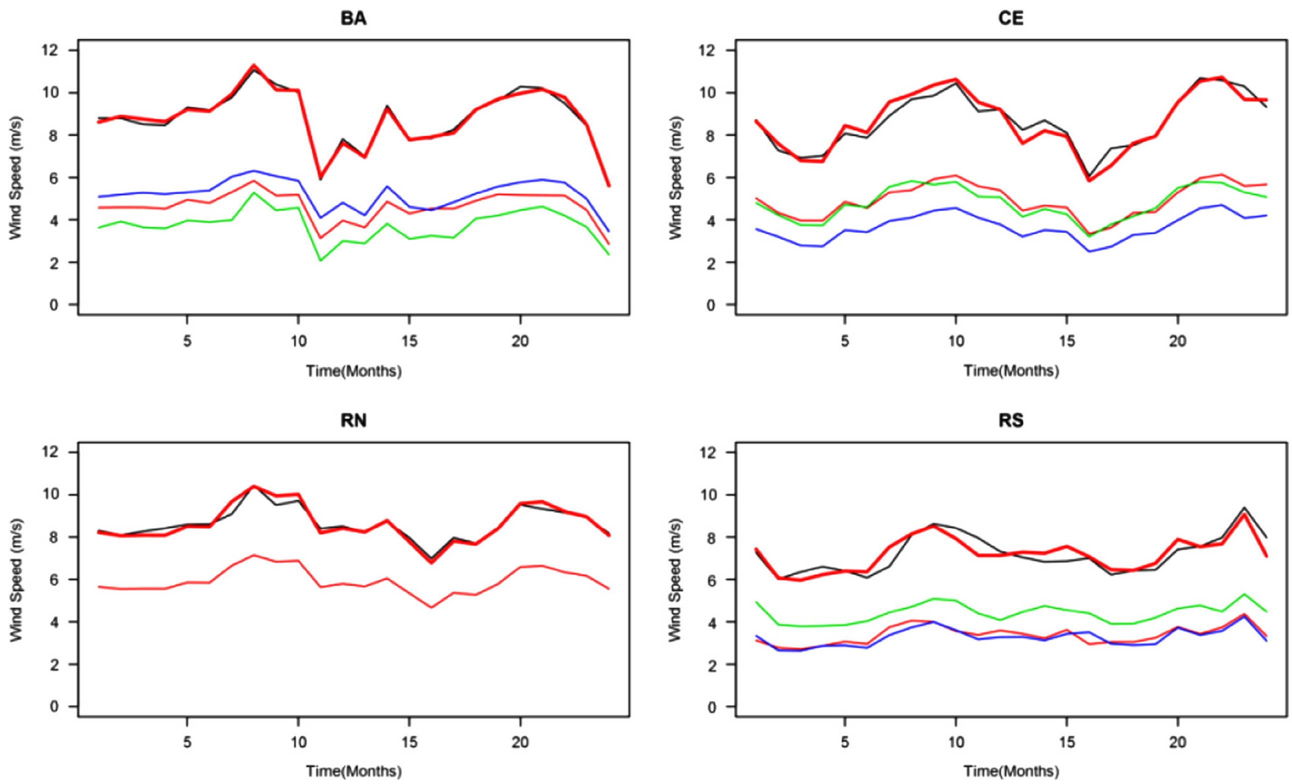

Fig. 2. Example of comparing average monthly wind speeds from ECMWF (ground level) and AMA data sets for the years 2012 and 2013. The data from ECMWF modelling points that best reproduce AMA data are shown. *Note*: the fat red line shows the mean of data from the different ECMWF stations, multiplied by the calibration factor, the black line is measurement data from AMA. The coloured thin lines correspond to data from individual ECMWF modelling points without calibration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

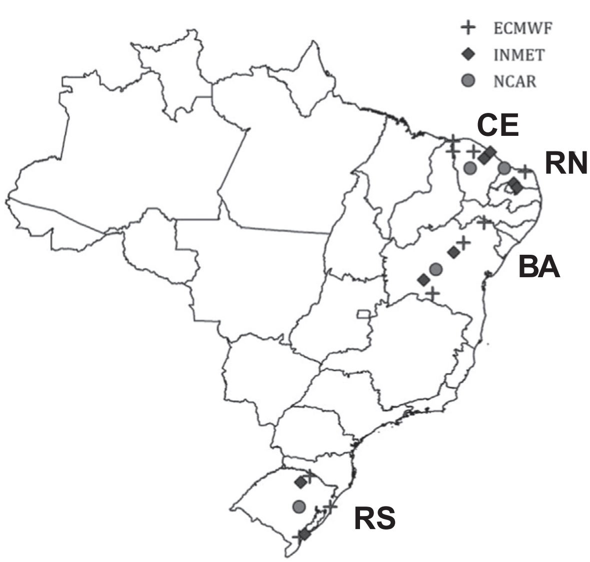

Fig. 3. Measurement locations for the three data sets in the four states BA, CE, RN, and RS.

INMET data. Windspeeds in CE are estimated to be 20% lower by both modelled datasets in comparison to INMET data, as indicated by the calibration factors in Table 4. For the case of CE, seasonality of NCAR strongly deviates from the other two timeseries, in particular due to an earlier peak of production. But ECMWF also deviates from INMET, as the former shows higher differences between the seasons than the latter. For RN, all datasets produce similar seasonality and the differences between the means of the timeseries is also low, as indicated by Table 4. Within the year RS has lower variability than winds in the other North-Eastern states of Brazil, i.e. BA and CE. While the difference in the mean is low between all datasets for RS, ECMWF better reproduces INMET seasonality.

Table 4
Factors for calibrating NCAR and ECMWF data to INMET for the period 1979–2013. The number shows the mean of INMET production divided by the mean of the respective dataset.

	NCAR	ECMWF
BA	1.23	1.03
CE	0.80	0.79
RN	1.01	0.96
RS	1.07	1.04

Results of correlating the residuals of the regression model using INMET data with the residuals of the regressions applying the other two data sets are shown in Table 5. First, it can be observed that ECMWF data is consistently higher correlated with INMET data than the NCAR dataset for all periods and all states. Second, correlation increases over time with the exception of the state of CE that shows a higher correlation for the first than the second period for both data sets and for RN which shows a slightly higher correlation for NCAR in the first period. This indicates that data and/or model quality is increasing over time. The state where seasonal production of the three data sources matches best, i.e. RN, also shows the highest correlation between the residuals with exception of the first period. With the exception of the second period and the ECMWF data set, BA is the state with the lowest correlation. Fig. 5 shows plots of the timeseries of the residuals. The figure confirms that the best match is achieved in the state of RN, and indicates that deviations from the monthly mean are lower for BA than for the other states. There is no agreement of data sources on the variance for the other states, though.

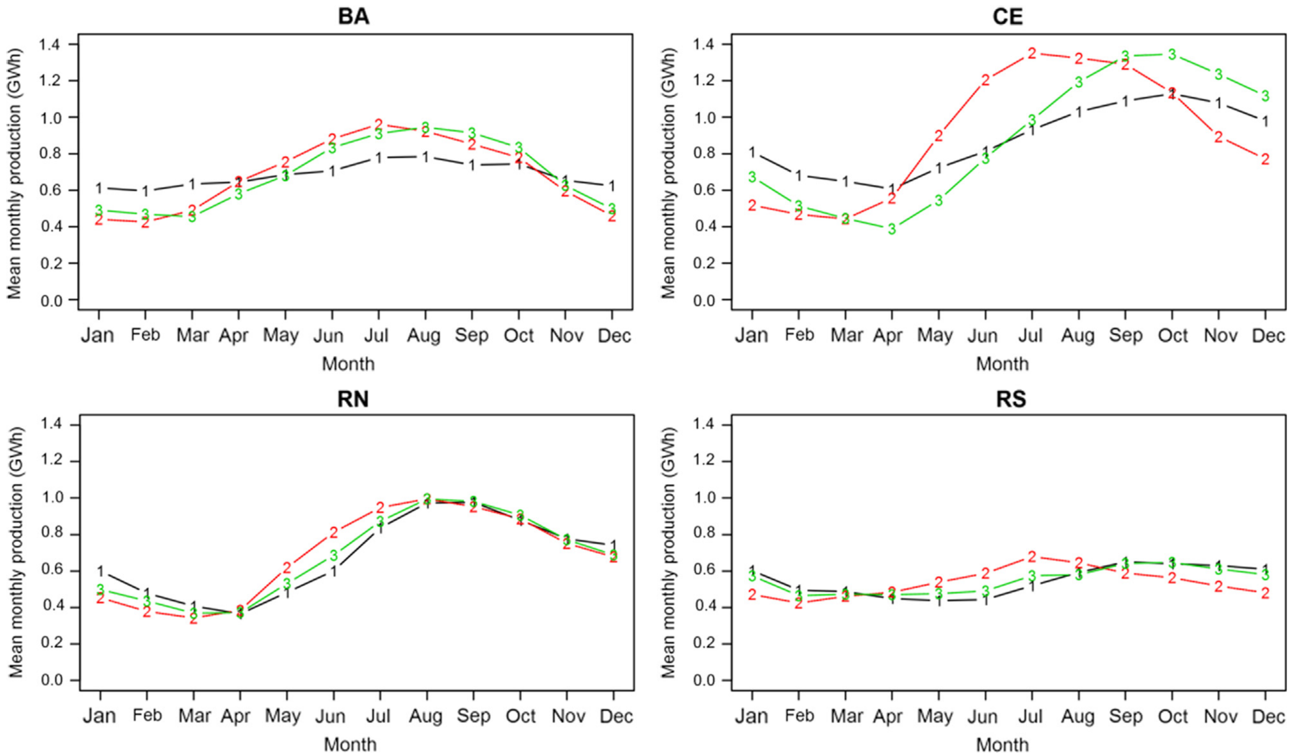

Fig. 4. Dummy variables of regression models for the period 1979–2013 and the four states, showing the average monthly production of a 2 MW wind turbine. *Note*: Black (1) shows INMET data, red (2) NCAR data, green (3) ECMWF data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Correlation between residuals of regression of INMET and NCAR/ECMWF data.

	NCAR	ECMWF	*n*
Complete period: 1979–2013			
BA	0.18***(***)	0.43***(***)	322
CE	0.35***(***)	0.51***(***)	258
RN	0.54***(***)	0.62***(***)	300
RS	0.40***(***)	0.46***(***)	326
First period: 1979–1996			
BA	0.20*(**)	0.26**(***)	106
CE	0.58***(***)	0.65***(***)	85
RN	0.59***(***)	0.60***(***)	99
RS	0.36***(***)	0.44***(***)	118
Second period: 1997–2013			
BA	0.30***(***)	0.60***(***)	216
CE	0.37***(***)	0.54***(***)	173
RN	0.56***(***)	0.78***(***)	201
RS	0.44***(***)	0.54***(***)	208

*,**,*** Significance level of 0.05, 0.01, 0.001 of Pearson correlation, respectively and, in parentheses, of Spearman correlation calculated using AS 89 [18].

Due to the better performance of ECMWF data when compared to AMA as well as to INMET data, we use the timeseries derived from this dataset for further analysis. The INMET data that consists of observed data contains long periods of non-availabilities of data and is therefore not used. However, we report results for those datasets in Appendix A.

3.3. *Test of correlation of windpower availability and hydropower inflows*

First, we show relations between hydropower production in the current system for the four Brazilian subsystems (see Fig. 6). Please observe that those subsystems are not coincident with the four states we use for aggregating windpower timeseries, but are rather a regional differentiation of the electrical system for the whole of Brazil. The most important subsystem is the South-East where 57% of total inflows occur. Seasonality is highest for hydropower production from the North region and lowest for the South region, where an increase in inflows can be observed in the second half of the year. Adding more hydropower from the North of Brazil to the system therefore increases seasonality further. Table 6 shows confidence intervals for correlations of monthly de-seasonalized timeseries. Correlations of inflows are high between the North-East, South, and North regions. The South region is negatively correlated with the North region. The correlation of the sum of all inflows with inflows in the four regions shows that the North, i.e. the region where most hydropower resources are going to be added in the coming decade, is positively correlated with the sum of current inflows.

When comparing Figs. 4 and 6, a strong seasonal complementarity can be observed between wind from the North-Eastern states of Brazil (i.e. BA, CE, RN) and hydropower inflows in the South-East, North-East, and North region. As hydropower inflows in the South region of Brazil are low in comparison to the rest of the system, adding windpower to the system therefore stabilizes seasonal availability of renewable energies. Our analysis confirms seasonal complementarity of wind from the North-Eastern states (BA, CE, RN) and hydrological resources as has been shown before. Bezerra et al. [11] also conclude that RS has the weakest and CE strongest seasonality. Correlations between states in the NCAR dataset are similar to Bezerra et al. [11]. Dutra and Szklo [9] only present results for windpower in CE and they show, similar to our results, lowest production in April and highest in September/October. The monthly values of production compare very well to ECMWF data.

Beyond seasonality, windpower production may also contribute to the system by stabilizing the deviations from the mean

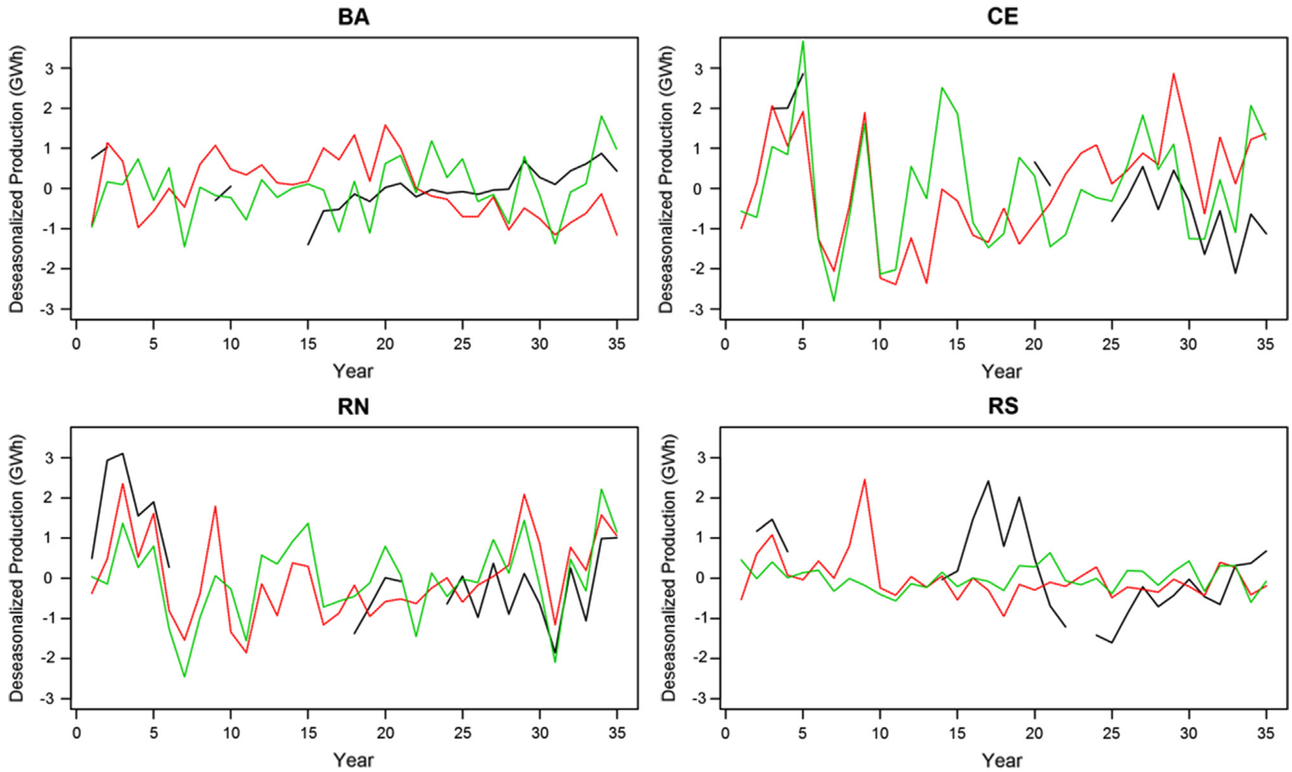

Fig. 5. Annually aggregated residuals of the regression analysis for the period 1979–2013, showing the annual deviation of power production of a 2 MW wind turbine from average production. *Note*: Black (1) shows INMET data, red (2) NCAR data, green (3) ECMWF data. Missing data causes the holes in the INMET timeseries. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

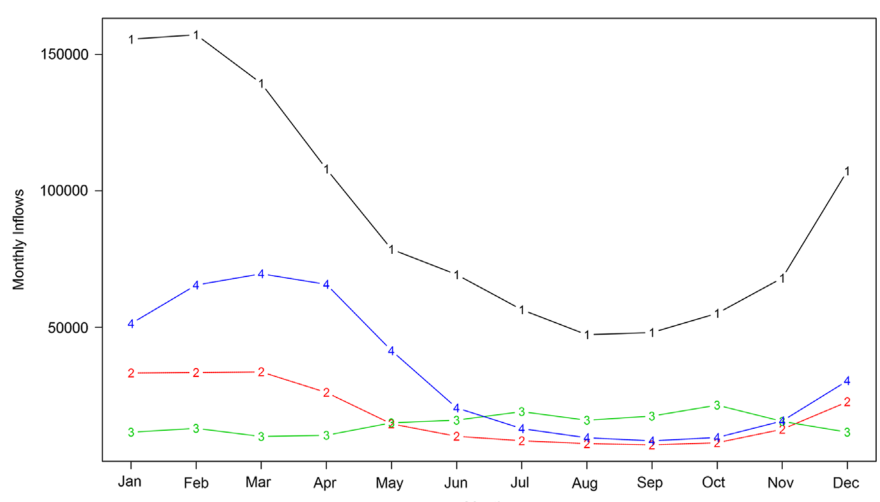

Fig. 6. Dummy variables of hydropower regression models for the period 1979–2013 and the four Brazilian subsystems. The curves represent the monthly average inflows into hydropower plants. *Note*: Black (1) shows inflows in the South-East, red (2) North-East, green (3) South, blue (4) North. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of hydropower inflows. We assess this effect by calculating correlations of the sum of all deseasonalized hydropower inflows with deseasonalized windpower production and with the sum of inflows and windpower production for the four states (see Table 7). The table shows results for ECMWF only, the correlations of INMET and NCAR with hydropower inflows are shown in Appendix A. For the states of BA, RN, and RS the null hypothesis of no positive or negative correlation between hydropower inflows and windpower cannot be rejected. Only CE shows a small positive correlation. In any case, the confidence intervals for the correlation coefficient of Northern hydropower inflows and of windpower production in any of the states do not overlap. This clearly indicates that the correlation of windpower residuals is lower than the correlation between hydropower inflow residuals from the North region and monthly residuals of hydropower inflows for the whole of Brazil. Therefore it can be expected that both effects, i.e. complementarity of seasonality and lower correlation with residuals, contribute to lower variability when adding windpower instead of hydropower from the North region.

3.4. Effect of windpower on variability of resource availability

Adding different shares of hydropower production from the North region or windpower production from any of the four states will affect the availability of renewable resources throughout the observed period of 35 years (1979–2013). Fig. 7 illustrates how the share of months below a certain threshold evolves when adding different levels of renewable generation from either wind or hydropower production from the North region. The share slightly increases for all threshold levels in case of adding hydropower from the North region. This indicates that months with a resource availability lower than 30%, 50%, and 70% of the average monthly availability are increasing with higher shares of hydropower from the North. The opposite is the case when adding windpower production from any of the four considered states: when windpower generation increases to 20% of combined hydro-wind power production, the share of months when resource availability is below 50% of the average drops to 0 for all states. It takes a little more wind for CE and RN than for the other states, as is also indicated by the higher correlation with hydro-inflows shown in the previous section. Still, the development is far better than for hydropower from the North region. For the 70% share, a similar outcome can be observed.

A positive effect is also confirmed by Fig. 8 which shows the longest consecutive period of time in which availability of renewables is below a certain threshold. The figure shows that, in case of hydropower from the North region reaching 20% of total hydropower production, resource availability falls below 30% of the average in up to 3 consecutive months. This can be considered as a very serious drought. When adding windpower production instead, no such period can be observed. Also, periods of low resource availability are shorter with higher shares of windpower production for the other threshold levels (50% and 70%). These results clearly indicate the positive effect of windpower production on decreasing the long-term risks of droughts.

Table 6
Confidence interval of correlation between deseasonalized monthly hydropower inflows in the four states (upper table, $n=420$) for the period 1979–2013. Confidence level=0.999 for Pearson correlation.

Monthly residuals	South-East	North-East	South	North
All inflows	[0.87,0.93]	[0.68,0.82]	[0.10,0.40]	[0.59,0.76]
South-East		[0.43,0.65]	[0.03,0.34]	[0.28,0.54]
North-East			[−0.25,0.06]	[0.61,0.77]
South				[−0.34,−0.03]

Table 7
Confidence intervals of Pearson correlation of deseasonalized residuals of ECMWF data and sum of hydropower inflows for the period 1979–2013. Confidence level=0.999. Hint: the number of observations is shown in parentheses.

BA	CE	RN	RS
[−0.17,0.15] (420)	[0.08,0.38] (420)	[−0.03,0.28] (420)	[−0.12,0.2] (420)

4. Discussion

Inter-annual complementarity has been assessed before by Chade Ricosti and Sauer [12] for the North-East region of Brazil. They used the NCAR data-set for this purpose. Our analysis shows that this data-set does not reproduce ground measurements of wind speeds. Also, the conclusion that there is multi-annual complementarity between hydro and wind resources is based on an analysis without testing for statistical significance. In our analysis the hypothesis of no correlation between the non-seasonal components of hydro- and windpower cannot be rejected with the exception of CE, where correlation is even slightly positive. However, there is strong evidence that correlation between simulated

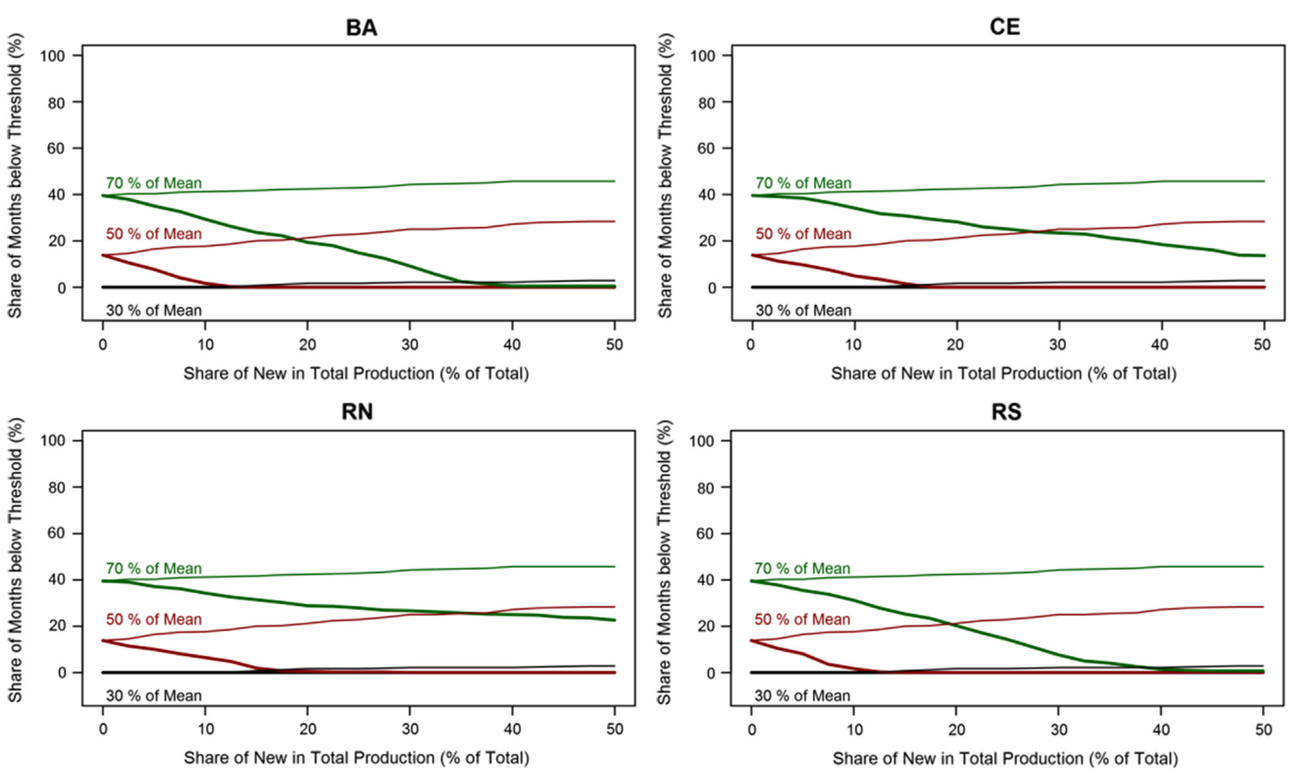

Fig. 7. Share of months that resource availability is below a certain threshold in relation to mean availability of resources. *Note*: the fat line shows the effect of adding windpower production, the thin line shows the effect of adding hydropower production from the North of Brazil.

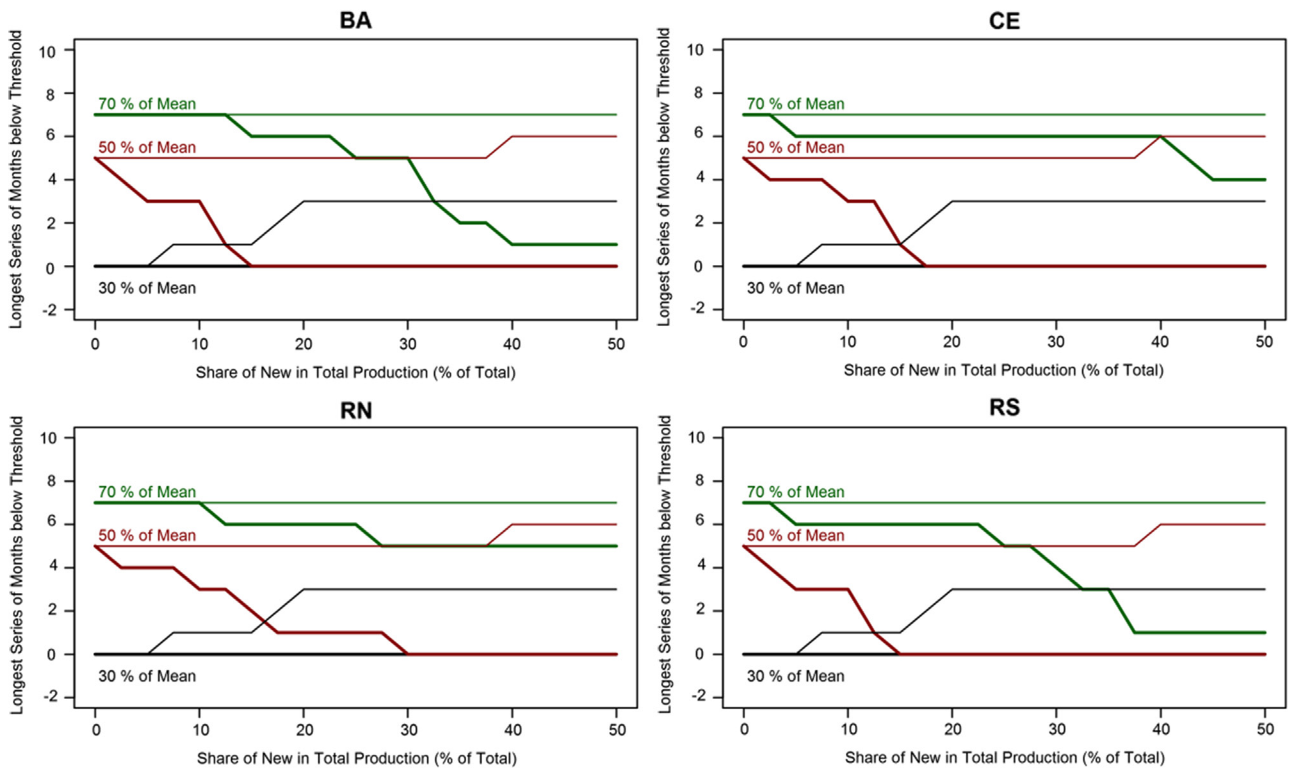

Fig. 8. The longest series of months that resource availability is below a certain threshold in relation to mean availability of resources. *Note*: the fat line shows the effect of adding windpower production, the thin line shows the effect of adding hydropower production from the North of Brazil.

windpower production and inflows into currently installed hydropower plants is significantly lower than the correlation between inflows into existing hydropower plants and hydropower resources in the North.

Although we suggest that including windpower into the power grid may decrease variability of renewable resources on the longer term, we have not assessed if the residual electricity system is able to cope with the intermittency of windpower on a much shorter period of time, i.e. minutes and hours. Integrating large amounts of windpower into the power grid may cause serious challenges for the grid and may require dispatching thermal and hydropower plants. There is therefore a trade-off between reducing monthly and multi-annual variability and short-term variability associated with the integration of wind into the system. Still, if monthly and inter-annual variability is reduced, existing hydropower reservoirs can be increasingly used for balancing of short term fluctuations of intermittent renewables.

We use monthly average wind speed measurements from AMA to select reference measurement locations for simulating windpower production in the four most important wind producing states in Brazil. As windpower production is a non-linear function of wind speeds, comparing our simulations to a very short time-series of average wind speeds may distort results significantly. However, more detailed data is not publically available. The very high fit of ECMWF data to AMA data for three of the four states suggests that the underlying process is modelled reasonably well though.

The lower fit of INMET and NCAR data to AMA data may be partly explained by the low spatial resolution of measurements available – there are between 5 and 10 times more measurement points available for ECMWF data than for INMET and NCAR data. If the distance to the measurement locations of AMA increases, agreement between the different sources naturally decreases. Unfortunately, information on the exact location of measurement locations by AMA is not publically available.

Future climate change may have an impact on the availability of both, wind and hydro resources. While overall uncertainties are still very high, assessments of climate change impacts on the windpower potential [22] and on inflows into hydropower plants [23] for the case of Brazil show that hydropower production may be decreased by around 2–10%. In contrast windpower production may increase by up to 10%.

5. Conclusions

For the integration of windpower into the Brazilian electrical system, the following conclusions can be drawn: if seasonal variability should be reduced, integration of wind from the North-East region is to be preferred over wind from the South region due to a higher complementarity with hydropower resources. In comparison to an expansion with hydropower from the North integrating wind from any state will decrease the risk of very low resource availabilities in the combined hydro – windpower system. Evidently, adding wind from BA and RS shows the most positive impacts.

From a modelling perspective, we can conclude that to a certain extent publicly available globally modelled data sets of wind speeds are able to reproduce ground measurements. Seasonality and deviations from seasonality of wind speeds seems to be captured reasonably well by those data sets, particularly for later periods of measurements. We conclude that ECMWF data better reproduces AMA and INMET data in comparison to NCAR. If long-term windpower production is to be simulated in the four states examined, we therefore recommend using ECMWF data.

Future work includes modelling of winds at other locations than at the existing windpower locations. This will allow a further examination of complementarity between wind sources and between wind and hydropower production. Also, integrating the produced windpower time series into dispatch models may allow estimating the economic value of reduced variability to the system. A detailed analysis encompassing the correlation between inflows from different river systems and in particular between potential and already planned hydropower sites is another important line of research.

Acknowledgements

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Appendix A

See Table A1.

Table A1
Confidence intervals of Pearson correlation of deseasonalized residuals of INMET, NCAR, and ECMWF data and hydropower inflows for the period 1979–2013. Confidence level=0.999. Hint: the number of observations is shown in parentheses.

	INMET Correlation of deseasonalized residuals	**NCAR**	**ECMWF**
BA	[−0.18,0.19] (324)	[−0.18,0.14] (420)	[−0.17,0.15] (420)
CE	[0.21,0.5] (252)	[−0.02,0.29] (420)	[0.08,0.38] (420)
RN	[0.04,0.40] (300)	[0.02,0.33] (420)	[−0.03,0.28] (420)
RS	[−0.02,0.34] (324)	[−0.11,0.21] (420)	[−0.12,0.2] (420)

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Article III

Schmidt, J., Cancella, R., Pereira Jr., A.O.
An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil.

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An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil

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A B S T R A C T

Brazil has to expand its power generation capacities due to significant projected growth of demand. The government aims at adding hydropower capacities in North–Brazil, additional to wind and thermal power generation. However, new hydropower may affect environmentally and socially sensitive areas in the Amazon region negatively while thermal power generation produces greenhouse gas emissions. We therefore assess how future greenhouse gas emissions from electricity production in Brazil can be minimized by optimizing the daily dispatch of photovoltaic (PV), wind, thermal, and hydropower plants. Using a simulation mo© 2015 Elsevier Ltd. All rights reserved.del, we additionally assess the risk of loss of load. Results indicate that at doubled demand in comparison to 2013, only 2% of power production has to be provided by thermal power. Existing reservoirs of hydropower are sufficient to balance variations in renewable electricity supply at an optimal mix of around 37% of PV, 9% of wind, and 50% of hydropower generation. In a hydro-thermal only scenario, the risk of deficit increases tenfold, and thermal power production four-fold. A sensitivity analysis shows that the choice of meteorological data sets used for simulating renewable production affects the choice of locations for PV and wind power plants, but does not significantly change the mix of technologies.

1. Introduction

Rising demand of electricity consumption in Brazil at historically 4% per year in the decade 2004–2013 is projected to continue by around 4.2% annually up to the year 2022. The generation capacity therefore has to be expanded rapidly [1], also due to a lack of generation capacities which triggered an electricity crisis in 2013/2014 that increased wholesale electricity prices by more than 100%. There are many options for capacity expansion: there is still untapped hydropower potential in the North of Brazil [1]. In the North-East and South region wind-power resources are significant [2,3]. Thermal power production may be a valid source of generation due to the availability of national gas fields, a possible expansion of nuclear capacities, and significant biomass potentials from co-generation in ethanol plants [4]. Brazil is also on the 10th position globally with respect to the technical solar potential [5].

Historically, hydropower production dominates the portfolio with 69%–84% of production coming from that source in the decade 2004–2013 [4]. A further increase of hydropower production is projected up to 2018 and partly under construction already [1]. Most of it, i.e. 18.4 GW of that expansion, is going to take place in the North of Brazil, while the other regions are planned to only expand hydropower capacity by a total of around 1 GW. Planned expansions of around 20 GW after 2018 are also, to a large extent, located in the North of Brazil. Most future projects are therefore located within the Amazon forest and negatively affect local populations due to displacements and due to deteriorating natural resources such as fish [6,7]. They also have negative impacts on the ecosystem in place, e.g. by reducing the amount of natural habitats and thus causing a decrease in bio-diversity [6]. Additionally, operational risks of the hydro-thermal system are further increased due to the strong seasonality of rainfall in Brazil and due to the large annual variability in hydrological conditions.

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Nomenclature

Variables

x_t^{cur}	*Curtailing of power (TWh)*
x^{h_deploy}	*Capacity of new hydro power plant that is deployed at location l (GW)*
$x_t^{h\_new}$	*Hydro power production from new hydro power plants at time t (TWh)*
x_t^{hr}	*Immediate hydro power production from inflows at existing hydro power reservoirs (TWh)*
$x_{l,t}^{p}$	*Photovoltaic power production at location l and time t (TWh)*
$x_l^{p\_deploy}$	*Capacity of photovoltaic power production that is deployed at location l (GW)*
x_t^{st+}	*Inflow into storage power plant (TWh)*
x_t^{st-}	*Hydro power production from storage power plant (TWh)*
$x_t^{st\_lev}$	*Level of storage (TWh)*
x_t^{th}	*Thermal power production at time t (TWh)*
$x_{l,t}^{w}$	*Wind power production at location l and time t (TWh)*
$x_l^{w\_deploy}$	*Capacity of wind power that is deployed at location l (GW)*

Parameters

d_t	*Daily demand for electricity (TWh)*
h_t^h	*Inflows into existing run-of-the-river plants (TWh)*
$h_t^{h\_new}$	*Possible production at new run-of-the-river plants for a capacity of 1 GW (TWh)*
h_t^r	*Inflows into existing storage plants (TWh)*
$p_{l,t}$	*Photovoltaic production at location l and time t for a capacity of 1 GW (TWh)*
s^{max}	*Maximum storage capacity (TWh)*
t^{max}	*Maximum thermal power production capacity (TW)*
$w_{l,t}$	*Wind power production at location l and time t for a capacity of 1 GW (TWh)*
ρ	Storage efficiency

Subscripts

l	*Locations for renewable energy deployment*
t	*Time index*

As most projects do not contain new reservoirs, but are operated as run-of-the-river power plants, the seasonal and multi-annual match of supply and demand by managing existing reservoirs is getting much more complicated. Furthermore, the expansion of hydropower in the Amazon region, in particular at the Belo Monte dam, may reduce regional rainfalls due to a decrease in evapotranspiration as a consequence of the deforestation necessary for building the dam [7]. The projected production levels of the hydropower projects may therefore not be attained, thus making the projects economically less viable [7].

Starting in 2006, wind power entered the Brazilian production matrix after discovering significant wind resources, in particular in the North-East and South Region of the country. The share in the production increased from almost no production in 2006 to 1.2% of annual demand in 2014 [8]. A series of studies have investigated the potentials of including wind energy in the Brazilian energy matrix [2,9–11]. They show that seasonal complementarity between hydro and wind resources is given, i.e. wind resources in the North-East of the country match well with hydropower resources in the North and South-East of Brazil as the first ones produce more in the second half of the year, and the second ones more in the first half. There are reports of environmentally and socially conflicting wind projects, however, as wind resources are spatially less concentrated as hydropower resources, finding alternative, less conflictive locations may be easier [12].

Solar power is another alternative to hydropower. Up to today, only 890 MW of photovoltaic generation (PV) was contracted in official auctions [13], although solar irradiation is sufficiently high to support above 1500 full load hours at many spots in Brazil [5,14]. Research on solar energy deployment in Brazil is currently restricted to static analysis of the potentials [14–16], with the exemption of Gemignani et al. [17] who model the integration of low shares of solar energy into the grid on a monthly basis for the year 2021. They conclude that the operation of the system is positively affected by increased solar energy production due to lower marginal costs of production and less probability of loss of load. However, solar systems are not economically feasible at current costs as the decrease in system-wide variable production costs are not sufficient to finance the investments in solar energy at current costs. Neither the official government plan for expansion of the power system [1], nor modelling studies [18] see a significantly growing role for solar PV up to 2020, although costs of PV have been decreasing in recent years and although the temporal availability of PV may provide a highly valuable contribution to the Brazilian system [19]: depending on the location in Brazil, daily, monthly, and inter-annual variations are lower than those of wind and hydropower. The high variation of the availability of PV during the day, i.e. short-term intermittency of PV, is an often discussed issue [20]. It may, however, be addressed by adding limited storage capacities (i.e. storage capacity for balancing hourly variability during one day) to the system. Longer-term variations such as multi-annual variations in the availability of renewables may much more seriously restrict the expansion of a particular power source as high long-term variations require much larger levels of storage.

Thermal capacity is planned to be increased by 5 GW up to 2022 to be better able to deal with the hydrological variability and the intermittency from wind power [1]. From 2020 on the energy sector as a whole may become the most important emitter of greenhouse gases in Brazil, replacing the land use sector which shows decreasing emissions due to successful measures against deforestation. Brazil will show increasing trends in total emissions due to emission from the energy sector by then [21]. Decreasing emissions from electricity generation, additional to measures in decreasing emissions from energy use in transportation, industry, and the buildings sector, may therefore help in lowering Brazilian total greenhouse gas emissions. Biomass, in particular from co-generation at ethanol plants, may be considered a low-carbon source of electricity. However, further expansion may directly or indirectly cause conversion of natural ecosystem and associated losses in carbon stocks and biodiversity [22].

In general, the large scale integration of intermittent renewables is often considered to be limited due to the intermittent nature of these electricity sources. Restrictions in the electrical grid, the storage capacity, and thermal backup capacities pose an upper bound on the level of renewables that may be deployed [23]. At the same moment, the Brazilian system has a significant amount of flexibility for accommodating sources of intermittent power production due to large hydro-reservoirs that can be used for regulation [24] and due to the existence of a far reaching transmission grid which allows connecting different locations for intermittent renewable energy production, thus reducing output variance [25].

Brazil therefore is an interesting case study in terms of studying a high share of renewables in a growing power sector. Taking a long-term approach, we assess an optimal portfolio of hydropower, windpower, and PV for the case of Brazil, minimizing the use of thermal power production. We study the achievement of an almost fully renewable system and use for that purpose simulated, validated daily time series of power production from two different data sources. Intradaily variations in supply are assumed to be balanced by a storage device. A simple optimization model is used to generate an optimal mix of technologies from a historical set of data. A simulation model is subsequently run on synthetic, bootstrapped time-series to test how a simple dispatch algorithm performs on the operation of the system with respect to thermal dispatch, curtailment of renewables, and loss of load. The results are compared to a case where only hydro and thermal generation is expanded.

The paper first introduces data and methodology. In the subsequent section, we show the results of the optimization and simulation models. The article closes with a discussion and a concluding section. In the appendix, a calculation of storage demand is presented as well as results for the validation of solar irradiation data.

2. Data & methods

We use an optimization model to first determine an optimal mix of renewable generation expansion from wind power, solar PV, and hydro power. Thermal power production is used as backup source of power in case the mix of renewables is not able to fully cover demand. We do not model thermal power production in detail, i.e. per technology, but we emphasize that thermal power production may be renewable too if biomass is used as feedstock. Our model of capacity expansion is using daily time-series of renewable energy production generated from historical meteorological data to determine the mix of generation capacities, assuming perfect foresight. The optimal mix is subsequently used in a simple model that simulates dispatch of power plants, also on a daily level. It uses 100 different bootstrapped scenarios for renewable energy production to assess if the system can be operated in a safe way even without perfect foresight about future meteorological conditions. The models and the input data are described subsequently.

2.1. Optimization model

We have developed an optimization model that chooses among different capacities of renewable energies at different regions, effectively optimizing the production mix as represented by the modelled timeseries of power production from wind, solar, and hydro resources. The model also manages the hydro reservoirs and backup thermal dispatch. The model uses daily timeseries of power production, assuming that sub-daily variations in production are balanced by the availability of storage of up to 24 h in the system. Appendix A1 elaborates on the quantity of storage that may be needed for that purpose. The model minimizes the production in thermal power plants to achieve a low-carbon electricity supply. The amount of renewables that are additionally deployed is restricted by the amount of electricity demand currently not covered by existing hydro projects. We optimize the system for a period of 34 years with different meteorological conditions in each year to assess daily, monthly, and inter-annual variability of resources.

The objective function is the simple sum of thermal power production x_t^{th} during the whole time period:

$$\min \sum_t x_t^{th} \tag{1}$$

The optimization program is restricted by an equation balancing demand d_t with the supply of existing run-of-the-river hydropower plants h_t^h, with the immediate use of inflows for production in existing hydropower plants with reservoirs x_t^{hr}, of wind and pv power production at all available locations l $\sum_l (x_{l,t}^w + x_{l,t}^p)$, of thermal power production x_t^{th}, of run-of-the-river hydropower production at new locations $x_t^{h\_new}$, of hydropower production using water stored in reservoirs x_t^{st-}, and of curtailing of power production x_t^{cur}, which occurs if renewable power production is too high to be used or stored:

$$d_t = h_t^h + x_t^{hr} + \sum_l \left(x_{l,t}^w + x_{l,t}^p \right) + x_t^{h\_new} + x_t^{th} + x_t^{st-} - x_t^{cur}, \forall t \tag{2}$$

Hydropower production from plants with reservoir x_t^{hr} and water withhold in reservoirs x_t^{st+} have to be equal to the availability of inflows into the reservoirs h_t^r at that moment:

$$x_t^{hr} + x_t^{st+} = h_t^r, \forall t \tag{3}$$

New hydropower production is assumed to have no storage capacities, hydropower production from new projects therefore equals the availability of hydropower resources at that moment in time $h_t^{h\_new}$ times a variable controlling the deployment of new hydropower resources x^{h_deploy}:

$$x_t^{h\_new} = h_t^{h\_new} x^{h\_deploy}, \forall t \tag{4}$$

The same applies to wind power production $x_{l,t}^w$ and pv power production $x_{l,t}^p$:

$$x_{l,t}^w = w_{l,t} x_l^{w\_deploy}, \forall t, l \tag{5}$$

$$x_{l,t}^p = p_{l,t} x_l^{p\_deploy}, \forall t, l \tag{6}$$

Observe that the deployment variables $x_l^{w\_deploy}, x_l^{p\_deploy}$ and x^{h_deploy} do not carry an index t, i.e. it is not possible to change the level of deployment during the optimized period. We restrict the produced renewable electricity to the difference between total demand in the whole period minus the production of the existing hydropower plants. This restriction is introduced to limit the deployment of renewable capacities to the amount that is needed to cover additional demand, i.e. to get as close as possible to a fully renewable system. As the time profile of renewables does not perfectly match the time profile of demand, there is still need for thermal backup power, though:

$$\sum_t (d_t - h_t) = \sum_t \left(x_t^{h\_new} + \sum_l \left(x_{l,t}^w + x_{l,t}^p \right) \right), \ \forall t \tag{7}$$

The level of reservoirs of hydropower plants $x_{t+1}^{st\_lev}$ is determined by the level in the previous period $x_t^{st\_lev}$, by inflows into the storage x_t^{st+} times storage efficiency ρ and by outflows from storage x_t^{st-}:

$$x_{t+1}^{st\_lev} = x_t^{st\_lev} + \rho x_t^{st+} - x_t^{st-}, \forall t \tag{8}$$

The storage level is restricted by the maximum amount of installed storage in the system s^{max}:

$$x_t^{st\_lev} \leq s^{max}, \forall t \tag{9}$$

Thermal dispatch is limited by the maximum of the installed capacity t^{max} which is predefined:

$$x_t^{th} \leq t^{max}, \forall t \tag{10}$$

2.2. Simulation model

The optimization model is used to come up with an optimal mix of renewable energies, minimizing thermal power dispatch. However, it is a deterministic program and uses 34 years of historical meteorological data to generate results (1979–2012). Real operation, however, has to deal with future uncertainty about meteorological conditions and our optimization model with perfect foresight is therefore no valid representation of the operation of the Brazilian system. To assess the operational risk imposed by the generation mix which is determined by the optimization model, we also run a simple simulation for dispatch of power plants. The simulation model matches demand and supply. As long as there is more renewable supply than demand, as long as there are water inflows into reservoirs, and as long as reservoris are not full, the inflows are stored. If demand is higher than supply of renewables, reservoirs are used for production until only 50% of the total capacity of the reservoir is left. In that moment, thermal power production is dispatched. This is a simple mechanism to deal with the risk of periods of low rainfalls. If thermal production capacity plus renewables plus run-of-the-river hydroproduction and production from reservoirs is not sufficient to cover demand, this event is considered to be a loss of load and is analysed to inform about the reliability of the power system.

Instead of using directly the same 34 years of historical meteorological data that we use for the optimization model, we produce 100 different time-series of 100 years of meteorological data by bootstrapping months from the available data of 34 years. We thus are able to generate different meteorological scenarios, still preserving correlation among meteorological variables and, to a limited extent, auto-correlation of the time-series. By bootstrapping from monthly data, we also preserve seasonality. However, as a January from the year 1985 may be followed by a February from 2007, auto-correlation between monthly aggregates of the time-series is not preserved. Strauss et al. [26] use the same procedure to bootstrap monthly residuals of time-series from historical data for future climate change scenarios, as they argue that climatic conditions generally remain stable for weeks but not for months. Additionally, we also produce extreme versions of the meteorological scenarios, for which once in the whole period randomly 3 consecutive months of hydro inflows are set to 0 to simulate long periods of drought.

2.3. Renewable generation data

2.3.1. Solar data

We use the solaR package [27] in the statistical software R, version 3.1.2, to simulate PV production at production maximizing inclination of panels. Cloud coverage is taken into account by using solar irradiation data from global, modelled data sets. There are ground measurements from the Instituto Nacional de Pesquisas Espaciais (INPE) available, however they cover a very short period of time and contain a high number of data omissions. We therefore validated modelled solar irradiation data from three data sources, i.e. the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis project [28], the National Center of Atmospheric Research (NCAR)/National Centers for Environmental Protection (NCEP) reanalysis project (NCAR) [29] and from the National Aeronautics and Space Administration (NASA) [30] against INPE data (see Table 1) and consequently used those data sets for further assessments. INPE provides data from more than 294 stations, however only a subset of stations was selected which had a sufficient amount of data available to be used for validation (i.e. more than one year of consecutive feasible measurements), was selected. Subsequently, only this subset of data points was used for further analysis. Validation results are reported in Appendix A2.

2.3.2. Wind data

The simulation of wind power production and the validation of the respective long-term time series, also using ECMWF and NCAR data (see Table 1), is explained in detail in Schmidt et al. [2]. We are using simulated time-series for 34 years (period 1979–2013) derived for the four most important windpower states of Brazil, i.e. Rio Grande do Norte, Ceará, Bahia, and Rio Gande do Sul. The data is validated both with long-term measurements from meteorological stations and with short-term time-series of wind measurements at real production locations. The production at different locations within a state and at four different points in time per day are aggregated to daily values per state.

2.3.3. Hydro data

The daily hydrological inflows into hydropower plants are taken from a database of the national system operator in Brazil (Operador Nacional do Sistema Elétrico – ONS) [31]. Power production at hydropower plants is simulated by taking into account the installed turbines and the height of the power plants, taken from the official data set for the decadal energy plan – PDE 2021 [32]. The production values of all hydropower plants without reservoir are subsequently represented by a single power plant in the model. Also, all power plants with reservoir are represented by one power plant with a reservoir of 215 TWh of energy equivalent of water. If water inflows into the run-of-the-river power plant exceeds production capacity, those inflows are assumed to be released bypassing the turbines and therefore do not contribute to power production. Total capacity of the run-of-the-river power plants is 44 GW and that of the hydropower plants with reservoirs is 45 GW.

2.4. Demand scenarios, thermal power capacities and sensitivity analysis

We use daily load data, aggregated from hourly load data for the whole system for the year 2013 [33]. The demand in the scenarios is growing from 2013 levels to 2.8 times that level in the different scenarios. An electricity demand growth of 4.2% annually is estimated up to 2022 [1]. Within 22 years, i.e. in the year 2037, the demand level would therefore increase to 2.8 times today's demand, if Brazil continues to grow at that rate after 2022.

We run two sets of scenarios: one allowing hydropower, PV and wind power expansion (NEW_RENEW), the other one hydropower and thermal power expansion production only (HYDRO). In NEW_RENEW, the maximum capacity of thermal power plants is limited to 15% of maximum load, while the maximum thermal capacity is increased to 40% in the HYDRO scenario. Both values are the minimum necessary to achieve a fully operational system

Table 1
Data sources.

Type of data	Meteorological source	Temporal resolution	Period	Spatial resolution
Solar irradiation	ECMWF [28]	8 times daily	1979–2014	0.75 x 0.75 Degree Grid, globally
	NCAR/NCEP [29]	4 times daily	1948–2014	2.5 x 2.5 Degree Grid, globally
	NASA [30]	Sum of daily irradiation	1985–2005	1 X 1 Degree Grid, globally
	INPE[a]	Sum of daily irradiation	1998–2014	294 locations throughout Brazil
Wind speed	ECMWF [28]	4 times daily	1979–2014	0.75 x 0.75 Degree Grid, globally
	NCAR/NCEP [29]	4 times daily	1948–2014	2.5 x 2.5 Degree Grid, globally
Water inflows	Operador Nacional do Sistema Elétrico (ONS) [31]	Daily	1931–2012	Measurements at Brazilian rivers where hydropower plants are installed

[a] INPE solar irradiation data was taken from http://sinda.crn2.inpe.br/PCD/historico/radsol_full.jsp. The site is now offline, but today the data may derived from http://sinda.crn2.inpe.br/PCD/SITE/novo/site/index.php after registration.

without loss of load in the optimization model. The validation shows that ECMWF data is better able to reproduce characteristics of measured timeseries for both wind speeds and solar irradiation (see Appendix A2 for solar and [2] for wind). ECMWF data is therefore used throughout the model analysis. In the sensitivity analysis we assess how a different meteorological input dataset, i.e. the NCAR dataset for solar irradiation and wind speeds, would affect the outcomes of our optimization model.

3. Results

3.1. Optimization model

Fig. 1 shows the results of the optimization for two different levels of demand, 140% and 200% of demand in 2013 and for the NEW_RENEW and the HYDRO scenario. The figures show that with increasing levels of demand, PV production is increased in NEW_RENEW, while no new hydropower production is installed and wind power production is held almost constant.

There is no regular dispatch of thermal power capacities necessary, as seasonal fluctuations are quite complementary and daily variations are well balanced by the existing reservoirs. However, in some years substantial thermal power generation is necessary due to low hydrological resources. When the share of PV power production in relation to the other sources increases, it can be observed that thermal power production declines and that dispatch is less often necessary. Spills and curtailing of power generation occurs mainly in the first years of the modelled period due to the availability of large hydrological resources. For the HYDRO scenario the figure shows that regular dispatch of thermal power capacities is necessary due to seasonal undersupply of hydropower. Also, spills are higher due to the larger correlation of hydropower resources. Maximum dispatch of thermal power plants is at very high levels, more than 100% above the level of the NEW_RENEW scenario: while in NEW_RENEW, thermal capacity is 15% of maximum load, this number increases to 40% in HYDRO.

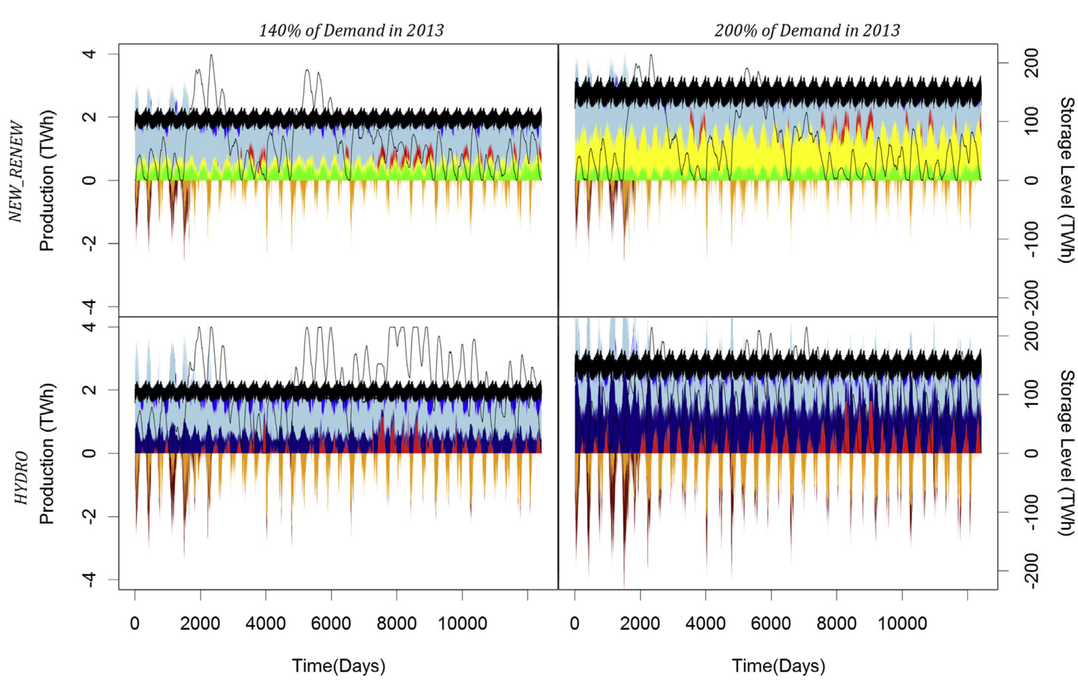

Fig. 1. Results of long-term optimization of the power system for 34 years. Left: 140% of demand in 2013, Right: 200% of demand in 2013. Above: NEW_RENEW scenario, below: HYDRO scenario. Note: light blue is hydropower production from inflows, dark blue is production out of hydropower reservoirs, darkest blue is production from new hydropower plants, red is thermal power production, yellow is solar PV power production, green is wind power production, orange are inflows stored in reservoirs and dark red denotes curtailment of power production. The thin black line shows the level of storage in the current scenario, while the fat black line shows system load. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

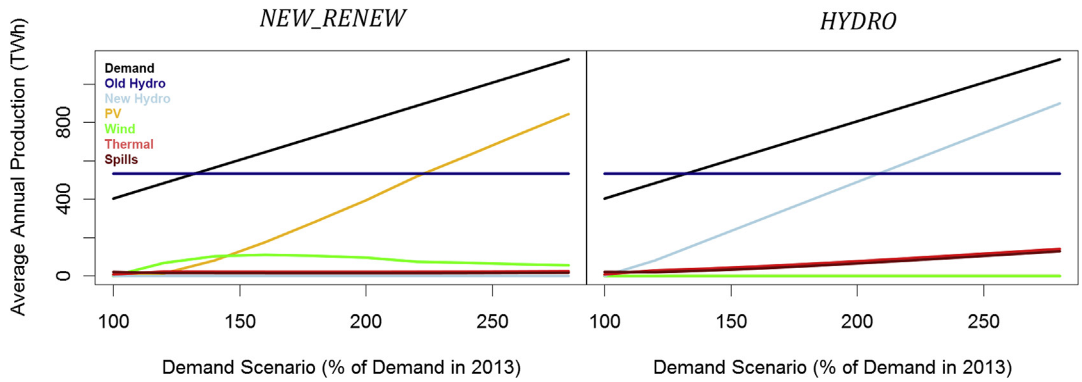

Fig. 2. Production from different electricity sources. Left: NEW_RENEW scenario, right: HYDRO scenario. Note: Black is total demand, yellow is PV power production, green is wind power production, dark blue is existing hydropower, light blue is new hydropower production, light red is thermal power production, and darkred is spills. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 2 shows in detail how the generation of solar PV, wind power, and thermal power develops when demand levels increase in the both scenarios. Observe that no new hydro production goes into solution in any of the demand scenarios in NEW_RENEW. The figure shows that in NEW_RENEW at low levels of demand, mainly wind power generation is expanded. Seasonal complementarity with hydrological resources is higher than for PV and explains this pattern. However, when demand increases above 130% of demand in 2013, PV starts to kick in and grows much faster than wind – wind power even decreases at higher demand levels. The reason is that daily, seasonal and interannual variation of PV is much lower than for wind power production, which increases the value of the power source to the system. This is also indicated by Fig. 3 which shows minimum daily production of the two systems. The daily guaranteed capacity of PV is much higher than that for wind when, for example, comparing a demand level of 150%, where annual generation of PV and wind is almost equal. PV has a guaranteed capacity of about 15% of maximum daily production, while wind has a guaranteed capacity of only 0.01% of maximum daily production. At higher deployment levels of PV, the guaranteed capacity rises to even 44% due to spatial diversification (see Fig. 3 below).

In HYDRO, only new hydropower production is allowed. While spills and thermal power production remain constant or even decrease slightly with increasing demand levels in NEW_RENEW,

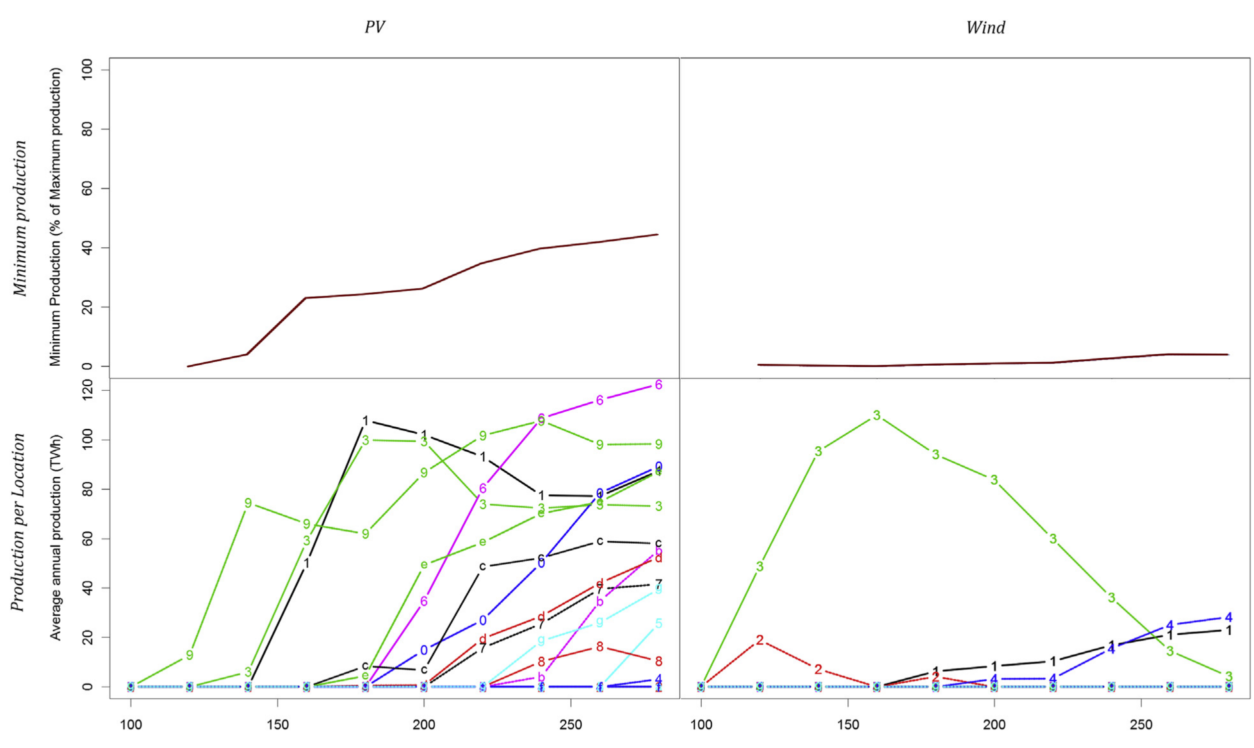

Fig. 3. Above: minimum guaranteed capacity for PV (left) and wind (right). Below: Locations chosen in the optimization model for PV (left) and wind (right) generation. Note: The numbers for solar refer to the numbers in Fig. A2.1. For wind power, (1) denotes Bahia, (2) Ceará, (3) Rio Grande do Norte, and (4) Rio Grande do Sul.

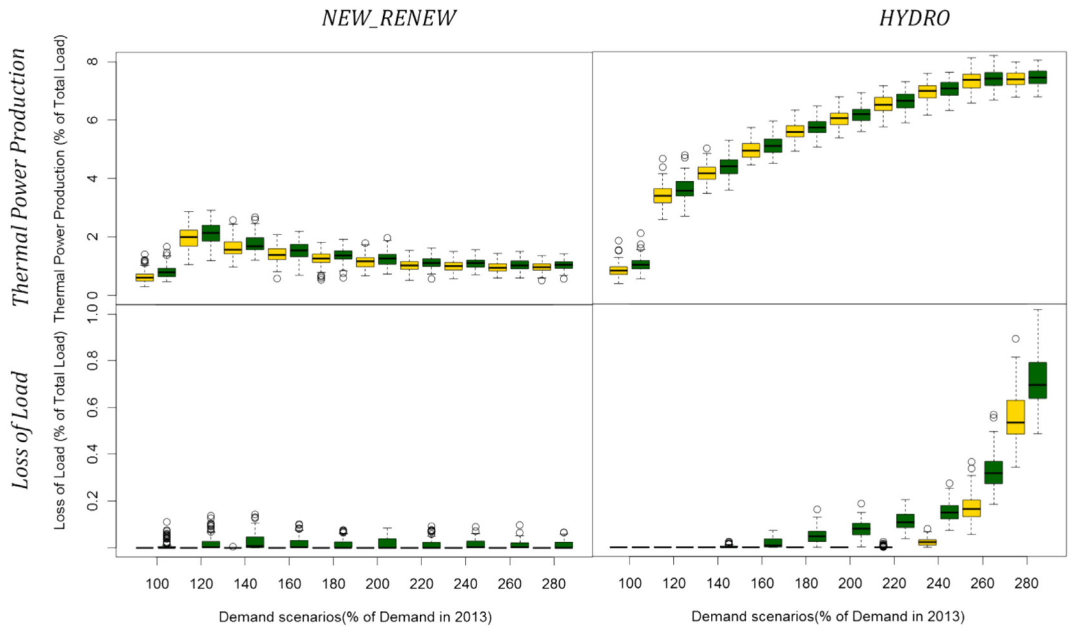

Fig. 4. Left: thermal power production (% of total production). Right: loss of load (in % of total load). Above: NEW_RENEW scenario. Below: HYDRO scenario. Yellow: Bootstrapped scenarios from historical data. Green: bootstrapped scenarios from historical data including a random 3 month period without any hydro power inflows.

in the HYDRO scenario spills and thermal power production grow steadily as a consequence of the high correlation between new and old renewable resources.

3.2. *Simulation model*

The simulation model shows results similar to the optimization model for both scenarios (see Fig. 4), although thermal power production is higher – this is a result of the simulation procedure which is not able to optimally allocate resources. Also, loss of load events occur. However, even in the extreme drought scenarios the loss of load does not exceed 0.2% in any of the NEW_RENEW scenarios. This is a result of the very stable output of combined solar, hydro and wind power production. However, in HYDRO up to 1% of total demand cannot be covered by the available production capacities when dispatching with the simple algorithm, even though thermal backup capacities are more than twice as large as in NEW_RENEW (40% instead of 15% of maximum load). Also, with increasing demand levels, the share of thermal power production, of spills and uncovered demand do increase while the opposite is the case for the NEW_RENEW scenario, i.e. adding more hydropower to the system will increase operational complexity due to higher variability in output while the opposite is the case for adding a mix of wind, solar, and hydropower. The simulation model shows that even with a very simple dispatch heuristic, the risk of loss of load can be held very low in a scenario that mixes the three renewable sources.

Currently, 5% of Brazilian power production comes from biomass [4]. If this level is maintained, all thermal power production in any of the NEW_RENEW demand scenarios may come from biomass. In HYDRO, thermal power production attains up to 8% of total generation in the high demand scenarios. In the 280% demand scenario, biomass production would have to be increased by a factor of 4 compared to today's biomass generation levels. Alternatively, fossil fuels would have to be used as feedstock in thermal power production.

3.3. *Sensitivity analysis*

In our sensitivity analysis we have assessed the impact of different meteorological data sources on the outcome of the optimization model in the NEW_RENEW scenarios. The overall picture remains the same, i.e. high shares of solar PV and much lower shares of wind power deployment. However, ECMWF shows higher levels of wind power for lower levels of demand and lower levels at higher levels of demand (see Fig. 5) and the contrary for solar PV. This is a result of a slightly different seasonality of wind power data in the data sets as shown by Schmidt et al. [2]. Also, different generation locations are chosen when using the two datasets.

4. Discussion

The dispatch problem in a system as the integrated Brazilian system is much more complex than our simple optimization model is able to depict. Therefore, several important assumptions have to be made to assume that the shown dispatch is feasible. First, the expansion of the electrical system as proposed in this article depends on the availability of an electricity storage that is able to store electricity production at least for 24 h at high efficiencies and at high capacities for charging and uncharging the system. This is necessary as we use time-series of wind and PV production of daily resolution. PV production has a very high variability during the day (i.e. no production in the night), this variability therefore would have to be balanced by storage (see Appendix A1 for an estimation of necessary storage capacities).

We did not assess if currently installed transmission and distribution lines would be able to handle the load. Of course, an expansion of the transmission system is necessary in any expansion scenario, independent of the generation technology, if electricity demand increases substantially in the long-term. As most of the expansion in our results comes from PV, this may even allow for more efficient use of transmission capacities: solar irradiation is by far not as concentrated as other sources of power such as

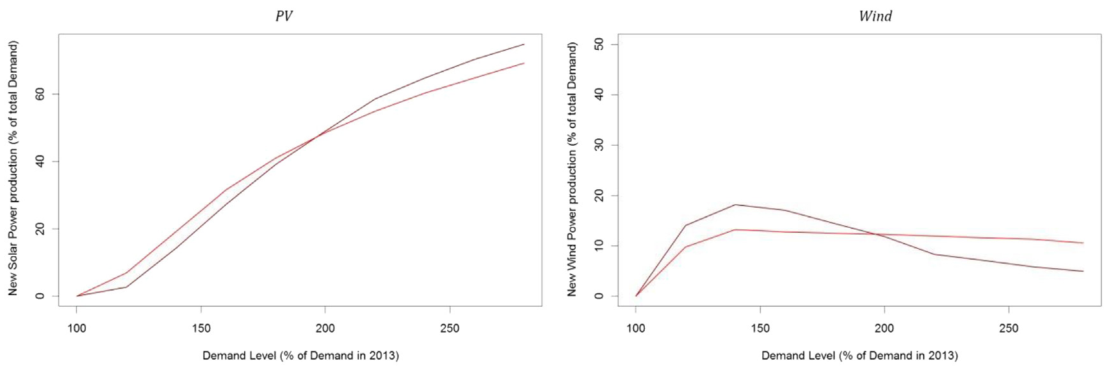

Fig. 5. Comparison of NCAR (light red) and ECMWF (dark red) results for the deployment of PV (left) and wind power (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

hydropower or wind power generation – or even gas power that has to be located close to gas producing sites or close to gas pipelines which are still rare in Brazil. Due to the low spatial variation of solar radiation, the location of a particular site for installing PV can be chosen to be close to an existing transmission line. Also, instead of building large scale PV plants, smaller scale plants closer to demand centres and even distributed generation could reduce the need for additional transmission lines – and could reduce the pressure on delicate ecosystems and on socially conflictive land. The geographical resolution of our data set is too limited to assess those options – however, our results can be considered conservative as further spatial diversification would reduce the total variance of renewable output and therefore further reduce the need for thermal backup generation.

There remains uncertainty on the meteorological input data. Validation of modelled solar radiation and wind speed data with ground measurements showed a relative large error margin. Increasing quality of both, modelled data and of future ground measurements, may therefore reduce the uncertainty on the behaviour of the meteorological system. Also, a better modelling of local conditions by combining ground measurements with modelled data as performed by Szczupak et al. [34] may increase confidence in results. It also has to be regarded that local and global climate regimes may be subject to long-term changes, which is not considered in the current analysis and which may alter our results. However, the sensitivity analysis confirms that independent of the source of data, the main results of our analysis – i.e. high shares of PV and no new hydropower production – are confirmed. Additionally, a stochastic model of the meteorological data, considering seasonality, auto-correlation, and correlation between different sources of renewable power and different production locations may allow to generate better synthetic time-series for assessment of uncertainty than the simple bootstrapping procedure used here. In particular the monthly auto-correlation in the variables is not considered by our sampling procedure and is an interesting line of future research.

We did not take into account costs of the different technologies but used the assumption that Brazil aims at a low carbon energy matrix, continuing past efforts. Obviously, PV generation is currently the most costly from the three regarded power sources and pure economic optimization would not allow PV generation at the moment. However, costs have been drastically decreasing in the last years and currently, levelized costs of electricity for PV are competing with costs of gas and wind power in the United States [35] – and are only around 40%–50% above wind costs in Brazil, already being able to compete with gas power plants when considering levelized costs of electricity [13]. Further steps down the learning curve may therefore allow an economically profitable operation of PV in Brazil at least at locations where solar irradiation is high. We did not assess the economics of our solution as future projections for PV are highly uncertain. Decreasing costs by expansion of the sector in Brazil is therefore of high importance to be able to profit from further cost decreases along the supply chain. The same is true for storage which is essential to accommodate a large share of PV. Pumped-storage plants may be a feasible option in Brazil [36], however, their costs may be prohibitive due to the high need for generation capacity (see Appendix A1). Batteries are currently still too expensive in terms of storage capacity. However, as occurred to PV, costs of storage may rapidly decrease. Storage is only necessary when installed PV capacity exceeds a certain threshold of total capacity. Up to that moment, developments in the storage market should be carefully monitored to assess future conditions for the further uptake of PV. It may also be considered that concentrated solar power plants have a daily and seasonal time profile of production similar to PV, but allow for a better temporal distribution of production throughout one day. It may therefore be an interesting line of future research to assess the integration of CSP instead of PV into the system.

We did not assess land use implications of a large expansion of wind and PV power plants. Again, PV has great advantage over other forms of renewable energy production as it depends less on particular sites for deployment due to the availability of significant solar irradiation in Brazil at many locations. Therefore, conflicts with other land uses may be minimized. Also, at least part of the capacity may be installed as decentralized generation on roofs of buildings, thus not contributing to land use conflicts. Still, a thorough analysis of the availability of land and the design of an open, transparent, and participative process in acquiring land for renewable energy production are subject to further research in particular as existing wind projects do create socio-environmental conflicts [12].

Other studies that take a more technical look into the system, modelling in detail the current electricity system and the integration of intermittent renewables come to much less optimistic conclusions with respect to the deployment of intermittent renewable sources. However, our approach is a long-term one and shows that variability of the renewable power sources, in case daily storage is available, can be very well balanced by combining different renewable sources, by relying on the current system of hydropower reservoirs, and by providing a limited thermal backup capacity.

5. Conclusions

We have shown that PV and wind can contribute to stabilizing the daily, monthly, and annual combined hydro-wind-PV output compared to a hydro-thermal system only and could substantially decrease the need for thermal power generation. Thermal power backup capacity would not have to be expanded from current levels to guarantee high levels of security of supply. Subdaily, i.e. hourly variation of PV and wind supply would have to be balanced by storage, however.

The expansion of hydro power from current sources is not found to contribute in decreasing the need for thermal backup capacities. The high seasonal and inter-annual variability of the resource and the fact that, in the future, very few reservoirs are going to be built, reduces the value of this renewable resource in providing a stable power output.

The expansion of wind power is less valuable in terms of stabilizing total output than PV, however up to 9% of demand may be supplied by wind power when demand is doubled from the levels of 2013. There is still high uncertainty on the long-term variance of that renewable power source, research in this area is therefore of outmost importance.

Acknowledgements

Gabriel Malta Castro (EPE) helped us in accessing and processing data sets for the hydro power production model, we are very grateful to him. We also want to thank Wilkens Filho (ONS) who provided load data from the Brazilian system to us. Stefan Höltinger and Dieter Mayr commented on late versions of the paper, we are very grateful to them. The research was supported by CNPq with a master scholarship for Rafael Cancella (grant number 134018/2013-3) and a Post-Doc scholarship for Johannes Schmidt in the program "Atração de Jovens Talentos – BJT" (grant number 375012/2013-3).

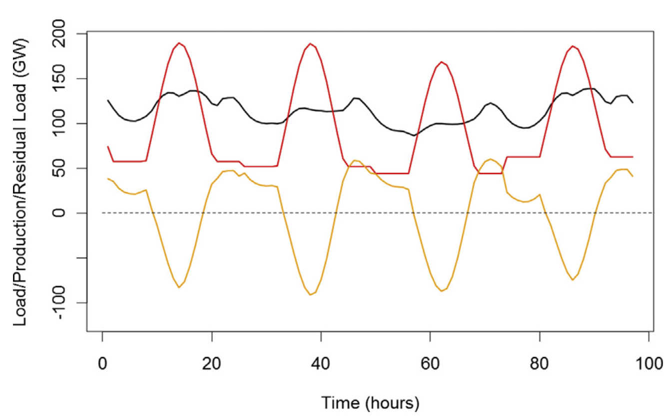

Fig. A1. 1: Load (black), production (red), and residual load (orange) for four sample days.

Appendix A1. Storage needs

We consider only daily dispatch in our model. However, solar PV and wind power show large hourly variation. In particular the production of PV is concentrated in few hours of the day. The shown dispatch of power capacities is therefore only possible if storage is added to the system to allow balancing supply and demand over the day. The amount of storage necessary can only be roughly estimated as there are no hourly estimates for neither hydro-power production nor wind-power production available to us. Still, hourly PV production can be simulated with the solaR package [23] in R. The hourly dispatch of other sources, i.e. run-of-the-river hydropower, hydropower from plants with reservoirs, wind power, and thermal power was distributed evenly over the day by dividing daily production by 24. This is obviously a very rough estimate: in particular wind power may have very large variations during the day, whereas power from thermal sources and from hydropower storage plants can be dispatched at will by the system operator. We therefore assume that the combined wind, thermal, hydrostorage, and run-of-the-river power production is stable during the day by dispatching hydro plants and thermal power plants at the right times during the day (i.e. when wind production is low). PV is added to base-load production and the difference to hourly load in the network is determined. Daily load values always match daily production values as a result of the optimization process, we therefore only have to consider the variations during one day. We calculate the maximum daily over- or underproduction in the system to determine the necessary storage capacity in GWh and the maximum over- or under-capacity in the system to determine the production capacity of the storage in GW. Fig. A1.1 shows an example of load, production, and residual load for four sample days. The results show that, when load is doubled from the level of 2013, a maximum of 167 GW of charging capacity have to be in place, while a maximum of 913 GWh of storage capacity have to be guaranteed for a feasible hourly dispatch along the simulated period of 34 years. While the storage capacity can be considered low for pumped-storage power plants – Brazil fosters a total of 215 000 GWh of storage capacity in hydro-reservoirs - the charging capacity is very high, i.e. a huge amount of additional turbines would have to be added to the system. The opposite is true for batteries: charging and discharging rates of around 5 to 6 are available in commercial batteries, but installing storage capacity of that amount is currently economically not feasible.

Appendix A2. Validation of solar data

17 INPE stations in Brazil have met the quality criteria to be used for validation of ECMWF, NCAR and NASA data. The data points are well distributed over the whole of Brazil (see Fig. A2.1) and represent well the variation in climatic conditions and in latitude over the whole of Brazil. There is a major gap in the North-West of Brazil, as most of the region is however currently sparsely populated and partly covered by the Amazon forest it may not be well suited for PV production anyhow.

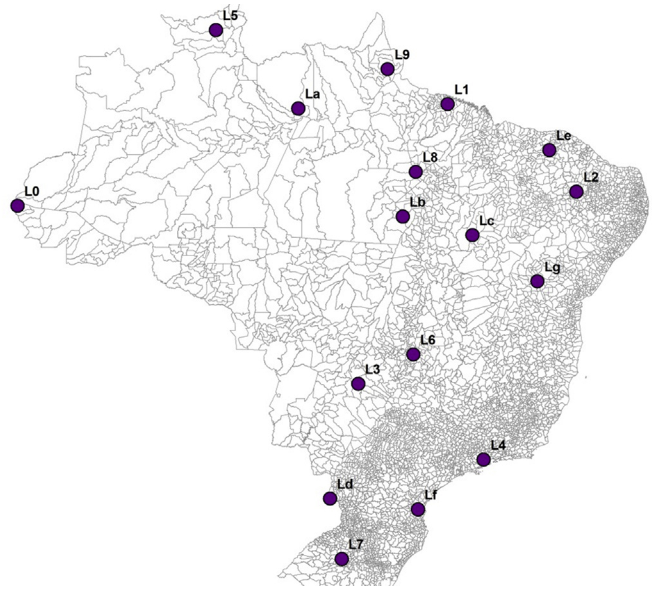

Fig. A2.1. Location of INPE stations used for validation.

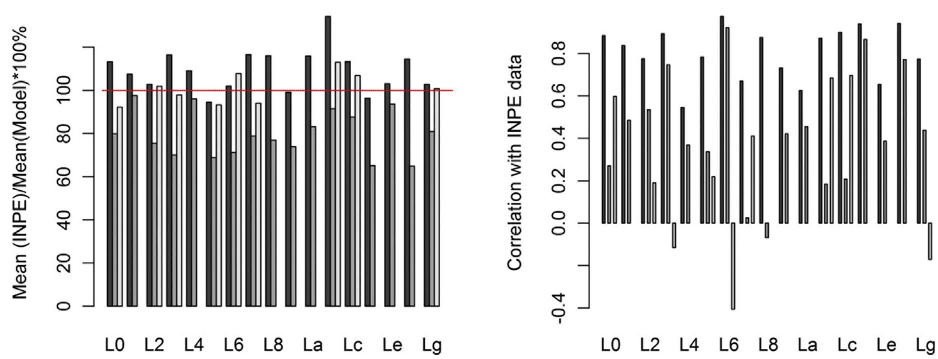

Fig. A2.2. Results of validation of solar irradiation data. Left: Comparison of Mean of Model Data to INPE data. Right: Correlation of Model Data with INPE data. Black is ECMWF data, grey is NCAR data, and light grey is NASA data.

Fig. A2.2 presents a comparison of the mean of the modelled data sources to INPE data and of the correlation between INPE and modelled data. NASA data is not shown in some of the comparisons due to a lack of temporal overlap with INPE data: NASA data is only available up to 2005 and INPE data, at some stations, is not available for the whole period 1998–2013. ECMWF data shows, for all stations, the highest correlation with measured INPE data. But even for ECMWF data, correlations are rather low with values below 0.5 for some stations. We have also calculated monthly correlation, which is above 0.5 for all locations, and above 0.8 for all but 5 locations. The production mean is lower at all locations but two for ECMWF data, however, deviation is not above 30% for any of the locations. NCAR and NASA data overestimate irradiation, NCAR data being the data set that shows the highest deviation. Variance of ECMWF data is higher than the one of INPE for all but three locations, while NASA data underestimates variance of INPE data for all but 2 locations. NCAR is rather extreme and shows both underestimates and overestimates of variance, depending on the location. ECMWF data seems to be the closest representation of INPE data and is therefore used in the further analysis. However, in a sensitivity analysis we also use NCAR data to see if the data source heavily influences results. NASA data does not seem to be a valid data source for our purposes because (I) validation was only possible for a subset of locations due to the limited temporal coverage of the data set (available only up to 2005) and (II) the dataset shows partly negative correlations with measured data, which is a rather poor performance. To adjust for the rather large differences in mean irradiation, the mean of ECMWF and NCAR datasets is calibrated to the mean of the INPE data for the model analysis.

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Article IV

Schmidt, J., Wehrle, S., Rusbeh, R.
A reduction of distribution grid fees by combined PV and battery systems under different regulatory schemes.

A reduction of distribution grid fees by combined PV and battery systems under different regulatory schemes

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***Abstract*—Depending on the chosen regulation, distributed generation reduces revenues for Distribution System Operators (DSOs) although costs for maintaining the system do not decrease – or even increase due to new load patterns such as peak generation of PV. We assess the impact of different forms of grid fees on household choices of PV and battery systems in a cost minimization framework and explore how those align with the requirements of DSOs. Fixed grid fees, independent of consumption and of peak demand of households, best allow for a full recovery of costs by DSOs. However, they pose a barrier to increasing distributed generation. Variable grid tariffs are not compatible with requirements of DSOs as they increase incentives for distributed generation but do not incentivize load shifting, thus increasing average and peak load at decreasing DSO revenues. Demand fees which are paid based on the peak load of households create incentives for decentralized storage. However, they may reduce revenues of DSOs significantly, while they do not necessarily decrease system costs to the same extent: peak load on the grid still remains high although the peak load of single households is reduced, due to changes in the correlation of loads of households after adopting battery technologies.**

***Index Terms*—Batteries, Photovoltaics, Supply and Demand, Power Grids**

I. INTRODUCTION

Distributed generation in households, in particular solar PV, decreases revenues for Distribution System Operators (DSOs) in most countries in the European Union, as network fees for households are based on variable consumption of electricity combined with a small fixed fee (refE et al., 2015). This is also the case for Austria, which is the focus of this study. Distributed generation substitutes energy from the grid and reduces DSO income through reduced revenues from consumption based tariffs. At the same moment, costs for the distribution grid operation remain constant or are even increased as peak loads on the network increase due to the feed-in of highly correlated PV generation. DSOs therefore increasingly demand from regulators to shift rates from variable consumption to fixed or demand rates to be able to recover costs [1], [2].

We compare three possible different tariff designs to assess how incentives for distributed generation and storage can be increased, while still maintaining revenues for DSOs: network fees can be completely based on consumption, which generates the problems of decreasing revenues for DSOs at stabilizing or even increased costs as the market share of distributed generation increases.

Tariffs can also be completely shifted to fixed rates, independent of the consumption or the maximum load in the household. The redistribution of costs, from consumption based to fixed, may however be considered unfair. Households with low consumption see their electricity rates significantly increased while high consuming households reduce their costs for electricity. Households cannot defer from a fixed rate, as they would have to completely disconnect from the electricity grid which is very costly when similar service quality is maintained.

As a third option, demand rates can be introduced. In that case, network fees depend on the peak demand of the particular consumer. Peak demand can be reduced if storage is introduced to households. Consumers can change their load profile to one that is less costly under the new regime by installing batteries which reduce their peak demand – and additionally integrate more of their own PV generation into the self-consumption of the household. The profitability of investments into decentralized electricity production of households therefore depends significantly on the chosen network tariff structure.

The adaptation of households to new tariff structures has two consequences for DSOs: first, revenue streams may change significantly, i.e. income from tariffs may decrease or increase compared to a baseline without change in tariffs. Second, a change in the load profiles after adaptation may also alter infrastructure costs of DSOs. In particular the average and the peak load on the network may be changed, which will affect future investment requirements and operational costs of the DSOs. When the adaptation of households to changed tariff structures is considered, new tariff schemes may therefore not fully cover costs implied by the adaptation to the scheme.

We apply a single-household optimization model which is able to choose between solar PV, batteries, and different distribution grid capacities to investigate the adaptation of cost-minimizing households to changed tariff structures. We use 15-minutes measured load profiles for 80 different households to assess the profitability of combined PV-battery-grid systems in comparison to grid-only systems. Additionally, we assess how the load is shifted by the battery system and how this affects the joint demand in the subsection of the distribution grid. We discuss the consequences for DSOs and conclude by giving policy recommendations.

II. Data & Methods

We first introduce the optimization model for the households and then show how individual household loads are related to the load on the subsection of the network. The empirical data used to solve the models and associated scenarios are presented subsequently.

A. Optimization model

A household with demand d_t faces costs for the amount of grid electricity x_g_t consumed $r_c \sum_t x\_g_t$, r_c being the electricity tariff, which is assumed to be time-independent[1]. Additionally, when a demand rate is applied, the household faces fixed costs depending on the peak consumption in a particular year $f_{grid}(x\_g^{cap})$. An additional fixed network fee does not change the investment decision into PV and batteries of the households, as the household's budget constraint is not considered here. To lower both, energy as well as variable grid tariffs, the household can install PV panels. We assume that the system is depending on weather conditions and production is therefore fixed at $x\_cap^{pv} * pv_t$, x_cap^{pv} being the installed capacity, and pv_t a production profile normalized to 1 kw_{peak}. The system costs $f_{pv}(x\_cap^{pv})$. Additionally, a battery system can be bought at cost $f_{battery}(x\_cap^{store})$. If distributed generation is installed in the household, the household may be able to sell surplus electricity x_p_t to the grid at a rate of r_p. The household therefore minimizes the following problem:

$$\min r_c \sum_t x\_g_t + f_{grid}(\text{x\_g}^{\text{cap}}) + f_{pv}(x\_cap^{pv}) + f_{battery}(x\_cap^{store}) - r_p \sum_t x\_p_t$$

The following balancing restriction applies, i.e. demand has to meet supply, allowing for the curtailment of surplus electricity $curtail_t$:

$$pv_t * x\_cap^{pv} + x_{g_t} + x\_storage_t^{out} = d_t + x\_storage_t^{in} + x\_p_t + x\_curtail_t, \forall t$$

[1] Some electricity rates in Austria differentiate prices between consumption during day and during night, which may make batteries more profitable. There are even time-dependent tariffs (such as from awattar.com). Those are neglected here.

Parameter d_t denotes the fixed load in the household[2], while $x\_storage_t^{out}$ and x$_storage_t^{in}$ denote the discharging and charging of batteries, respectively.

Storage is balanced with the help of the following equation, taking into account simplified linear storage efficiency σ, $x\_storage_t^{lev}$ indicating the current storage level:

$$x\_storage_{t+1}^{lev} = x\_storage_t^{lev} + \sigma x\_storage_t^{in} - x\_storage_t^{out}, \forall t$$

The storage can only store a particular amount of electricity, given by its storage capacity:

$$x\_storage_t^{lev} \leq cap^{store}, \forall t$$

The storage can only charge and discharge at a certain rate, which is defined as being the fraction δ of the purchased storage capacity:

$$x\_storage_t^{in} \leq \delta cap^{store}, \forall t$$
$$x\_storage_t^{out} \leq \delta cap^{store}, \forall t$$

Finally, the amount of electricity taken from and fed into the grid is limited by the capacity of the grid connection:

$$x\_g_t \leq x\_g^{cap}, \forall t$$
$$x\_p_t \leq x\_g^{cap}, \forall t$$

B. Cost for DSOs

Costs of the distribution grid for the DSO depend mainly on the peak capacity (we neglect here wear-out of equipment due to utilization). We can assume a linear relationship between peak capacity (in the subnet of the distribution grid) and costs, such as:

$$(1) \quad C(x_{peak}) = c_{fixed} + f_{cap}(x_{peak})$$

where $x_{peak} = \max(\sum_i x\_g_{t,i}, \sum_i x\_p_{t,i})$. Costs are therefore constituted of a fixed part c_{fixed} and a variable part $f_{cap}(x_{peak})$. The load is either generated by consumption or by feed-in of PV generation.

The question arises how x_{peak} is related to the peak demand of the single households: the computation of the demand fee depends on that relation. In general, the diversity factor indicates how the peak load of a single household is related to the peak load in the (sub-)network. The diversity factor depends on the correlation of energy consuming processes, i.e. it is high for heating while it is lower for cooking devices [3]. We define it here as the relation of maximum load in the sub-grid and the sum of the maxima of the individual loads: $div = \frac{Max_t(\sum_{i=1}(Load_{i,t}))}{(\sum_{i=1} Max_t(Load_{i,t}))}$. Introducing the diversity factor, equation (1) can be written, in terms of peak load of single households, as:

[2] We neglect demand side reactions to changed prices as well as technical demand side management options here.

$$C(grid) = c^{fixed} + f_{cap}(div \sum_i g_i^{cap})$$

When adaptation of households is considered, div is not a fixed parameter but a variable. The introduction of solar PV will change div: solar PV generation in a subsection of a low-voltage grid is highly correlated, peaks in feed-in to the grid therefore also are highly correlated. It is not clear, however, if the diversity factor changes with the introduction of batteries. Depending on the operational mode of the battery, it may contribute to lowering the impact on the grid – or it may even increase the peak load. This means, that the costs of grid supply now depend on the generation and storage facilities installed in the subsection of the grid, as div becomes a function of PV and battery capacities, i.e. $div = f^{diversity}(cap_i^{pv}, cap_i^{store})$:

$$C(grid) = c^{fixed} + f^{cap}\left(f^{diversity}(cap_i^{pv}, cap_i^{store}) \sum_i g_i^{cap}\right)$$

We do not aim at determining in detail the costs in the subsection of the distribution grid, but aim into exploring how different policies affect adaptation of technologies in the households and how these change the overall load pattern on the subnetwork.

C. Load Data

Load data was measured in the period April 2010 - March 2011 for 1330 households in Upper Austria in 15 minutes intervals, using smart meters. None of the households had PV units installed. We selected a subset of households that consumed electricity under the same tariff structure (458 households). Within the datasets, some of the measured profiles had very low quality due to long incomplete periods of measurement. We chose 80 households with almost complete samples. Annual average consumption in the 80 households was 3,927 kWh, below the reported average of Austrian households of 4790 kWh for the year 2009/2010 [4]. We assumed that the 80 households are connected to the same low-voltage grid. Average load on the grid was 35 kW, while the peak load on the simulated subsection of the grid was 114 kW.

D. PV Data

PV data for the respective period (April 2010 – March 2011) and respective location (Linz in upper Austria) was derived from the model developed for PV-GIS [5]. Based on satellite images from DWD, which reports direct and diffuse irradiation, the horizontal irradiation was calculated. Considering temperature and shadowing based on a digital elevation model, the irradiation data was converted to timeseries of PV production, assuming an inclination of 35 degrees of PV modules, facing south-wards. This is very close to the optimum for the considered location. Sub-optimally installed PV systems are therefore not considered. Losses from inverters, cabling, and other system losses were assumed to sum up to 10% of production. PV production was modelled on an hourly basis only. To fit the more highly resolved load data, PV production in a particular hour was interpolated into four subhourly values. In the full year, the simulated system generates 1023 kWh per kw_{peak} of installed PV panel.

E. Scenarios

We optimized one year of operation for all households and assessed three different policy scenarios:

(1) Fixed: Implementation of a fixed network tariff, where consumption and peak demand are not taken into account in the tariff. This is the most adverse tariff structure with respect to the profitability of distributed generation and batteries.

(2) Variable: A continuation of the current Austrian tariff structure for households, which consists mainly of a variable grid tariff per kWh depending on consumption. This is the most favourable tariff for distributed generation, as an avoided kWh of electricity from the grid is worth the electricity rate plus the variable grid fee. As batteries can increase the self-consumption of generated PV electricity of households, the tariff also incentivizes battery storage to some extent.

(3) Demand: The introduction of a demand fee which is calculated on basis of the peak demand of the household. We assume a linear relationship between peak demand and costs for the households. In that case, there is an incentive for installing battery systems to lower the peak load in the household.

The values for variable and demand tariffs were tested for the range shown in TABLE 1. Fixed fees were chosen so that the compensation of DSOs equals the currently used variable fees.

Investment costs into PV and in particular into batteries are currently not competitive in any of the scenarios. To allow for the installation of those technologies in the simulated housholds, we assumed very low system costs of 1000€/kw_{peak} for PV panels and 200 € / kWh usable storage capacity of batteries.

TABLE 1: CHOSEN VALUES FOR POLICY SCENARIOS (PER HOUSEHOLD)

	Fixed (€/Year)	Demand fee (€/kW/Year)	Electricity Tariff (€/kWh)	Variable Grid Tariff (€/kWh)	Feed-in Tariff (€/kWh)
Fixed	120	-	0.14	-	0.05
Variable	-	-	0.14	0.02 – 0.30 (steps of 0.04)	0.05
Demand	-	20 – 160 (steps of 20)	0.14	-	0.05

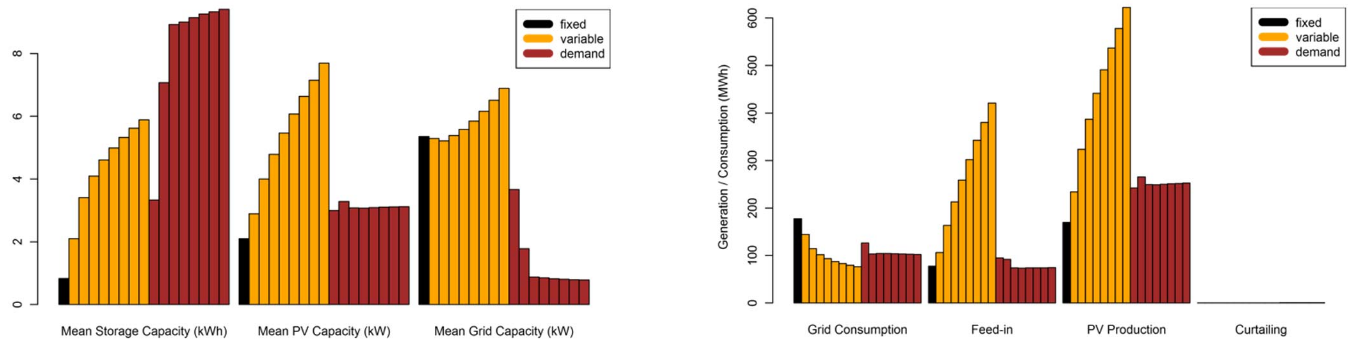

Figure 1: Left Panel: Average investments of households into distributed generation and peak grid capacity in the 17 policy scenarios. Right Panel: Grid consumption, feed-in into the grid, PV generation and curtailing in the 17 policy scenarios.

Currently, PV systems trade for around 1500€/kw_{peak} for system sizes of 4 kw_{peak} [6] and battery systems for about 800 €/kWh (Li-Ion battery systems, 90% roundtrip efficiency, a lifetime of 10,000 cycles) [7]. We assume a linear scaling of costs with capacity for both technologies, although this is not realistic as specific costs decrease significantly with increasing system size. However, it allows for a fully linear formulation of the optimization model which was necessary at this stage to reduce computational complexity.

The results of the optimization model strongly depend on the relation of PV to battery costs. We assume a stronger future cost decrease for batteries than for PV, as PV has travelled down the learning curve to a larger extent than batteries. Battery roundtrip efficiency is assumed to be 90%[7] , while we assume that the maximum charging and discharging power in kW is half the maximum storage capacity in kWh (i.e. δ =0.5). Investment costs are annualized, as we are only simulating one year of operation. We assume an interest rate of 3% and a lifetime of 20 years for the PV panels and 11 years for the batteries.

I. Results

Figure 1 (left panel) shows the average results of the optimization for all households. In all scenarios, the cost-minimal solution allows for an investment in PV and batteries in all three policy scenarios. However, investments into batteries are much higher in the demand fee scenario: this is a result of a reduction in demand fees when the peak load is decreased. Investment into PV is highest in the variable grid fee scenario.

In the demand fee policy the peak load of the simulated households is reduced to less than 1kW (from 5.66kW) on average when demand fees are increased. This is possible due to high battery capacities of up to 8kWh. However, there is a saturation effect at demand fees above 60€/kW: battery capacities do not further increase if fees rise above that level because additional storage capacities do not allow decreasing the peak load further. In the demand fee scenario, PV investments are lower than in the variable fee scenario because avoided costs from buying electricity from the grid are lower in the first. System sizes are consistently lower than 3kW_{peak}, while they reach up to 8kW_{peak} in the variable fee scenario at very high variable grid fees.

Consumption of grid electricity decreases in all scenarios due to the installation of PV panels, (see Figure 1, right panel). Feed-in into the grid is highest in the variable fee scenario, as installed PV capacity is high and battery capacities are low. Feed-in into the grid remains almost constant for increasing demand fees in the demand fee scenario, as increasing PV generation is consumed in the households due to higher battery capacities. This is different for the variable grid fee scenario, where feed-in grows linearly with PV generation. In the demand scenario, a very small share of PV generation is curtailed to not exceed peak capacities.

Revenues for DSOs, costs of electricity supply for households and changes in the load pattern are shown in Table 2. In the fixed grid fee scenario, revenues of DSOs remain stable by definition. Total costs for households do not change, although some PV and storage capacity is installed. The peak load increases to 108%, while the average load on the network is increased to 106% due to PV generation.

In the variable grid fee scenario, an increase of fees does not necessarily lead to an increase in revenues. In the model, households start adapting to increased fees by installing larger PV capacities and batteries to increase auto-consumption and therefore decrease grid fees. At the same moment, the peak load in the grid increases significantly, as does the average load. The reason is the highly correlated feed-in of PV generation. Peak load increases relatively more than revenues of DSOs. Therefore, an increasing variable fee on grid consumption creates a vicious circle of increasing investment requirements for DSOs and increasing costs for households.

If a demand fee is implemented, the relative difference between the demand fee and battery costs matters. At the chosen parameter settings, a demand fee of 20€/kW/Year would not be sufficient to recover costs for DSO because the fee triggers investments into batteries and therefore lowers peak load in the households. Nevertheless, the combined peak load on the grid increases significantly as a consequence of increasing diversity factors due to PV production and storage. Costs for households are slightly lower than in the baseline scenario.

When the demand fee increases above 20€/kW/Year, households are incentivized to invest into larger battery capacities. Costs for households start to increase above the baseline scenario. At 60€/kW/Year a saturation effect can be observed: installed capacities neither of PV nor of batteries change.

TABLE 2: CHANGES IN COSTS AND LOAD PATTERNS ON DISTRIBUTION GRID

	Tariff Level	Revenues DSO (% of Baseline)	Costs Households (% of Baseline)	Peak Load Grid (% of Baseline)	Average load on network (%of Baseline)	Diversity Factor
Fixed (€/Year)	120	100	100	108	106	0.25
Variable (€/kWh)	0.02	27	90	158	119	0.36
	0.06	64	108	225	144	0.52
	0.10	95	123	277	166	0.62
	0.14	122	136	320	187	0.70
	0.18	147	148	371	206	0.77
	0.22	171	160	413	225	0.81
	0.26	194	171	451	243	0.84
	0.30	215	182	496	262	0.87
Demand (€/kW/ Year)	20	54	98	166	110	0.55
	40	53	111	131	90	0.90
	60	39	115	71	67	0.99
	80	50	118	70	66	0.99
	100	61	121	67	66	0.99
	120	71	123	65	66	0.99
	140	82	126	65	66	0.99
	160	93	129	64	66	0.99

At this level, revenues for the DSO are reduced to 39% of the baseline and costs for households are increased to 115%. At the same moment, the peak load is reduced to 71% and the average load to 67%. Increasing levels of the demand fee above 60€/kW/Year increases the revenues for the DSO while the other parameters remain constant, as households cannot adopt further to changing incentives.

The reduction in peak load of single households from an average of 5.66kW to 0.8kW in the more drastic scenarios does not translate to a similar reduction in peak loads on the grid level. Households adapt to changing grid fees by installing batteries. Therefore, under optimal control of the storage batteries, the load profiles of households show higher correlation, increasing the diversity factor.

Figure 2 shows the load profiles in 3 different policy scenarios and the baseload scenario for four seasons. While highly correlated PV production causes high (negative) peaks in load when the variable fee scenario is applied, those peaks are decreased significantly when the demand fee is applied as batteries store most of the overproduction.

I. CONCLUSIONS AND DISCUSSION

We have shown that changing the current tariff structure in the distribution grid from the currently applied mainly variable cost structure to demand fees is a possibility to better align household consumption patterns with requirements for the distribution grid. However, depending on future costs for storage systems, introducing demand fees causes households to decrease their own peak load significantly, while the peak load in the distribution grid does not decrease by the same amount. Therefore, costs for grids do not decrease as rapidly as revenues.

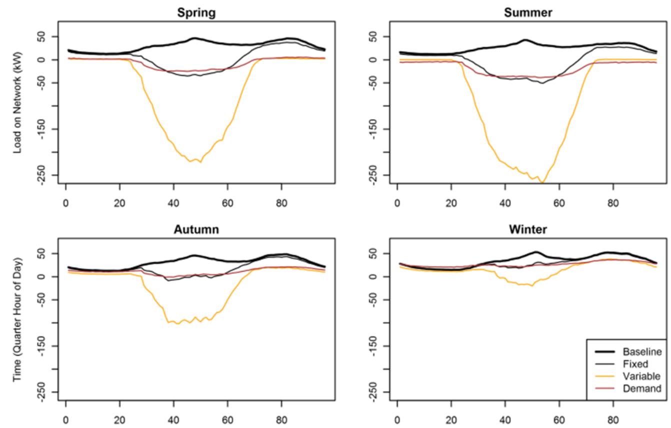

Figure 2: Load profiles on the grid for four different seasons and four different scenarios. The results for the scenario with a tariff level of 0.30€/kWh (Variable) and for the scenario with a tariff level of 160€/kW (Demand) are shown.

Fixed network fees can help in reducing the problem. However, they may be considered to be unfair (as consumers are equally contributing to network revenues, independent of their utilization) and they reduce incentives for low-carbon distributed generation significantly. Also, the systemic value of decentralized storage to distribution grid operators and the electricity system as a whole cannot be exploited. It can be considered to be a very defensive strategy therefore.

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Article V

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The impact of residential photovoltaic power on electricity sales revenues in Cape Town, South Africa.

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The impact of residential photovoltaic power on electricity sales revenues in Cape Town, South Africa

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ABSTRACT

In South Africa, electricity is provided as a public service by municipalities. The combination of (a) rising electricity rates, (b) decreasing photovoltaic technology costs, and (c) a progressive tariff system (under which wealthier households support low tariff rates for indigent residents) leads to incentives for high-income households to cover part of their electricity demand by self-produced photovoltaic (solar) electricity. This development is simulated with hourly load profiles and radiation data, and an optimization model for a case study in Cape Town through the year 2030. Results indicate that the majority of higher-income residents are incentivized to invest in photovoltaic power production by 2020 and additionally use home battery systems by 2028. This leads to a steadily increasing gap between revenues and expenditure needs in the budget of the municipality. The budget gap can be reduced by replacing the energy-based tariff with a revenue-neutral fixed network-connection fee implementation of which is particularly effective in reducing incentives to invest in storage.

1. Introduction

With a population of about 3.7 million people, the municipality of Cape Town represents one of the cultural, commercial, and political centers of South Africa (City of Cape Town (2012); Jenkins and Wilkinson, 2002). Similar to other South African cities, Cape Town still bears the legacy of apartheid through inequality and geographical separation (Lemanski, 2007; Smith, 2004). This leads to various efforts my municipal authorities to improve living conditions for underprivileged residents, such as seeking to improve housing infrastructure or provide basic services at low tariffs (Swilling, 2010). Access to affordable electricity is considered a basic need with high political importance in South Africa, as it has also been a central point in the government's Reconstruction and Development Program (ANC, 1994). The City of Cape Town has introduced a pro-favorable tariff structure for public services, such as electricity, based on its Equitable Services Policy Framework (Government of Western Cape (2003)).

Such a policy is relatively easy to implement in South Africa, since electricity is provided as public service by municipalities in contrast to privatized and liberalized power markets found in Europe and the USA. The municipalities purchase electricity at bulk-power tariffs mainly from the monopolistic power operator ESKOM, and then supply it to customers. In the case of Cape Town, the Electricity Services Department is in charge of designing different tariffs for customers depending on their consumption level as well as certain indigence criteria. This leads to a progressive tariff structure with high and middle-income households paying up to double the rate of the tariff compared to subsidized, low-income households (City of Cape Town (2014a)). With about 35% of the total budget, the electricity revenues are the largest share of general public revenues for the city (City of Cape Town (2013a)). According to officials and the city's annual book of budget[1], revenues from electricity are also partly used for cross-subsidization of other

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[1] Table 24 provides evidence and explains of the surplus of the electricity service department being used for transfers and contributions (City of Cape Town (2013a)).

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0957-1787/

Nomenclature

$Egrid_{t,h}$ hourly electricity consumption from the grid, kWh
$Egrid\_block_{h,block}$ block-specific monthly electricity consumption from the grid, kWh
$Epv_{t,h}$ hourly electricity consumption from the PV system, kWh
$EstorageInflow_{t,h}$ hourly Electricity stored in the ST system, kWh
$EstorageLevel_{t,h}$ hourly level of battery storage, kWh
$EstorageOutflow_{t,h}$ hourly electricity consumption from the ST system, kWh
$EtoGrid_{t,h}$ hourly excess electricity fed into the grid, kWh
Expenses objective variable representing expenses for electricity, ZAR
$Gridcost_{h}$ electricity bill for electricity consumption from the grid, ZAR
$Ipv_{h,kwp}$ binary variable for the PV investment decision, Binary
$Istorage_{h,stcap}$ binary variable for the ST investment decision, Binary
$PVannuity_{h}$ annuities for the PV investment, ZAR
$STannuity_{h}$ auxiliary variable for calculation ST annuities, ZAR

Parameters
$Blockcap_{h,block}$ monthly caps of blocks of each tariff, kWh
$Edemand_{t,h}$ hourly electricity demand of each household, kWh
$FreeE_{h}$ subsidized monthly free electricity, kWh
i interest rate, %
Inverterreplace costs for replacement of the inverter in of system costs, %
MaxDisCharge maximal level of discharge depending on the ST capacity, %
$Netfee_{block}$ monthly fixed network-connection fee being calculated and externally included, ZAR
OMcost operation and maintenance cost in of the investment costs, %
$PVannuitycost_{kWp}$ cost parameter for calculation PV annuities, Numeric
$PVcost_{kWp}$ price for a PV system per kWp including installation and excluding inverter, ZAR
PVeff efficiency of the PV system, %
$Radiation_{t,kWp}$ hourly radiation output depending on the installed capacity (kWp), kWh
$STannuitycost_{stcap}$ cost parameter for calculation ST annuities, Numeric
$STcost_{stcap}$ price for a ST system per kWh capacity, ZAR
$Stmax_{stcap}$ capacity of the ST system, kWp
Storageeff efficiency of the ST system, %
$TariffLevel_{h,block}$ block-specific per kWh rate of each tariff, ZAR
ypv life time of PV system, Years
yst life time of ST system, Years

Subscripts
t hourly time step, Hour
h household, Nr. of households
block tariff block
stcap storage capacity, kWh
kWp PV generation capacity, kWp

public services such as water supply and sanitation (City of Cape Town (2013a); Swilling, 2010). In addition, electricity revenues entail the advantage of being sold mostly via a pre-paid system, which minimizes risks of non-payment problems (McDonald, 2009).

Apart from the progressive tariff structure, Cape Town's customers have also faced significant annual tariff increases in recent years, due mainly to rising demand for electricity caused not only by increasing living standards but in particular by the government's mass electrification programs over the past decades. Inadequate investment in infrastructure recently led to power shortages and calls for new capacities. The cost of new investments combined with traditionally low electricity prices caused an underfunding of ESKOM and eventually resulted in a sharp rise of electricity rates by about 16% annually (on average) over the last 10 years (City of Cape Town (2013a); Kohler, 2014; Pegels, 2010). This development evokes an under-discussed but relevant issue not confined to South Africa: with declining costs of residential photovoltaic technology (PV) and rising electricity rates, it becomes increasingly attractive for households to generate PV electricity. Even though this development supports the transition to a sustainable energy system, an increase of self-supply with PV electricity might lead to an eroding revenue base for South African municipalities such as Cape Town. The combination of (a) continuously increasing electricity rates, (b) the progressive end-user tariff design, and (c) the decreasing PV costs may incentivize especially higher-income households (with higher electricity consumption and sufficient financial means) to save electricity expenditures through residential PV electricity generation. From the city's perspective, this leads to a decline of electricity sales to higher-income households, which decreases the electricity revenues used to support the low tariff for indigent residents (South African Department of Energy (2011)). As illustrated in Fig. 1, this might result in a budget gap between electricity expenses and revenues from sales. Without any remuneration for excess PV electricity fed into the grid (such as a feed-in tariff), PV systems are not yet cost-effective, which is a disincentive for large-scale rollout of the technology by private households. However, if grid parity is achieved (in the early stages only for high-income households with higher rates), the city's electricity sales revenues are expected to decline steadily (Gets, 2013).

These trends reveal a potential trade-off between renewable electricity supply and maintaining the current poor-favorable energy policy. On the one hand, the city administration depends on electricity sales revenues, in particular from middle- and high-income households, for expanding electricity access and providing subsidized electricity to indigent households. On the other hand, as described by Becker and Fischer (2013), South Africa also identifies development of renewable energies as important. Rapid growth of residential PV would be in line with aims of decreasing CO_2 emissions and increasing the share of renewable energies (Msimanga and Sebitosi, 2014; Winkler, 2007; Winkler et al., 2011). Both aspects of energy policy have to be considered carefully.

This research is especially relevant in non-liberalized power markets where electricity is provided as a public service (generally by state-owned enterprises). While this is often the case in developing countries (Hall et al., 2010), the majority of published studies deals with the effects of distributed electricity generation in restructured or competitive supply markets (Fouquet, 1998; Haas et al., 2013; Menges, 2003; Milstein and Tishler, 2011). In particular, the impact of PV on retail electricity rates and consequently utilities is the focus of recent articles (Cai et al., 2013; Satchwell et al., 2014). Bode and Groscurth (2013) analyze PV grid parity in the German electricity market and find a substantial financial

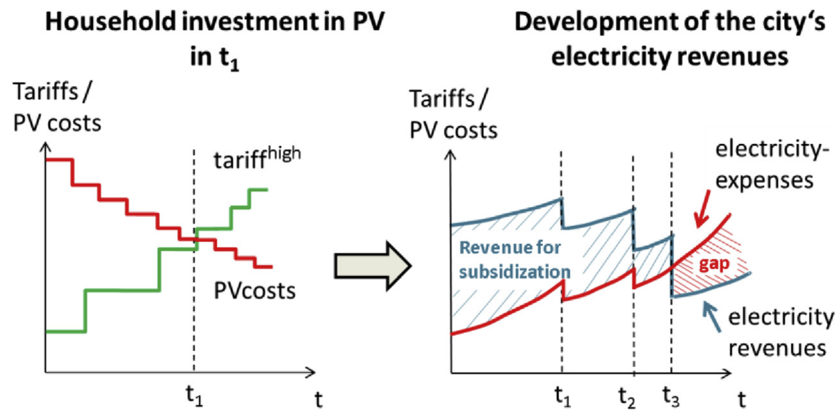

Fig. 1. Illustration of the impact of household PV investments affecting trends in electricity revenues. Note: At time point t1, very high-income households face an incentive to invest in PV as it becomes cost-effective. At t2 and t3 these investments become further attractive for high-income and middle-income households. Investments in PV reduce electricity consumption from the grid and thus reduce both electricity revenues and electricity expenses for the city. In this schematic example, the process would lead to a budget gap for the electricity department at t3.

burden passed on to the public as self-generation and consumption is currently relieved from several costs, such as grid usage, electricity taxes, and concession fees.

A study by Jägemann et al. (2013) analyzes the economic efficiency of grid parity by combining a household optimization model with an electricity system optimization model. Similar to Bode and Groscurth (2013), they find that households with PV cause substantial excess costs for the network operators and for other market participants. Several discussions about the financial impact of a high penetration of PV on electricity sales revenues focus on South Africa, where progressive tariff policies make this issue more complicated (Gets, 2013; Reinecke et al., 2013; Sustainable Energy Africa, 2014; Trollip et al., 2012).

This research is relevant beyond South Africa, as electricity markets in developed and developing markets, liberalized or not, might experience revenue declines resulting from a high penetration of PV systems. We contribute to the literature by analyzing how expanded use of PV self-supply will affect revenues needed to ensure provision of electricity to indigent residents. We simulate returns on investment for various household investing in PV and battery storage systems as well as their respective impact on electricity revenues over the period from 2015 to 2030. Additionally, we analyze the effect of a simple change in the tariff structure; instead of charging for electricity exclusively on a per-kWh basis, the customer's bill is split into a per-kWh price and a fixed network-connection fee. Since a PV investment only affects per-kWh revenues through savings on the electricity bill, but not revenues from the fixed network-connection fee, this tariff-change potentially mitigates the negative impacts of PV expansion on electricity sales revenues (as further explained in Section 2.3).

In Section 2, we present the data and methods for our analysis. We report our results in Section 3 and further discussion of our approach and limitations in Section 4. In Section 5 we draw conclusions from our analysis.

2. Data and methods

This analysis simulates residential electricity consumption and corresponding effects on household electricity bills. Fig. 2 gives an overview of the approach, in which Cape Town's 570,000 residential electricity consumers are divided into groups G1 to G4, depending on their electricity consumption level and socio-economic status. Hourly measured load profiles are assigned to each group. In the household optimization model, the electricity bill is minimized for each load profile by considering the possibility of reducing electricity purchased from the grid by investing into PV and battery storage (ST). This model is applied for the years 2015–2030. By keeping the current tariff structure unchanged and by using the average electricity bill for each group, we are able to assess the impact on the electricity revenues of the City of Cape Town.

As described in Section 2.3, additional scenarios consider a modification of the tariff structure in which a revenue-neutral fixed network-connection fee influences the households' investment returns as well as the electricity revenues.

2.1. The household optimization model

For the assessment of the influence of residential PV electricity generation on electricity revenues, a household electricity model is developed using the optimization software package General Algebraic Modeling System (GAMS). The objective function in Equation (1) minimizes the annual expenses for electricity for an individual household. In the case of no PV being installed, a household consumes only electricity from the grid and pays $gridcost_h$. In case of an investment in PV and ST, the respective annuities for investments in PV and ST are added to a household's expenses for electricity. For simplicity this model is displayed for only one year, but the simulation is repeated for each year until 2030.

$$\min(expenses) = \sum_h (gridcost_h + PVannuity_h + STannuity_h) \tag{1}$$

Load balancing is represented by Equation (2), in which household demand ($Edemand_{t,h}$) equals electricity supply. Electricity is provided by the grid ($Egrid_{t,h}$). If a PV system is installed, the hourly demand may also be covered by PV generation ($Epv_{t,h}$). If ST is available, the battery may be an additional source of supply ($EstorageOutflow_{t,h}$).

$$Edemand_{t,h} = Egrid_{t,h} + Epv_{t,h} + EstorageOutflow_{t,h} \ \forall t, h \tag{2}$$

The described tariff structure considering different block rates ($TariffLevel_{h,block}$) depends on the level of monthly consumption and socioeconomic categorization, which is explained in more detail in Section 2.2.1. The monthly consumption of electricity from the grid $Egrid_{t,h}$ therefore has to be transformed into block-specific, monthly consumption by block $Egrid\_block_{h,block}$. Subsidized free electricity ($FreeE_h$) is excluded because it causes no costs for the household, as shown in Equation (3). The caps for each block are defined by $blockcap_{h,block}$ in Equation (4). For instance, a monthly consumption in the *Domestic* tariff of 1000 kWh is divided into consuming

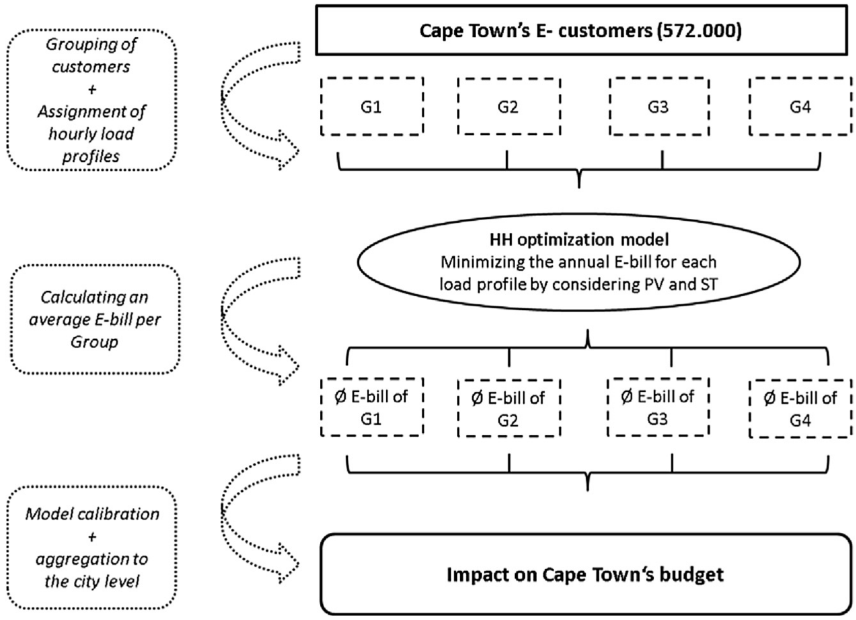

Fig. 2. Methodology for assessing the impact of residential PV on Cape Town's electricity revenues.

600 kWh in block1 and 400 kWh in block2. The variable $gridcost_h$ represents a household's electricity bill, which also includes the parameter $Netfee_{block}$ and is set to different levels depending on the scenarios described in Section 2.3.

$$\sum_{block}(Egrid\_block_{h,block}) = \frac{\sum_t Egrid_{t,h}}{12} - FreeE_h, \forall h \tag{3}$$

$$Egrid\_block_{h,block} \leq Blockcap_{h,block}, \forall h, block \tag{4}$$

$$Gridcost_h = \sum_{block}(Egrid\_block_{h,block}*TariffLevel_{h,block} + Netfee_{block}), \forall h \tag{5}$$

Hourly electricity output of PV systems ($Epv_{t,h}$) is determined by hourly radiation per kWp ($radiation_{t,kWp}$), system efficiency ($PVeff$), and a binary investment-decision variable ($Ipv_{h,kWp}$). The available capacity sizes are 1 kWp, 2 kWp, 3 kWp, 4 kWp, 5 kWp, 6 kWp, 10 kWp, 15 kWp and 20 kWp. By maximizing each household's returns the model endogenously chooses the level of household investment and the respective capacity size. If generation exceeds demand, electricity may be either stored in ST ($EstorageInflow_{t,h}$) or fed into the grid ($EtoGrid_{t,h}$). Since there is currently no feed-in tariff, feeding electricity into the grid is assumed to be neither financially remunerated nor penalized.

$$Epv_{t,h} = \sum_{kWp}\left(Radiation_{t,kWp}*PVeff*Ipv_{h,kWp}\right) - EtoGrid_{t,h} - EstorageInflow_{t,h}\ \forall t, h \tag{6}$$

The ST system consists of three variables: electricity fed into the grid ($Estorageinflow_{t,h}$), electricity consumed from the system ($EstorageOutflow_{t,h}$), and electricity currently stored in batteries ($EstorageLevel_{t,h}$). Inflows and outflows are reduced by efficiency losses and the storage level is set to 0 at the beginning of the period.

$$EstorageLevel_{t,h} = 0\ \forall t = 1,\ h \tag{7}$$

$$EstorageLevel_{t,h} = EstorageLevel_{t-1,h} + Storageeff * EstorageInflow_{t,h} - StorageEff * EstorageOutflow_{t,h}\ \forall t > 1, h \tag{8}$$

The term $EstorageLevel_{t,h}$ is restricted by the chosen capacity maximum $Stmax_{stcap}$, with available limits of 5 kWh, 10 kWh, 20 kWh, 35 kWh, and 50 kWh. They are selected by the binary investment decision variable $Istorage_{h,stcap}$. Additionally, the minimum charging level is also restricted, as it may not be feasible to discharge batteries completely. Discharging of the battery is limited by $MaxDisCharge$ as a percentage of the total battery capacity in Equation (10).

$$EstorageLevel_{t,h} < \sum_{stcap}\left(Stmax_{stcap}* Istorage_{h,stcap}\right)\ \forall t, h \tag{9}$$

$$EstorageLevel_{t,h} > \sum_{stcap}\left(Stmax_{stcap}* Istorage_{h,stcap} * MaxDisCharge\right)\ \forall t, h \tag{10}$$

In order to express PV and ST investment in monetary units, annuities of the PV investment ($PVannuity_h$ and $STannuity_h$) are calculated. For PV, we consider annual operations and maintenance costs ($OMcost$) depending on size (including the replacement of the inverter after a certain period).

$$PVannuity_h = \sum_{kwp}\left(Ipv_{h,kwp}*PVannuitycost_{kwp}\right)\ \forall h \tag{11}$$

$$STannuity_h = \sum_{stcap}\left(Istorage_{h,stcap}*STannuitycost_{stcap}\right)\ \forall h \tag{12}$$

The number of PV and ST systems per household is restricted by less than or equal to 1 in order to restrict the number of batteries to one:

$$\sum_{kWp}\left(Ipv_{h,kWp}\right) < 1 \tag{13}$$

Table 1
Electricity tariff structure and tariff rate forecasting.

Tariff-class	Tariff criteria and free electricity			
	Life-line	Life-line	Domestic	Domestic
Criteria:	1) Value of property (e.g. suburb) 2) Indigent rebate, pension, etc. 3) Monthly consumption (in kWh):			
Consumption limits for free electricity p.m.	<250 kWh	250 – 450 kWh	<600 kWh	>600 kWh
Amount of free electricity p.m(2014)	60 kWh	20 kWh	0 kWh	0 kWh

Year	Tariff rate levels			
Limits of each tariff	Life-line block 1 <350 kWh p.m	Life-line block 2 >350 kWh p.m	Domestic block 1 <600 kWh p.m	Domestic block 2 >600 kWh p.m
2013	0.8828	1.4723	1.3278	1.5981
2014	0.9086	2.109	1.425	1.7328
2015	0.9868	2.1872	1.5032	1.811
2016	1.0758	2.348	1.6231	1.9493
2017	1.1631	2.5114	1.7431	2.0889
2018	1.2931	2.7219	1.9077	2.2741
2019	1.4363	2.9506	2.0877	2.476
2020	1.5942	3.199	2.2846	2.6961
2021	1.7388	3.4397	2.4705	2.9066
2022	1.896	3.6986	2.6715	3.1337
2023	2.0669	3.9773	2.8887	3.3786
2024	2.2526	4.2772	3.1236	3.6427
2025	2.4544	4.6001	3.3775	3.9276
2026	2.6736	4.9476	3.6519	4.235
2027	2.9118	5.3217	3.9485	4.5665
2028	3.1704	5.7245	4.2691	4.924
2029	3.4512	6.1581	4.6157	5.3098
2030	3.7562	6.6249	4.9903	5.7258

$$\sum_{stcap}\left(Istorage_{h,stcap}\right) < 1 \tag{14}$$

2.2. Parameters and data

2.2.1. Residential electricity tariffs in Cape Town

Electricity tariff regulation classifies residential customers in two major tariff categories: *Life-Line* represents the highly subsidized tariff rate, while *Domestic* is considered the regular residential tariff rate. The subsidized *Life-Line* tariff rate is only available for residents fulfilling certain indigence criteria based mainly on property valuation (depending on suburb) and low demand (City of Cape Town 2014a, 2013b). Additionally, each tariff is subdivided into two blocks as shown in Table 1.

First, monthly consumption is charged by block 1, but if demand exceeds a certain threshold, the higher block rate is applied to the additional consumption. For instance, *Life-Line* customers must pay the block 1 rate for the first 350 kWh per month and then block rate 2 for any further kWh. The same approach is applied to block 1 and block 2 of the *Domestic* tariff. The high tariff levels of *Life-Line* result from the allowance of free electricity (20–60 KWh), which effectively leads to significantly lower household bills compared to bills under the *Domestic* tariff.

The detailed tariffs are published annually and are available up to 2014 (City of Cape Town (2014a)). The 'Annex A of the Budget 2014/15 to 2016/17' (City of Cape Town (2014b)) provides for an annual average tariff rate increase until 2017. We use the average of the annual increase (8.09%, real) to forecast the tariff rate levels through 2030[2]. The tariff structure is assumed to remain constant, but with annual increases in the average rate. Tariff levels represent real values including inflation as well as VAT.

In addition, Cape Town's Electricity Services Department implemented a special feed-in tariff for residential PV electricity generation in 2014. The feed-in tariff and its impact on the city's electricity revenues are discussed in Section 2.2.3.

2.2.2. Load profiles, household grouping, and calibration

The electricity consumption of Cape Town's 570,000 residential electricity customers is represented by 181 measured hourly load profiles of single households, applied in an optimization model for an entire year. This is done first by subdividing all electricity customers into the four groups, G1 (subsidized low consuming, poorer consumers) to G4 (subsidizing high consuming, wealthier consumers), depending on their consumption level and tariff designation. Load profiles within the groups are not weighted and contribute equally to each group's performance (e.g., electricity consumption from the grid). Second, load profiles are assigned to these groups and each load profile is used in the optimization model. Third, average electricity bills are calculated for each group and these are used later to assess the impact of PV and ST investments on the city's electricity revenues.

Based on information provided by the city's Electricity Service Department (City of Cape Town 2014a, 2014b; Electricity Services, 2013) all residential electricity customers are grouped as illustrated in Table 2. Even though a larger number of groups would enhance the analysis, limited information about the monthly electricity consumption and shares of overall revenues prevented a more detailed classification.

All subsidized *Life-Line* customers are pooled in group G1. *Domestic* customers being more inclined to make PV investments (with higher consumption levels as well as higher electricity rates) are subdivided into the three remaining groups (G2 to G4) depending on their monthly electricity consumption. Cape Town's Electricity Service Department provides information about the distribution of the majority (about 76%) of electricity customers according to their monthly electricity consumption as well as their impact on electricity revenues. The distribution of the remaining customers as well as their impact on electricity revenues is

[2] Even though the annual average increase of the last 10 years was about 16%, we assume moderate 8.09% (real) being in line with the city's forecasts as sharp annual increases of more than 20% are not likely to occur again.

Table 2
Overview of electricity customers classified by four household groups (G1–G4).

	G1	G2	G3	G4	Total
Electricity customers					
kWh p.m.	0–450	450–600	600–1000	1000+	
Suburb	Khayalitsha	Rontree Estate & Tafelsig			
Tariff-affiliation	Life-Line	Domestic	Domestic	Domestic	
Nr. of customers	306,000	94,000	117,000	55,000	572,000
Share of total customers (in %)	53.5%	16.4%	20.5%	9.6%	100%
Nr of household load profiles per group	64	64	23	30	181
Energy					
Annual electricity consumption per group (GWh p.a.)	989	533	956	860	3338
Share of total electricity consumption (in %)	29.6%	16.0%	28.6%	25.8%	100%
Monthly consumption for an average HH (per group, kWh p.m.)	270	474	679	1310	487
Electricity revenues					
Estimated electricity revenue (in Million Rand)	698	665	1191	1071	3625
Share of total electricity revenues (in %)	19.3%	18.3%	32.9%	29.5%	100%
Calibration					
Factor for calibrating electricity revenue of each group	0.95	1.09	0.84	0.93	

calculated on the basis of the summary of sales (Electricity Services, 2013) by considering additional confidential data from the city.

Load profiles are provided by the University of Cape Town and have been measured in Cape Town's suburbs of Rontree Estate, Tafelsig, and Khayelithsha between 2000 and 2005. These 181 available hourly load profiles are first pre-classified according to the suburb where they were measured: profiles from the low-income township suburb of Khayelitsha are pre-selected for the *Life-Line* tariff group G1 as both electricity consumption levels and property values are in accordance with the indigent tariff criteria. The other profiles are categorized on the basis of monthly consumption (kWh p.m.) in the *Domestic* tariff groups, G2 to G4.

Table 2 provides an overview of these groups and their share in total customers, total energy consumption, and total electricity revenues. The impact of the city's electricity subsidies becomes evident: while subsidized households of G1 represent 54% of customers, their share of total electricity revenues is below 20%. In contrast, 10% of all households in G4 yield 30% of total electricity revenues. The same can be observed for energy, where the majority of residents (54% in G1) account for only around 30% of electricity consumption.

Again, load profiles were applied to calculate an average annual electricity bill for each group. Since multiplying these average electricity bills with the number of customers does not match perfectly with the published revenues of 2013, a calibration factor is implemented for each group. These factors are then applied in the optimization model to calibrate the model with forecast data.

In this analysis, no technical restrictions were considered with regard to the number of residences for each group that could install PV systems. The majority (more than 69%) of all households (especially those with higher income) is comprised of single detached bungalows (single-level, or multi-level with own roofs) and not in multi-story apartments blocks (City of Cape Town (2012)). Detached homes are generally suitable for private PV systems. However, the on-site conditions occasionally might not allow PV installation (e.g. due to shadowing, orientation of the roof or constructional conditions). Thus, the actual number of households with PV may remain below the number of households estimated by our strictly economic analysis.

2.2.3. Feed-in tariff and excess electricity

From the city's perspective, an important issue is the potential for feeding excess PV electricity into the grid. As of 2014, the Electricity Service Department began to implement a special feed-in tariff for residential PV generation. However, the city's electricity tariffs (including the feed-in tariff) are usually changed annually and the city is not able (by law) to guarantee consumers that the tariff structure against which the consumer decided to install PV will continue in the future[3]. Due to this uncertainty, we took the conservative approach of analyzing household PV investment under the current tariff structure and without considering any feed-in tariff. A feed-in tariff would increase the financial incentives to invest in PV and thus support our findings of declining electricity revenues.

2.2.4. Model calibration and impact on electricity revenues and electricity expenses

Details about Cape Town's budget are described in the annually published book of budget (City of Cape Town (2013a)). Electricity Services represents about 34% of the total city budget, with residential electricity customers accounting for about 40% of all electricity revenues and about 14% of the total city revenues. Electricity revenues from sales to residential customers are represented by the sum of all electricity bills. In line with the book of budget, electricity expenses initially equal electricity revenues.

Expenses for on providing electricity to residential customers are more difficult to assess without detailed information. These are divided into non-energy expenses (similar to fixed costs) of the city's Electricity Services Department and bulk-power expenses (energy based) for purchasing electricity. The non-energy expenses include costs related to administration, operation and maintenance, infrastructure, etc., including expenses related to providing service to indigent households. No detailed data are available on the exact composition of these non-energy costs and thus are assumed to amount roughly to 30% of total electricity expenses on the basis of other publications (Janisch et al., 2012; NERSA, 2011; Trollip et al., 2012). The trend in costs is highly unclear: operating costs may be positively or negatively affected by an increasing share of PV in the grid. For instance, PV might either lower distribution systems costs by lowering capacity needs or increase costs because of necessary updates of the infrastructure and higher maintenance costs. Population trends clearly indicate that there will be further need for subsidies based on a poor-favorable policy. Based on historical experience and in line with Trollip et al. (2012), an annual increase of non-energy expenses of 8.09% (real) is assumed for this analysis, as further discussed in Section 4.

Bulk (wholesale) power purchasing expenses (70% of total electricity expenses) are affected by decreasing consumption due to

[3] Information provided by officials of the Electricity Service Department of the City of Cape Town.

PV self-supply. Even if no feed-in tariff is assumed, excess electricity might be fed into the grid as a potentially substitute for the bulk power purchased in this case from ESKOM. Since the future of electricity tariffs and feed-in tariffs is highly uncertain, we modeled a range of electricity expenses. The two projections of electricity expenses are calculated as follows:

(a) ExpensesLOW refers to the best case from the city's perspective in which excess electricity is fed into the grid without remuneration, but perfectly substitutes bulk-power purchases, and
(b) ExpensesHIGH is less optimistic by ignoring the potential for excess PV electricity to decrease bulk-power purchases.

The motivation for the second calculation is that the city can only partly use excess electricity due to intermittency and seasonality, additional costs due to load balancing, or households refusing to feed excess electricity into the public grid. The actual value is assumed to be in between these extreme values that portray different budgetary situations of the city.

For the calculation of the bulk-power expenses, an average per-kWh price based on electricity expenses of 2013 is used (City of Cape Town (2014a)). Derived from historic data, it shows a similar trend as electricity end-user tariffs and is assumed to rise annually by 8.09% (real). Even though in reality the city purchases electricity at different, hourly varying tariffs, the assumption of an average bulk-power tariff rate is necessary as we have no access to more detailed data on Cape Town's electricity purchasing. This limitation is discussed in Section 4.

2.2.5. Solar irradiation, technological, and economic data

Measured radiation data as well as forecast data on PV and battery system costs and efficiencies are used in the optimization model to simulate returns on investments in PV and ST through 2030. Specific parameter values are presented in Table 3.

Measured radiation data from the region Nietvoorbij, Stellenbosch, was used for the calculation of PV electricity generation. The region is about 10 km outside of the Cape Town municipality region. As radiation data is available in terms of global horizontal radiation, it is converted to a 32% inclined south-facing PV system (Madhlopa and Ngwalo, 2007) representing an output maximizing orientation for that location (Bekker, 2007). Radiation data is available for the same years as load-profile measurements.

We match the solar radiation and load-profile measurements by year in order to preserve a possible correlation between climatic conditions and electricity demand.

It is unclear which battery storage system will dominate the market in future. Due to relatively easy handling we selected lithium ion batteries, which are currently still expensive but among the most promising battery systems for future use.

As indicated in Table 3, an interest rate of 10% is assumed, which represents the average interest rate of the last 7 years. Additionally, a 2% return expectation by households is included, assuming that an investment with a ROI lower than that hurdle will not be deemed worthwhile. Annuities calculated in Equations (11) and (12) are based on the parameters $PVannuitycost_{kwp}$ and $STannuitycost_{stcap}$. They are derived from the respective system costs and annuity factors determined by the interest rate and the expected lifetime (*ypv* and *yst*) of the systems. To simplify the replacement of

Table 3
Technical and economic parameter values.

Parameter	Value	Unit	Description and comment	Reference:
Technical parameters				
Max. depth of discharge	20	%	In order to maintain the ST's life time full discharging has to be avoided. For simplicity capacity is thus reduced to 80%.	Zeh and Witzmann (2014)
PV life time	25	years	A system life time in years	Cucchiella et al. (2012); Lazou and Papatsoris (2000)
PV system losses	25	%	Efficiency losses (inverter, cables, etc.) of the PV system area assumed in 25%. Further degradation decreases performance by 3% every 5 years.	Hoppmann et al.(2014)
Radiation data	Hourly data	kWh	Hourly radiation data measured in Nietvoorbij, Western Cape Town between 1998 and 2007. The year is selected to match the year of the measurement of the specific load profile.	Ciolkosz (2009): South African Solar Radiation Data Base SASRAD
ST charging efficiency	90	%	Efficiency assumed for charging and discharging.	Bruch and Müller (2014)
ST life time	16	years	As recommended by Bruch and Müller (2014) life time of Lithium-Ion battery is reduced from 18 to 16 years in order to simply consider capacity loss.	Bruch and Müller (2014)
Economic parameters				
Inflation	5.90	%	Average inflation in the last 10 years in South Africa.	City of Cape Town (2013a)
Annual decrease of PV prices	11.6/3	%	Literature suggests PV modules to decrease by annually 11.6% (nominal), non-module costs are assumed to decrease by annually 3%.	De La Tour et al. (2013)
Annual decrease of ST prices	10	%	ST prices are assumed to decrease annually by 10% until 2030.	Own assumption based on findings of Weniger et al. (2014) and Recharge (2013)
Exchange rate	1:14	Euro/ZAR	An average exchange rate for the year 2014 used for converting (international) PV and ST costs.	South African Reserve Bank (2014a)
Interest rate	10	%	Average interest rate (of the last 7 years) of 10%.	South African Reserve Bank (2014b)
Inverter replacement	10	%	Inverter replacement as percent of the system costs.	Branker et al.(2011); Stevanović and Pucar (2012)
Non-module PV prices	56	%	All non-module installation costs (including inverter) as a share of total PV system price.	Mitscher and Rüther (2012)
Operation and maintenance	10	%	As the share of total PV investment cost.	Hoppmann et al. (2014)
PV modules price	31.200	ZAR	Price in Rand for 3 kWp PV modules in 2013. Prices correspond to real market prices.	pvXchange, (2013)[a]
Size dependent PV price decrease	7–27	%	Size dependent system price decreases of large PV systems are included on basis of the Solar Choice Price Index. Per kWp values decrease between 12% (5 kWp) and 27% (20 kWp) on basis of a 3 kWp system price.	Solar Choice (2014)
Size dependent ST price decrease	20–36	%	Price decreases of large ST systems are based on findings of Bruch and Müller. Per kWh values decrease between 20% (10 kWh) and 36% (50 kWh) on basis of a 5 kWh storage system.	Bruch and Müller (2014)
ST system price	148.500	ZAR	Assumed price for a 5 kWh lithium ion battery storage system in 2013.	Akhil et al. (2013)

[a] System prices are compared with South African real market prices and are in line with retailer offers available at: http://www.sustainable.co.za/.

Table 4
Overview of tariff structure in the scenarios.

Composition of the average electricity bill (in %)	Scenarios		
	BAU	Net1	Net2
per-kWh charging	100%	70%	50%
network-connection fee	0%	30%	50%

the inverter, we follow the approach used by Branker et al. (2011). They include inverter replacement as additional maintenance cost (*inverterreplace*) being a share of the system costs. Operation and maintenance costs (*OMcost*) are included as an annual payable share of household PV costs.

$$PVannuitycost_{kwp} = \left(PVcost_{kwp} + PVcost_{kwp} * Inverterreplace\right) * \left(\frac{(1+i)^{ypv} * i}{(1+i)^{ypv} - 1} + OMcost\right) \ \forall kwp \tag{15}$$

$$STannuitycost_{stcap} = stcost_{stcap} * \frac{(1+i)^{yst} * i}{(1+i)^{yst} - 1} \ \forall stcap \tag{16}$$

2.3. Scenarios

For this analysis, we apply three scenarios shown in Table 4. In the business-as-usual scenario (BAU), the current tariff structure is unchanged. As a policy to adapt to the potential budget gap between electricity expenses and electricity revenues, the implementation of a revenue-neutral fixed network-connection fee is analyzed: instead of charging electricity rate based only on per-kWh consumption (100% variable charges), a fixed network-connection fee is considered. This is assumed to amount to 30% (Net1 scenario) and 50% (Net2 scenario) of the average per household electricity bill. The incentive to invest in PV is thereby reduced, as PV can only reduce the cost of per-kWh but does not affect the fixed network-connection fee. While the network-connection fee is increased from zero to 30% and 50% of the average household electricity bill, the respective per-kWh portion of the bill is reduced to 70% and 50%. The 30% fixed network-connection fee in Net1 would potentially represent the coverage of the city's fixed costs, amounting to 30% of electricity expenses. Thus, the fixed network-connection fees in Net1 and Net2 are considered as bill-neutral, meaning that, on average, a household's electricity bill remains unchanged if no investment in PV is made. No price elasticity effects are assumed, as further discussed in Section 4.

Through 2030, the level of the fixed network-connection fee is simulated for electricity bills without any PV investment, which also means that the fee is continuously increasing along with the variable rate. The respective new tariff fees and rates for the scenarios are included into the optimization model in Section 2.1 and considered in the calculation of annual electricity bills ($gridcost_h$). Notably, a similar fee structure has been discussed by officials in Cape Town (Jones, 2014), but not implemented to date. However, the focus of this research is not to analyze Cape Town's tariffs, but to assess the long-term deployment of residential PV and how it is likely to affect electricity revenues and electricity expenses.

3. Results

3.1. Household PV investment decision

The optimization model is applied with forecast economic data (such as PV cost or electricity tariffs) to analyze the household choices to invest in PV and ST.

Table 5 shows the share of households (represented by individual and unweighted load profiles per group) investing in PV in the BAU scenario. For the majority of households with high electricity consumption (G3 and G4), investments in PV become cost-effective at least by 2018. Our model simulates that by the year 2024, 100% of these households would be incentivized to invest in PV. G2 lags several years behind, where we see more than 50% investing in PV by 2028. Almost none of the *Life-Line* households (G1) invest in PV, due to the fact that the electricity consumption levels as well as electricity rates are relatively low for G1. These results and the intermittent character of PV electricity generation show that low-income households are not likely to supply themselves with PV electricity. Instead, it emphasizes the need for subsidized electricity for indigent residents. As expected, ST

Table 5
Results of the optimization model in the BAU scenario. Note: Shaded areas indicate that more than 50% of households of the respective group are affected. Values of the average annual return on investment include the assumption of 2% return expectation.

Year	Share of households investing in PV in %				Share of households investing in ST in %				Average electricity self-supply of households with PV and ST in %				Average annual return on investment of HH with PV and ST in %			
	G1	G2	G3	G4	G1	G2	G3	G4	G1	G2	G3	G4	G1	G2	G3	G4
2015	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2016	0	0	0	10	0	0	0	0	0	0	0	31	0	0	0	11
2017	0	0	17	23	0	0	0	0	0	0	24	26	0	0	3	16
2018	0	0	30	37	0	0	0	0	0	0	28	29	0	0	7	20
2019	0	0	43	63	0	0	0	0	0	0	25	27	0	0	13	23
2020	2	0	70	83	0	0	0	0	16	0	22	27	3	0	17	29
2021	2	0	78	87	0	0	0	0	16	0	26	27	10	0	20	37
2022	3	3	83	97	0	0	0	0	20	24	25	28	10	3	29	43
2023	3	6	100	97	0	0	0	0	20	24	26	31	18	8	31	47
2024	6	8	100	100	0	0	0	0	20	25	27	32	17	13	39	49
2025	6	25	100	100	0	0	0	0	20	25	25	34	25	10	53	51
2026	6	38	100	100	0	0	0	37	20	25	22	43	34	13	62	48
2027	8	48	100	100	0	0	22	77	22	26	37	53	35	17	54	57
2028	9	53	100	100	3	0	83	100	31	27	68	62	28	22	42	68
2029	9	55	100	100	3	22	91	100	30	48	77	65	40	22	49	85
2030	9	80	100	100	3	64	96	100	30	67	83	66	48	19	60	101

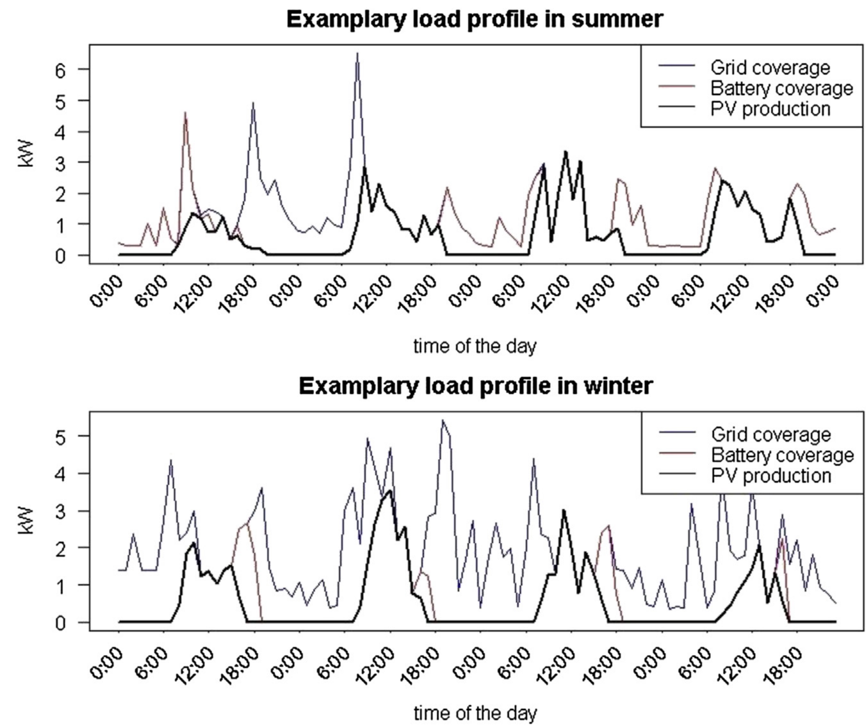

Fig. 3. Hourly load curve of a high-consumption household (G4) with PV (6 kWp) and ST (20 kWh capacity) in 2024 in the BAU scenario. Upper graph: 28th until 31st of January (summer). Lower graph: 4th of June until 7th of June (winter).

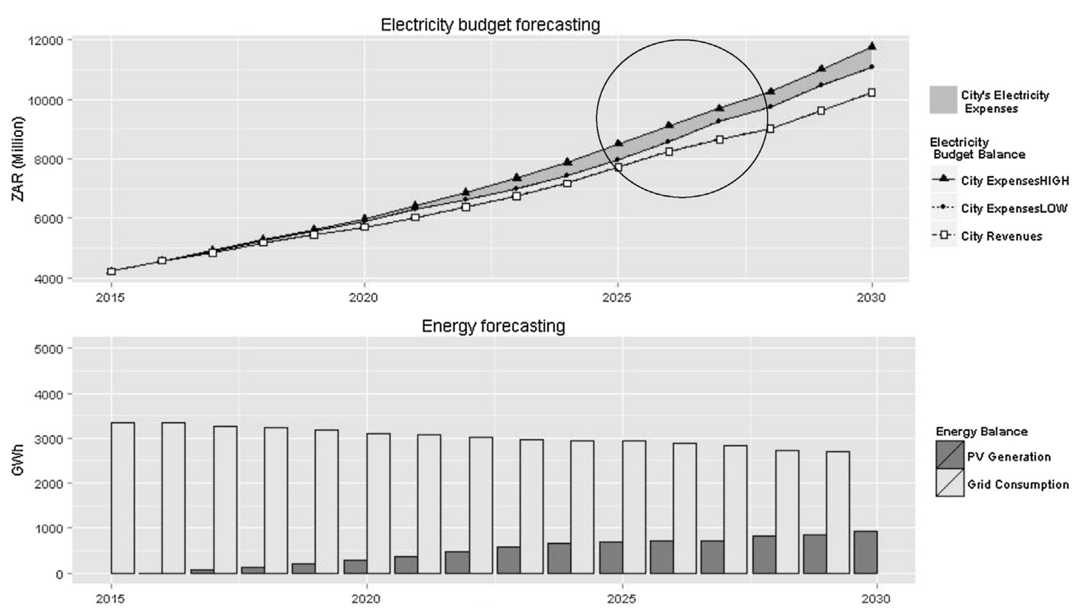

Fig. 4. Trends in electricity revenues and cumulative residential PV electricity generation through 2030 (BAU scenario).

systems are not cost-effective in the first years. However, they become a meaningful complement to PV systems by 2026 and increase the share of electricity self-supply. The shaded areas show that ST is mainly responsible for achieving electricity self-supply levels above 50%. The return on investments (ROI) including the 2% return expectation of the household, clearly indicates the rising cost-effectiveness of PV and that households with high electricity consumption will enjoy high ROIs from PV investments. Fig. 3 provides an example of a randomly selected G4 household's load curve in 2024 (monthly average consumption of about 1400 kWh) that is covered by PV generation (6 kWp), a ST battery system (20 kWh capacity), and electricity supply from the grid. It illustrates that a PV system combined with ST may allow a household to reasonably increase electricity self-supply in summer, but not during winter. Deploying larger PV (>20 kWp) and ST (>50 kWh) capacity would make it theoretically possible to enable electricity self-sufficiency but it seems unrealistic due to limited roof space and high costs. The largest possible capacities (20 kWp PV and 50 kWh ST) are only chosen by the model for two households with the largest consumption levels in years 2028–2030.

3.2. Effects of PV investment on Cape Town's electricity revenues

Fig. 4 shows the impact of PV investment on the city's electricity revenues and electricity expenses under the BAU scenario. As discussed in Section 2.2.4, electricity expenses are assumed to fall between the two calculated values in the grey shaded area. In 2015, in the absence of PV and ST, the budget gap is zero, as expenses of the Electricity Service Department (including the cost of serving indigent households) are balanced with electricity revenues (City of Cape Town (2013a)). With household deployment in PV, a moderate gap appears in 2016. As more households invest in PV, the gap increases continuously over the years. The corresponding cumulative annual electricity generation is shown in the lower part of the figure. Apparently, the structure of electricity expenses (30% fixed costs and 70% variable costs for bulk-power purchases) flattens the impact of PV generation by reducing purchases of bulk power. However, as indicated by the circle in the figure, the implementation of ST systems in G3 and G4 around year 2027 changes the slope of electricity revenues and electricity expenses, resulting in an increase of the budget gap.

The budget gaps of 6% and 9% (based on expensesLOW and expensesHIGH) by 2020 increase only partly to about 6%–16% by 2025. In 2030, with the majority of households having installed ST systems, the budget gap rises to 29%–58%. By 2020, annually generated residential PV electricity amounts to 398 GWh (12% of Cape Town's annual residential electricity consumption), increasing to 882 GWh (26%) in 2025 and 2160 GWh (65%) in 2030. In the context of South Africa's desire to lower CO_2 emissions and increase electricity generation from renewable resources, this high level of PV coverage of residential electricity consumption represents a substantial achievement.

3.3. Results with a fixed network-connection fee in scenarios Net1 and Net2

Results of the scenarios Net1 and Net2 are illustrated in Fig. 5. The major implications of both scenarios are the reduced investments in PV and the lower market penetration of ST systems. While the given tariff structure incentivizes households to increase electricity self-supply by investing in ST around the year 2028 in the BAU scenario (see Table 5), the fixed network-connection fee is a disincentive for almost all households to invest in ST (except some in G4). While the majority of G4 households still make use of PV comparable to the BAU scenario, fewer middle-income households in the groups G2 and G3 install PV. Furthermore the capacity of PV systems is on average about 20% lower than in the BAU scenario (for G3 and G4).

Through 2026 these trends affect electricity revenues, which increase steadily due to the rising fixed network-connection fee (Fig. 4). In case of Net1, the budget gaps are substantially smaller compared to BAU: between 5% and 13% in 2025 and between 14% and 22% in 2030. The more drastic tariff shift in Net2 leads to relatively similar results, with a budget gap between 3% and 10% in 2025 and between 10% and 15% in 2030. However, these results are achieved at the expenses of PV generated electricity, which develops slower and remains at a lower level. The Net1 scenario leads to reductions of residential PV electricity generation by 12% (2025) and 52% (2030) compared to the BAU PV electricity generation. The Net2 scenario reduces PV generation by more than 22% (2025) and 59% (2030) compared to the BAU scenario.

Consequently, based on our analysis, there is indeed a trade-off between PV electricity generation and revenue sufficiency for the city.

3.4. Sensitivity analysis

Our analysis requires assumptions about costs, tariffs, and technologies through 2030. In general, we relied on assumptions derived the existing literature and official documents. However, an additional sensitivity analysis was applied in order to identify critical parameters and limitations affecting interpretation the results. As shown in Fig. 6, for the sample year 2025, we display the

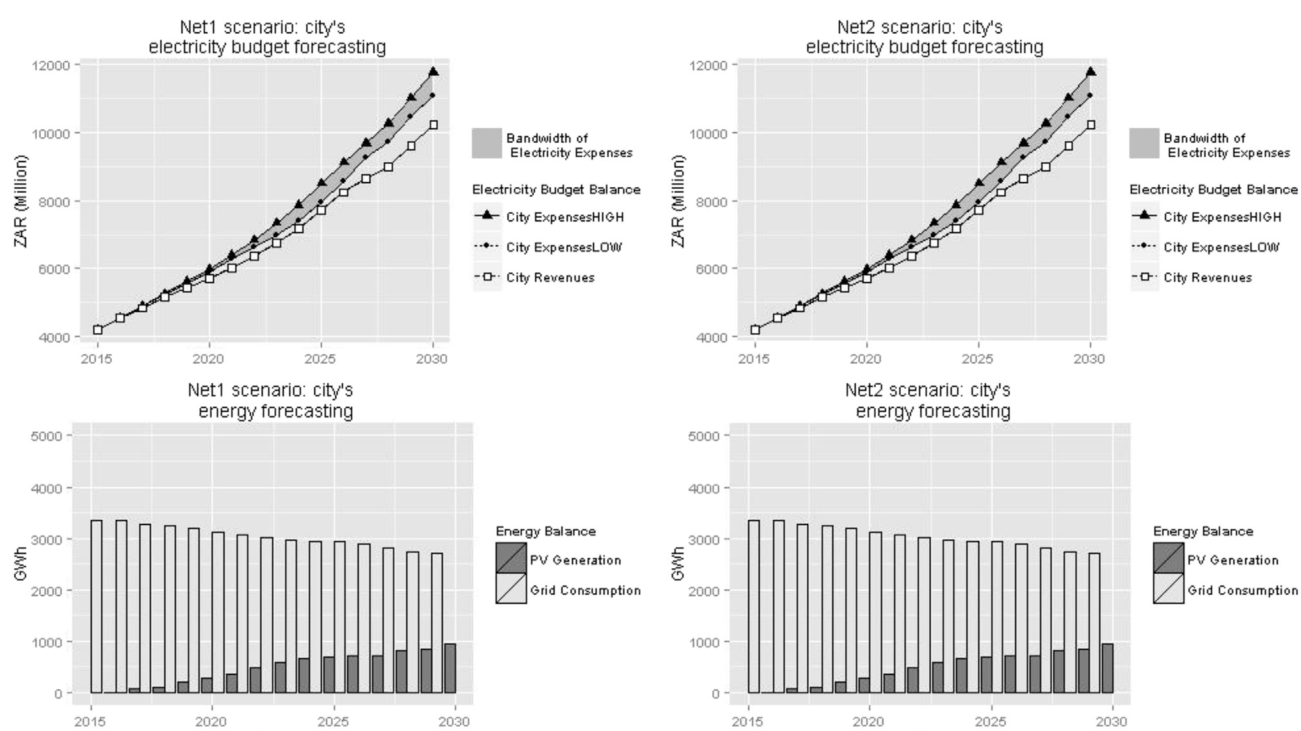

Fig. 5. Trends in electricity revenues and share of PV generation in total electricity consumption for scenarios Net1 and Net2.

percentage change in electricity revenues based on ranges for several parameters (−20% and +20%). Variations in the parameters correspond to electricity revenue changes of less than 13%. Higher PV and ST costs have a positive impact on electricity revenues as they make household investment in these technologies less attractive. An increase in the interest rate would affect household expenditures for PV and ST with a similar effect. A 20% improvement in PV output and the ST efficiency rate correspond to a reduction of electricity revenues by 8% and 2%, respectively. This suggests that possible variations of the radiation (such as at different location in the Cape Town region) would not have a substantial impact on our findings.

In order to control for changes in consumption, usage levels in the load profiles are increased and decreased proportionally for all hours. A 20% increase of the load profile is associated with a decline in electricity revenues by about 2%; a 20% decrease of the load profile is associated with a rise in electricity revenues by about 4%. This finding can be explained by the effects of economies of scale: PV investments become relatively more cost-effective at higher electricity consumption levels which lead to a decrease of electricity revenues. Similarly, a 20% decrease of PV electricity generation is associated with a rise in electricity revenues by about 10%. Unsurprisingly, tariffs have a substantial effect on electricity sales revenues. A 20% increase in tariff rates leads to a decline in electricity sales revenues by about 10%; a 20% decrease of tariff rates is associated with a rise in revenues by about 12%.

Apart from the parameters shown in Fig. 6, the lifetime of PV and ST was analyzed as well, but was not associated with significant changes in revenues (less than 4%). As the availability of data restricts the selection of representative load profiles, a different selection of load profiles is tested in the model. By randomly dismissing 30% of the available load profiles, electricity revenues were generally unaffected (less than 2%) and thus do not alter our overall results.

4. Discussion

An optimization model was developed to analyze the effects of household investment in PV and ST systems. Rising tariff rates, in combination with declining costs for PV and ST technologies, make these investments increasingly attractive for wealthy households. These households usually have high electricity consumption and thus the potential to see meaningful savings on electricity bills. Our model results show that for the majority of households (with the exception of *Life-Line* households) investments in PV are cost-effective. By the year 2025, this trend results in a decline in Cape Town's electricity revenues, thus reducing resources available for the poor-favorable policy.

We modeled the implementation of a fixed network-connection fee as one possible solution that would enable the continuation of a poor-favorable policy without preventing the deployment of residential PV. A fixed network-connection fee is already under discussion by the city administration would be relatively straightforward to implement. Furthermore, the 30% fixed network connection fee in scenario Net1 would roughly cover the fixed costs of the city's electricity expenses. Results show that this fee particularly affects household investments in ST, which becomes less cost-effective for the majority of households. Cheaper per-kWh tariff rates make expensive ST systems for self-supply financially unattractive.

We do not consider a demand response to the increasing tariffs and the changed tariff structure, i.e. we implicitly assume a price elasticity of zero. There is some evidence of negative electricity price elasticities in South Africa (Inglesi-Lotz, 2011). Increasing tariff rates therefore might decrease consumption, which could decrease cost-effectiveness of PV and ST investments. If a fixed network-connection fee is introduced, there is also a contrary effect when assuming negative price elasticities as the implementation of such a fee with lower variable electricity costs could increase consumption levels. However, these effects are uncertain and are not assumed to have a large impact with respect to this analysis. For instance, Ziramba (2008) emphasizes increasing incomes as the main determinant for residential electricity consumption and does not find any statically significant effects of electricity prices on demand.

Importantly, the fixed network-connection fee is not the only option for continuing the poor-favorable policy. The issue of financing a poor-favorable policy is basically an issue of income redistribution. From an economic perspective, it can be argued electricity subsidies should be funded by tax revenues and not necessarily by electricity revenues. This implies the imposition of new taxes or tax increases and brings up the possibilities of nonpayment and tax evasion. These are prevented by Cape Town's pre-paid electricity policy. Similarly, taxes or regulative barriers on PV could also alleviate the negative consequences of PV on the city's electricity revenues. However, implementing the fixed network-connection fee considered here seems relatively straightforward and would comply with the current tariff structure designed recently by the Electricity Service Department.

We only consider PV and ST systems for reducing electricity

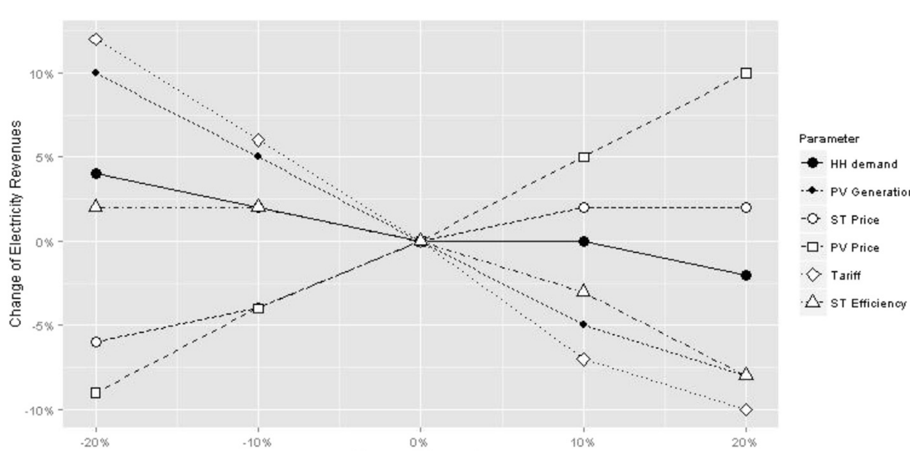

Fig. 6. Sensitivity analysis concerning the impact of technical as well as economic parameters on electricity revenues in 2025.

consumption, but alternative measures are available as well, including energy efficiency measures and the usage of solar thermal systems to replace electrical water heaters. Furthermore, we have focused only on the residential sector; with appropriate data, a similar analysis for the non-residential sector would allow a more detailed discussion on the impact of PV on Cape Town's budget.

We note additional limits of our analysis and ideas for future research. First, using more recent load profiles may alter results due to potential changes in consumption patterns. Load profiles are not weighted within each group due to a lack of detailed information about the relevance of socio-economic characteristics to load profiles within the groups. However, our sensitivity analysis suggests that alternative load profiles only lead to minor changes in the results. Second, another aspect not discussed in detail is the technical condition of the metering systems. The majority of households have pre-paid meter systems that currently do not support net-metering. If a household is remunerated for feeding electricity into the grid (which is not assumed in this analysis) meter replacement or re-programming would be required. Third, trends in the city's expenditures for electricity purchasing and cross-subsidization are modeled exogenously, and each year is calculated separately. In reality the city might revise the tariffs in order to cover costs and alleviate a potential budget gap. However, higher electricity tariff rates would worsen the revenue problem by increasing incentives for household investment in PV. Fourth, according to officials of the Electricity Department there are several different, hourly varying tariff rates for bulk-power purchases. These rates vary depending on transmission costs, time of day, season of year, and other technical criteria. Details about applicable tariffs and respective quantities are not publicly available, which makes it impossible to assess how PV production affects bulk-power purchase costs in detail. For that reason, we rely on one single average bulk-power tariff rate. However, by applying hourly varying rates, PV is assumed to have an even stronger impact on electricity expenses: while bulk-power tariff rates are usually high in peak hours (morning and evening) as well as in winter (for electric heating), excess electricity from PV is mostly available in non-peak hours. This means, taking an average tariff represents a conservative approach to estimating the impact of PV on electricity expenses as PV is likely to replace electricity at prices below average. Fifth, in this analysis no changes in the population are considered due to lack of reliable data. Ideally, Cape Town's poor-favorable policy would lead to a rapid improvement of socio-economic conditions, which could decrease the number of indigent residents and the need for subsidized electricity. However, as illustrated by Trollip et al. (2012), the city assumes population growth but almost entirely among low-income and unserved households. The number of high-, medium- and even low-income households with electricity access remains almost constant until 2030, but the share of indigent, non-electrified residents in informal settlements is assumed to grow. We assume the total population to remain unchanged for the purpose of our analysis, but consider continuously rising non-energy costs related to infrastructure renewal (electrification of informal settlements) and serving indigent households. Finally, the results of our analysis reflect optimal profit-maximizing investment decisions from the household perspective, which do not take into account investment barriers such as transaction costs, imperfect information, lock-in effects, and capital constraints. It is also unlikely that household's decisions are always completely rational. Thus, our results concerning the share of installed PV and the effectiveness of the network-connection fee may deviate from real uptake rates. The results here represent an upper bound of investments. In further research, the model could be improved by including technology diffusion dynamics see Cai et al. (2013).

Additional research could also consider the potential for CO_2 reductions due to PV electricity generation. By assuming a price for CO_2 emissions (as in Europe), the financial losses arising from the budget gap could be compared with the monetary value of reduced CO_2 emissions. This would represent a valuable contribution to designing policies toward both poverty alleviation and the deployment of low-carbon energy technologies.

5. Conclusion and policy implications

According to the results of our model distributed residential PV electricity generation is becoming increasingly cost-effective for residential customers in Cape Town. While lower-income households mainly consume electricity from the grid, the majority of high-income households will have a financial incentive to cover some of their electricity consumption by PV self-generation in the near future. Under the applied assumptions, the deployment of battery systems (ST) is not cost-effective until the year 2026. Nonetheless the combination of PV and ST has a meaningful negative impact on the electricity revenues of the City in the simulated period.

Thus, our findings indicate an expanding budget gap between electricity expenses and electricity revenues of the municipality. Without additional policy measures, this gap is likely to lead to any or all of the following developments: (a) electricity tariff rates must be further increased in order to cover costs, a feedback loop that further incentivizes households to invest in PV; (b) available funding for subsidized electricity and other services will fall; (c) other revenue sources will be needed to maintain the current poor-favorable electricity policy in Cape Town; and (d) the share of renewables will increase, which is in line with aims to reduce GHG emissions.

The implementation of an electricity revenue-neutral fixed network-connection fee is in line with current proposals by city officials to alleviate the negative impacts of household PV on electricity revenues. This measure actually decreases the per-kWh price and thus makes PV less competitive. Our simulation reveals that this change in the tariff structure indeed decreases the budget gap and results in less PV electricity generation. Apart from the introduction of a fixed network-connection fee, we also want to emphasize the potential for further modifications of the electricity tariffs for instance with tiers or breakpoints for variable costs.

For further research projects, we recognize the need for more detailed consideration of the municipality's cost structure. Additionally, the impact of excess PV electricity on the city's electricity costs should be investigated in more detail in order to improve the assessment of the city's budgetary situation. Also, other measures that households might take to decrease conventional electricity consumption, such as energy efficiency measures or the use of other forms of distributed generation, should be investigated.

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1. Annex

Year	3 kWp PV system	5 kWh ST system
2013	67.773	19.397
2014	67.214	19.585
2015	66.786	19.775
2016	66.481	19.967
2017	66.296	20.161
2018	66.228	20.356
2019	66.273	20.554
2020	66.428	20.753
2021	66.690	21.369
2022	67.056	22.004
2023	67.525	22.658
2024	68.093	23.330
2025	68.760	24.023
2026	69.523	24.737
2027	70.381	25.472
2028	71.333	26.228
2029	72.377	27.007
2030	73.513	27.809

Annex A. Forecast system prices (in Rand) for a 3 kWp PV system and a 5 kWh ST system. Prices include inflation of about 5.9%

Acronyms and abbreviations	
ANC	African National Congress
Domestic	Regular electricity tariff for non-indigent residents
ESKOM	Electricity Supply Commission (power utility)
GWh	Gigawatt hour
HH	Household
kWh	Kilowatt hour
Life-Line	Subsidized electricity tariff for indigent residents
NERSA	National Energy Regulator of South Africa
PV	Photovoltaic
ST	Battery storage system
VAT	Value added tax
ZAR	South African Rand (currency)

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Article VI

Höltinger, S., Salak, B., Schauppenlehner, T., Scherhaufer, P., Schmidt, J.

Austria's wind energy potential – a participatory modeling approach to assess socio-political and market acceptance.

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Austria's wind energy potential – A participatory modeling approach to assess socio-political and market acceptance

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HIGHLIGHTS

- Including social barriers could reduce Austria's wind potential from 92.78 to 3.89 TWh
- Costs for attaining a 20% wind energy share vary by 20% between the scenarios
- Socially acceptable wind area potential ranges from 0.1 to 3.9% of Austria's total area
- Excluding forest areas lowers the maximum wind energy potential by 45%

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ABSTRACT

Techno-economic assessments confirm the potential of wind energy to contribute to a low carbon bioeconomy. The increasing diffusion of wind energy, however, has turned wind energy acceptance into a significant barrier with respect to the deployment of wind turbines. This article assesses whether, and at what cost, Austrian renewable energy targets can be met under different expansion scenarios considering the socio-political and market acceptance of wind energy. Land-use scenarios have been defined in a participatory modeling approach with stakeholders from various interest groups. We calculated the levelized cost of electricity (LCOE) for all of the potential wind turbine sites, which we used to generate wind energy supply curves. The results show that wind energy production could be expanded to 20% of the final end energy demand in three out of four scenarios. However, more restrictive criteria increase LCOE by up to 20%. In contrast to common views that see local opposition against wind projects as the main barrier for wind power expansion, our participatory modeling approach indicates that even on the level of key stakeholders, the future possible contribution of wind energy to Austrian renewable energy targets reaches from almost no further expansion to very high shares of wind energy.

1. Introduction

In recent years, several studies have explored wind energy potentials at different scales: global (Hoogwijk et al., 2004; Lu et al., 2009), European (EEA - European Environment Agency, 2009; McKenna et al., 2015; Resch et al., 2008) and national and regional (Gass et al., 2013; Grassi et al., 2012; McKenna et al., 2014; Schallenberg-Rodríguez and Notario-del Pino, 2014; Winkelmeier et al., 2014). Recent studies on Austrian wind energy potential have assessed the realizable potential until 2030 assuming current policy support schemes and a constant rate of new installations (Winkelmeier et al., 2014) and the optimal level of feed in-tariffs for attaining renewable energy targets for wind (Gass et al., 2013). All of these studies conclude that the technical wind energy potential exceeds the current electricity consumption. Thus, the potential contribution of wind energy to a renewable low carbon energy system will not be limited by its physical availability, but by ecological, spatial and social restrictions and the amount of intermittent wind generation that can be economically integrated into the power system.

In Austria, wind energy contributed to approximately 6% (3.64 TWh) of the electricity demand in 2014 (E-Control Austria, 2014; OeMAG, 2015). The eco-electricity act of 2012 defined a goal of 6 TWh wind production in 2020, which is equivalent to approximately 10% of the electricity demand in 2014. For 2030, the

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EU reference scenario for transport, energy and greenhouse gas (ghg) emissions (Capros et al., 2013) projects that Austrian wind energy production could rise to 13.4 TWh. This would equal 17.5% of the electricity consumption in 2014. Wind integration costs are not likely to represent a major barrier to reach this share as previous studies have shown that integration costs remain moderate for wind penetration rates of up to 20% (Georgilakis, 2008). However, at high wind energy shares of 40%, integration costs can reach the same magnitude as generation costs and thus become a major economic barrier to a large-scale deployment of wind energy (Ueckerdt et al., 2013).

The most important limitations to tapping the full technical potential of wind energy are ecological, spatial and social barriers. These restrictions have been considered in previous assessments either by defining suitability factors for certain land use categories or by excluding protected areas. Hoogwijk et al. (2004) excluded nature reserves and defined suitability factors for different land use-categories. McKenna et al. (2014) followed a similar approach – however, additionally, they exclude several protected areas and defined buffer zones to nature reserves and national parks. Previous studies for Austria do not consider variations in the suitability of different land use categories, but only exclude Natura 2000 areas (Gass et al., 2013) or both Natura 2000 areas and protected sites that are listed in the Common Database on Designated Areas (CDDA) (Winkelmeier et al., 2014).

The importance of including social barriers in wind potential assessments is acknowledged by several studies (EEA - European Environment Agency, 2009; Gass et al., 2013; McKenna et al., 2014). However, none of them have considered the opinions and preferences of decision makers and key stakeholders regarding the future development of wind energy. Therefore, the analysis may not be very robust as social barriers may hamper wind energy deployment and constrain techno-economic potentials. Future research should therefore integrate social aspects into spatial explicit analyses of wind power potential (Gass et al., 2013) and account for social barriers and costs (McKenna et al., 2014). A recent assessment for the German federal state of Baden-Württemberg takes into account socio-economic constraints by considering landscape aesthetical aspects (Jäger et al., 2016).

In the 1990s, the social acceptance of wind energy was largely neglected due to the high level of general public support for renewable energies (Wüstenhagen et al., 2007). With the expansion of wind energy, negative externalities such as visual impact, noise and effects on wildlife and ecosystems became much more pronounced (Horbaty et al., 2012). This resulted in growing opposition against specific wind energy projects and a growing recognition of social acceptance in the scientific literature. Several authors have conceptualized the social acceptance of wind energy (Batel et al., 2013; Bidwell, 2013; Horbaty et al., 2012; Sovacool and Lakshmi Ratan, 2012; Wüstenhagen et al., 2007) and renewable energy technologies in general. We follow Wüstenhagen et al. (2007) in their definition of social acceptance. They contributed to clarify the understanding of social acceptance by differentiating between three aspects of social acceptance: socio-political, community and market acceptance.

The focus of this research paper is to assess socio-political and market acceptance, as defined by Wüstenhagen et al. (2007). Community acceptance, which involves issues of procedural and distributional justice and trust are not assessed, as acceptance in those terms can hardly be derived from an assessment on a national scale such as ours. Wüstenhagen et al. (2007) frame socio-political acceptance as the acceptance (or lack of acceptance) of technologies and policies by the public, important stakeholders, and policy makers. The focus of market acceptance is on consumers and investors and includes aspects such as the distribution of costs and benefits (Horbaty et al., 2012). The public, as confirmed by many surveys (Eurobarometer, 2006; Wunderlich and Vohrer, 2012), is generally in favor of wind energy generation (if asked about wind energy in general - and not about particular projects in the neighborhood). However, important stakeholders, e.g., from the environmental sector, partly oppose wind energy due to external effects with respect to birds, bats, wildlife, and visual impact, while other groups, such as wind park developers and operators, have a strong interest in deploying more wind turbines.

In Austria, four out of nine federal states have defined suitability and exclusion zones for wind energy to reduce conflicts with local communities and to create more predictable framework conditions for investors. However, the legal status, applied approaches and criteria to define those zones vary greatly among the federal states. Structurally, political oriented top-down and bottom-up processes are used in the regulatory process for wind turbine installation in Austria; exclusion and suitability zones are defined top-down by the federal states, while the actual designation of areas for the construction of wind turbines is the responsibility of the municipalities. Consultation processes with civil society were organized in the top-down definition of suitability zones, e.g., in Lower Austria, but there is no general, coherent process for defining those zones and, consequently, conflicts arise after definition. Additionally, the economic impact in terms of higher system costs due to different criteria is, in general, not evaluated at that level.

Our specific aim was therefore to empirically employ the concept of social acceptance and to assess, in particular, the socio-political and market acceptance of wind energy in Austria and also to report the economic consequences in terms of installation costs for the whole country. For that purpose, we applied a participatory modeling approach to develop a criteria catalogue that considers techno-economic, environmental and socio-political restrictions. Together with an expert oriented stakeholder group from different fields of interest, we defined spatial and topological restrictions, minimum distances to settlements and infrastructure and the suitability of different protected and forest areas. The results provide a bandwidth for suitable areas for wind energy generation and the corresponding wind energy potentials that are acceptable by key stakeholders and decision makers. The contribution of wind energy to the energy system in 2030 is assessed by assuming a bandwidth for the end energy demand in 2030. Additionally, we calculate the wind energy potential and the costs for attaining renewable energy targets with the existing suitability and exclusion zones that have been defined by the Austrian federal states.

The paper is structured as follows: first, we describe our participatory modeling approach and the data and model that were used to calculate the socio-political and market acceptable wind energy potential. We then present the results with respect to the different area scenarios and identify the key parameters that determine the wind potential. Finally, we discuss the results and highlight major policy implications.

2. Methods

As outlined in the introduction, we frame the analysis of our wind power potentials with the social acceptance concept as proposed by Wüstenhagen et al. (2007). In particular, we focus on socio-political and market acceptance. The first category, i.e. socio political acceptance, is addressed by deriving land availability scenarios in cooperation with stakeholders. Acceptance of the public and important stakeholders is reflected in those scenarios. The second category, i.e. market acceptance, also relies on those scenarios as important market actors defined the availability of land for new projects as fundamental. Additionally, we apply a

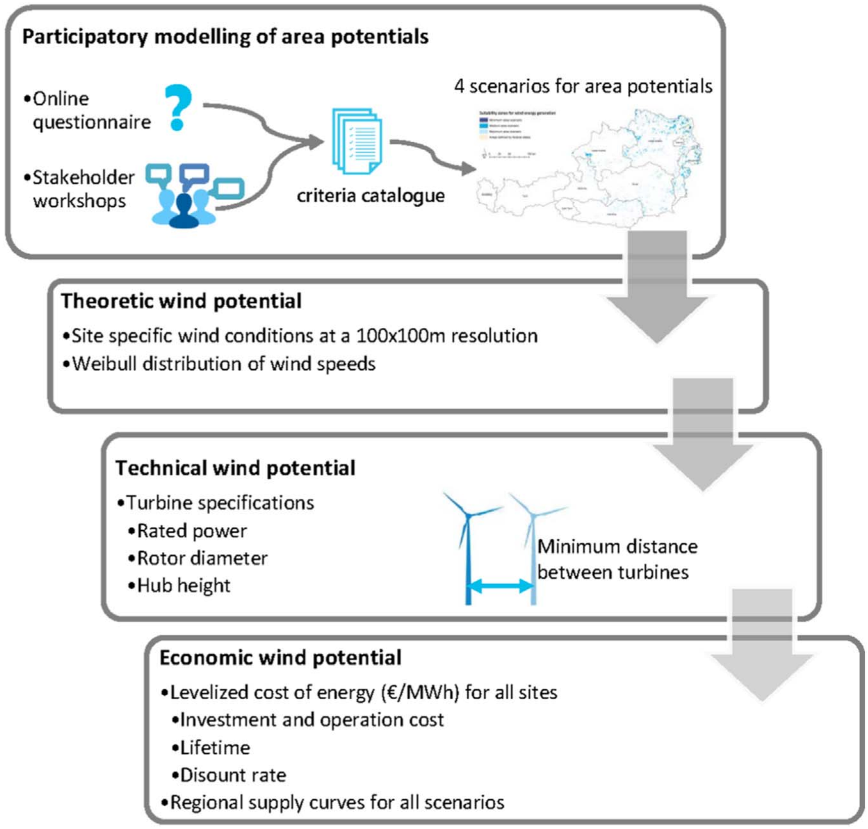

Fig. 1. Overview of the modeling steps that were applied to assess the economic wind potential in a participatory modeling framework.

techno-economic analysis of wind power projects by deriving levelized costs of electricity (LCOE), as profitability of projects is, obviously, also fundamental for supply side actors on the markets. Wüstenhagen et al. (2007) also consider distributional issues to be part of the market acceptance concept. Those could arise, e.g., by a redistribution of costs and benefits from producers to consumers due to an increase in electricity tariffs (or taxes) when the share of wind energy in the production portfolio increases. This aspect was not directly addressed in our participatory modeling approach, however, we are able to derive total costs of wind power deployment from our modeling approach.

The economic wind energy potential as determined by the participatory modeling framework is calculated in four steps (Fig. 1). First, four scenarios (min, med, max and federal suitability zones) were defined in the participatory modeling process to identify areas that are suitable and acceptable for wind energy. Second, the theoretical wind energy potential was simulated based on mean hourly wind speeds from the Weibull distributions that were provided by the Austrian wind atlas (Krenn et al., 2011). In the third step, the technical potential was derived by transforming hourly wind speeds to power production using the performance coefficient of the most common wind turbine in Austria. In the last step, the LCOE was calculated for all of the wind sites by including a range of estimates from the literature for investment and operation costs, discount rate and wind turbine lifetime. Subsequently, wind supply curves were generated by sorting and adding the LCOEs of all of the potential wind energy sites.

2.1. Participatory modeling approach

Participatory modeling means incorporating stakeholders such as the general public or decision-makers into the modeling process (Voinov and Gaddis, 2008). This approach is widely applied in environmental and natural resource modeling to include administrative, professional and local knowledge, increase the legitimacy of model results, guarantee their practical applicability (Hare et al., 2005; Mitter et al., 2014) and trigger learning effects among participants to allow a co-construction of possible futures (Bauer,

Table 1
Overview of participating organizations.

Group	Organizations
Public authorities	Austrian Ministry for Transport, Innovation and Technology, Federal Ministry of Science, Research and Economy, Austrian Energy Market Regulator – E-control, Chamber of Labor, Chamber of Commerce
Federal state authorities	Burgenland, Lower Austria, Salzburg, Styria, Ombuds Offices for Environmental Protection (Umweltanwaltschaft) of Burgenland, Lower Austria and Styria
Wind park developers and operators	Energie Burgenland Windkraft GmbH, EVN Naturkraft GmbH, Ökostrom AG, PÜSPÖK Group, WEB Windenergie AG, Windkraft Simonsfeld AG
Environmental and nature conservation groups	Austrian Environmental Umbrella Association (Umweltdachverband), BirdLife, Coordination Center for the Study and Protection of Bats
Others	Austrian Power Grid (APG), Austrian Wind Energy Association (IG-Windkraft), the processing and administration center of the subsidies for eco-electricity (OeMAG)

2015). We included key stakeholders from public and federal state authorities, nature conservation groups, and wind park developers and operators (Table 1). Federal state authorities, especially those from Burgenland and Styria, contributed with their experience from planning processes for existing suitability zones and their expertize on regional spatial planning laws in the context of wind energy. Wind park developers shared their knowledge of technical restrictions (e.g., the maximum feasible slope). Experts from nature conservation groups provided insight into relevant ecological criteria, such as the type of protected areas that should be excluded. Besides improving the quality of the results in terms of expertize, the contributions also increased the legitimacy of the results and triggered learning effects among the participants. In total, the 28 experts from the various organizations provided a diverse picture of social, environmental, economic and technical barriers that have to be considered when assessing the future wind energy deployment.

Previous studies suggest including stakeholders as early and often as possible (Bots and Daalen, 2008; Voinov and Gaddis, 2008). To foster engagement, we organized two stakeholder workshops and carried out one online survey and several e-mail consultations. In the first workshop, we introduced the project to the stakeholder group, agreed upon rules of collaboration and presented our online questionnaire to the group. Stakeholders were asked to assess the suitability of different land use categories for wind energy generation. The online questionnaire was answered by 23 out of 28 stakeholders (for more details see Appendix A1). Its results and the input of the first participatory workshops were summarized in a criteria catalogue and were used to define three scenarios (min, med and max) for suitable wind turbine sites. The contributions and results were collected on a webpage (www.transwind.boku.ac.at) to encourage continuous stakeholder feedback. In the min scenario, we consider several strict restrictions and large setbacks to protected and settlement areas so that all of the stakeholders agreed that no more areas should be excluded as potential sites. This implies that even the stakeholders who were the most restrictive with respect to wind power deployment agreed that such a scenario would be feasible from their point of view. The max scenario was chosen in a way so that the stakeholders agreed that no more areas should be considered to be potentially suitable, i.e., by using lower setbacks to protected and settlement areas (max scenario). This implies that even the stakeholders who had the greatest interest in wind power expansion agreed that wind power should not be deployed beyond that point. The min and max scenarios represent the lower and upper bounds of the acceptable wind energy potential in Austria from a socio-political perspective, as defined by the stakeholder group. The large bandwidth of the min and max scenario made it difficult to draw conclusions about the potential contribution of wind energy to decarbonization strategies in Austria. To provide a more meaningful estimate within the range of acceptable wind energy potential, we defined a med scenario. Due to the heterogeneity of the stakeholder group, it was not possible to reach consensus on the med scenario. Therefore, the assumptions and offset distances of the med scenario are based on current national and federal state legislations and recommendations by experts and from previous studies.

In a second workshop, six months later, we discussed the criteria catalogue for the scenarios of potentially suitable wind turbine sites with our stakeholder group. The recommendations and comments of the key stakeholders were collected and used to update the criteria catalogue. Experts from regional land use planning authorities argued that current settlements and buildings as well as potential future settlement expansions should be considered. Therefore, we gathered information on land-use plans to include land that was dedicated as a building area as an additional exclusion zone. Our approach to generally exclude or include forest areas was criticized for being too simplistic. Stakeholders suggested that the main function of a forest area (productive, protective, recreational and social welfare function) according to the Austrian forest development plan (Fürst and Schaffer, 2000) should be integrated, and only those areas with prevailing productive function should be considered to be suitable. Another concern was whether the defined maximum elevation for wind sites was a proper criterion. Critics argued that using the alpine timber line instead of the maximum elevation would better reflect the topological differences between Eastern and Western Austria. For the integration of the alpine timber line as a new criterion, we used the results of Kilian et al. (1994). The wind park developers noted that the assumed maximum slope of up to 20° was too high. According to the wind energy experts in our stakeholder group, it was not economically feasible to build wind turbines on sites that are steeper than 5.7°. The values that were found in the scientific literature were much higher, ranging from 11.3°, or 20% (Grassi et al., 2012), to 15° (Gass et al., 2013; Winkelmeier et al., 2014) and 16.7° or 30% (Lütkehus et al., 2013). We assumed a range between the expert values (5.7°) and the lower values that were found in literature (11.3°). In a third step, the redefined values for the min and max scenario were approved by all of the stakeholders.

2.2. Scenarios for potential wind turbine sites

The first modeling task to assess the wind potential of a certain region was to estimate the potentially suitable area for wind energy generation. The main challenge was the availability and accessibility of the necessary geographic information to consider all of the criteria for the four scenarios of potentially suitable wind turbine sites. We used GIS data on land-use categories, topology (elevation and slope), settlement areas, infrastructure (roads, railways and power transmission lines), federal land use plans, protected areas and important habitats and migration routes for wild animals, the regional alpine forest line and the main function of forests (productive, protective, recreational and social welfare function). A comprehensive overview of all of the criteria that were used and the respective data sources is provided in Table 2.

We used the criteria catalogue to create a GIS layer for each restriction including the applied minimum distances. The overlap of all of the layers showed the areas that were excluded from wind energy generation for each scenario (min, med, max). The remaining areas are potentially suitable to develop wind energy projects. The three scenarios from our participatory workshops were complemented by a fourth scenario based on federal suitability and exclusion zones of Burgenland, Lower Austria, Styria and Upper Austria - the only federal states that have defined suitability and exclusion zones so far.

The criteria can be grouped into the following three main categories: topological restrictions, distance to infrastructure and settlements and ecological restrictions. Topological restrictions include the maximum slope, the exclusion of water bodies and areas above the alpine timber border line. The distance to settlements, buildings and infrastructure such as roads, railways or power lines are subject to national and federal laws in Austria. The required distances to settlements range from 800 m in Upper Austria to 1200 m in Lower Austria. However, according to the answers in the online questionnaire from our stakeholders, we assumed equal distances to settlements for all federal states that range from 2000 m in the min scenario to 1000 m[1] in the max scenario.

[1] Some stakeholders demanded a larger distance of 1200 m for the federal state of Lower Austria. This was accepted in consensus by the whole stakeholder

Table 2
Criteria catalogue for the three participatory scenarios of potential wind turbine sites (min, med, max).

	Scenarios of potential wind turbine sites			GIS data-set	Ref
	Min	**Med**	**Max**		
Topological restrictions					
areas above alpine forest line	excluded	excluded	excluded	Kilian et al. (1994)	1, 2
maximum slope (degrees)	5.7	8.5	11.3	SRTM DEM 90 m	2, 3
water bodies	excluded	excluded	excluded	Corine LC 5	2
Offset distance to settlements and infrastructure					
settlement areas (m)[a]	2000	1200	1000	IACS	1, 2
buildings outside of settlement areas (m)[b]	1000	750	750	OSM buildings	1, 2
building land outside of settlement areas (m)	1000	750	750	federal land use plans	2
built-up areas[c]	300	300	300	federal land use plans	2
railways	300	300	300	OSM	2
motorways, primary and secondary roads	300	300	300	OSM	2
airport public safety zones[d]	5100	5100	5100	Austro Control	4
power grid (> 110 kV)	250	250	250	OSM	2, 5
Suitability of protected areas and offset distances					
national parks (m)	no (3000)	no (2000)	no (1000)	CDDA	1, 2
Natura 2000 - habitats directive sites (m)	no (2000)	no	potentially[f]	Natura 2000	1, 2
Natura 2000 - birds directive sites (m)	no (2000)	no	no	Natura 2000	1, 2
other protected areas (m)[e]	no (2000)	no	no	CDDA	1, 2
important birdlife areas	no	potentially[f]	potentially[f]	IBAs	2
major migration routes for wild animals	no	potentially[f]	potentially[f]	ACC,Köhler (2005)	1
forest areas	no (1000)	yes[g]	yes	Corine, AFDP	1, 2
lakes > 50 ha (m)	3000	1750	1000	Corine LC 512	1

(a) Except Lower Austria with 1200 m, (b) data quality varies regionally, (c) industrial and commercial units and mining areas were considered for Burgenland, Salzburg, Tirol, Vorarlberg and Vienna, (d) radius of 5100 m around airports, (e) biosphere reserves, landscape protection areas, natural monuments and sites, protected habitat and landscape section, (f) areas are only potentially suitable and ecological restrictions have to be evaluated in site specific assessments and (g) excluding areas in communities with a forest share below 10%

Acronyms: ACC (Alps-Carpathians Corridor), AFDP (Austrian forest development plan), APG (Austrian Power Grid AG), Corine LC (Coordination of Information on the Environment Land Cover), CDDA (Common Database of designated areas), IBA (Important Bird Areas), IACS (Integrated Administration and Control System), OSM (Open Streetmap), SRTM DEM (Shuttle Radar Topography Mission digital elevation model)

References: (1) questionnaire (2) stakeholder workshop (3) Suisse éole, 2015 (4) Information of the air navigation services provider -Austro Control (5) Information of Austrian Power Grid (APG)

For buildings and building plots that were outside of settlement areas, we implemented the range of federal state regulations with distances from 750 m in the max and med scenario to 1000 m in the min scenario. For all of the other built-up areas, railways and roads, we applied a general distance of 300 m and, to power transmission lines, a general distance of 250 m. For distances to airports, we included the airport public safety zones, which ban wind turbines within a distance of 5100 m.

The ecological restrictions included protected areas and other environmentally sensitive areas. For protected areas, we considered all of the areas that were listed in the Common Database on Designated Areas (EEA, 2014), including national parks, Natura 2000 areas, biosphere reserves, landscape protection areas, natural monuments and sites, protected habitat and landscape sections.

In the min scenario, we applied an additional buffer of 3000 m around national parks and 1000 m around all other protected areas. Additionally, we excluded important bird life areas (IBAs), the Alpine-Carpathian Corridor and other migration routes of supra-regional importance (Köhler, 2005) and forest areas with a buffer of 1000 m. Tourism and recreation are frequently mentioned as conflicting issues. We therefore excluded potential sites that were close to lakes. The applied distance ranged from 1000 m in the max scenario to 3000 m in the min scenario.

2.3. Calculation of the wind energy yield

For all of the potential wind energy sites that have been identified in the previous step (scenarios of potentially suitable wind turbine sites) and the existing wind energy sites in 2014, we calculated the annual power output. Several probability density functions have been proposed in the scientific literature to describe the frequency distribution of wind speeds. A review by Carta et al. (2009) showed that, compared with other probability density functions, the two-parametric Weibull distribution is best suited to describe the frequency distribution of wind speeds We used Monte Carlo simulation to derive hourly wind speeds from the Weibull distributions of wind speeds provided by the Austrian wind atlas (Krenn et al., 2011). The distributions are available at a spatial resolution of $100 \times 100\ m^2$. Based on the time series of hourly wind speeds, we calculated the energy output of each site considering the rated power of the turbine, rotor diameter, hub height and the elevation of the site. To account for existing capacities, we included power generator data from open street map (available from http://download.geofabrik.de). As rotor diameter and hub height are not specified in this dataset, we estimated the parameters based on the rated power using a regression model that was fed with the complete dataset of wind power plants from Lower Austria (for more details, see Appendix A2). For new installations, we assumed Enercon E-101 turbines with a rated power of 3.05 MW, 101 m rotor diameter and 135 m hub height, as this is the most common 3.05 MW wind turbine in Austria according to the Austrian wind energy association (www.igwindkraft.at). Approximately 80% of the wind turbines that were installed in Austria in 2014 and 2015 were of this type. For the scenarios up to 2030, we assumed that the existing wind turbines will be replaced by new turbines after they reach their assumed lifetime of 20 years. Wind turbines located outside of the areas allowed in the scenarios were not replaced after reaching their maximum lifetime. The minimum distance between two turbines in a wind park – which is usually expressed as a multiple of the

(*footnote continued*)
group and was consequently applied in the model.

Table 3
Baseline and range of parameter values for assessing the economic potential.

Cost element	unit	baseline value	range	references
Capital costs	EUR kW^{-1}	1675	1600–1900	1, 2, 3, 7
Operational costs	EUR MWh^{-1}	26.4	18.5–34.2	3, 2, 4, 5
Lifetime	years	20	–	5, 6, 7
Discount rate	%	5	–	4, 5, 7

References: (1) Arántegui and González, 2015, (2) Gass et al. (2013), (3) Hantsch et al. (2009), (4) Rehfeldt et al. (2013), (5) Kost et al. (2013), (6) McKenna et al. (2014) and (7) Falkenberg et al. (2014).

rotor diameter - depends on whether the turbines are placed in main or secondary wind directions. Studies that consider wind direction apply minimum distances between five times the rotor diameter (Grassi et al., 2012; McKenna et al., 2014), up to eight times in secondary wind direction (McKenna et al., 2014) and ten times (Grassi et al., 2012) in the main wind direction. Other studies apply general minimum distances of five (Winkelmeier et al., 2014) to six (Gass et al., 2013) times the rotor diameter. We based our assumption on the distance between existing 3 MW turbines in Austria (OSM data), which range between 390 m (10-percentile) and 535 m (90-percentile). As the Austrian wind atlas (Krenn et al., 2011) does not contain information about wind direction distribution, we did not differentiate between main or secondary wind direction and used a general minimum distance of 500 m (five times the rotor diameter).

The site's elevation above sea level (z) was used to estimate the site specific air density (ρ) with the following formula (Suisse éole, 2015):

$$\rho=1.247015*e^{-0.000104*z} \tag{1}$$

Wind speeds of the Austrian wind atlas were adjusted to the respective hub height for all of the sites (EEA - European Environment Agency, 2009):

$$V_{hub} = V_{WA} * \ln(H_{hub}/rf) / \ln(H_{WA}/rf) \tag{2}$$

H_{hub} represents the hub height (m), HWA represents the wind atlas reference height (100 m), Vhub represents the wind speed at hub height (m/s), VWA represents the wind speed at 100 m height (m/s) and rf represents the roughness factor, ranging between 0.04 (pasture), 0.50 (urban fabric) and 1.00 (forest). We assumed a factor of 0.04, as according to our GIS analysis, most Austrian wind turbines are placed on pastures or arable land. The theoretical hourly power output (P) was calculated for all wind turbines using the following formula (Gass et al., 2013):

$$P(V_{hub}) = \int_{V_{in}}^{V_n} 0.5*cp*\rho*V_{hub}{}^{3}*\pi*(0.5*D)^2 + \int_{V_n}^{V_{out}} Pt \tag{3}$$

V_{hub} represents the wind speed at hub height (m/s), V_{in} represents the cut-in wind speed (3 m/s), V_n represents the rated wind speed (m/s), V_{out} represents the cut-off wind speed (28 m/s), cp(V_{hub}) represents the wind turbine specific performance coefficient, depending on the wind speed (for details on the turbine power curve see Appendix A3), ρ represents the air density, D represents the rotor diameter (m) and Pt represents the rated power output (W). The actual amount of electricity that is fed into the power grid is lower due to array losses (the shadowing effect of neighboring wind turbines in a wind park), electrical transformation losses to higher voltages and downtime due to maintenance and repairs. In total, the net generation is usually 10–15% lower than the theoretic wind energy output (Blanco, 2009; Tegen et al., 2013). We assumed that array losses would amount to 10%, transformation losses would amount to 3% and downtimes would amount to 2% (McKenna et al., 2014; Suisse éole, 2015). For information on the model validation with historic wind power production of Austria, refer to Appendix A4.

2.4. Assumptions for calculating the economic wind potential

To assess the economic wind potential, we calculated the LCOE for each potential wind energy site. We refined a model that has been used in previous studies to assess the economic wind power potential in Austria (Gass et al., 2013; Schmidt et al., 2013). The LCOE methodology is frequently used to compare different energy technologies (Gass et al., 2013; Kost et al., 2013) or to estimate supply curves for renewable energy technologies (Mai et al., 2014; McKenna et al., 2014). The LCOE assumes that the electricity price will break even over the lifetime of a wind project and is calculated by dividing the discounted lifetime costs by the discounted lifetime energy generation:

$$LCOE = \left(CapEx + \sum_{t=1}^{n} OpEx_t/(1+r)^t \right) / \left(\sum_{t=1}^{n} AEP_t/(1+r)^t \right) \tag{4}$$

CapEx and OpEx stand for the capital and the operational expenditures, AEP stands for the annual energy production, t stands for the plant lifetime and r stands for the discount rate. Assumptions for the respective parameters are based on an extensive literature review. We considered uncertainty ranges as shown in Table 3 and discussed in more detail in Appendix A5.

We generated supply curves for each scenario of potentially suitable wind turbine sites (min, med, max, federal suitability zones) by sorting the LCOEs and adding the wind energy production off all of the sites. The supply curves depict the range of LCOEs depending on the range of capital and operational expenditures (Table 3). The levelized costs did not include grid profile, balancing and grid related costs (Hirth, 2013).

2.5. Sensitivity analysis – assessing key parameters for the max scenario

The scenarios of potentially suitable wind turbine sites that are aligned with our stakeholder group differ in many aspects, so that the effect of single criterion variations on the model results cannot be reconstructed. Therefore, we selected the criterion from each of the three main categories (topological restrictions, minimum distance to infrastructure and settlements and ecological restrictions) that had the largest impact on the available areas in the preceding GIS-analysis for the sensitivity analysis. We assessed the effect of using more restrictive assumptions compared to the max scenario for the maximum slope, distance to settlements and forest areas. Therefore, we reduced the maximum feasible slope from 11.3° to 5.7°, extended the minimum distance to settlements from 1000 to 2000 m, excluded forest areas completely instead of allowing wind turbines on commercial forest areas and combined the effects of all three of the changes. Furthermore, wind park developers stated that the selection of a 3.05 MW turbine with a rotor diameter of 101 m might underestimate the future wind energy potential, since latest developments show a trend towards larger turbines. Therefore, we calculated the wind energy potential for a turbine with 4.2 MW and a rotor diameter of 126 m. The hub height and the specific investment costs per MWh are assumed to stay constant.

3. Results

3.1. Potential areas for wind turbines

The potential areas for the siting of wind turbines were defined after considering topological and ecological restrictions and

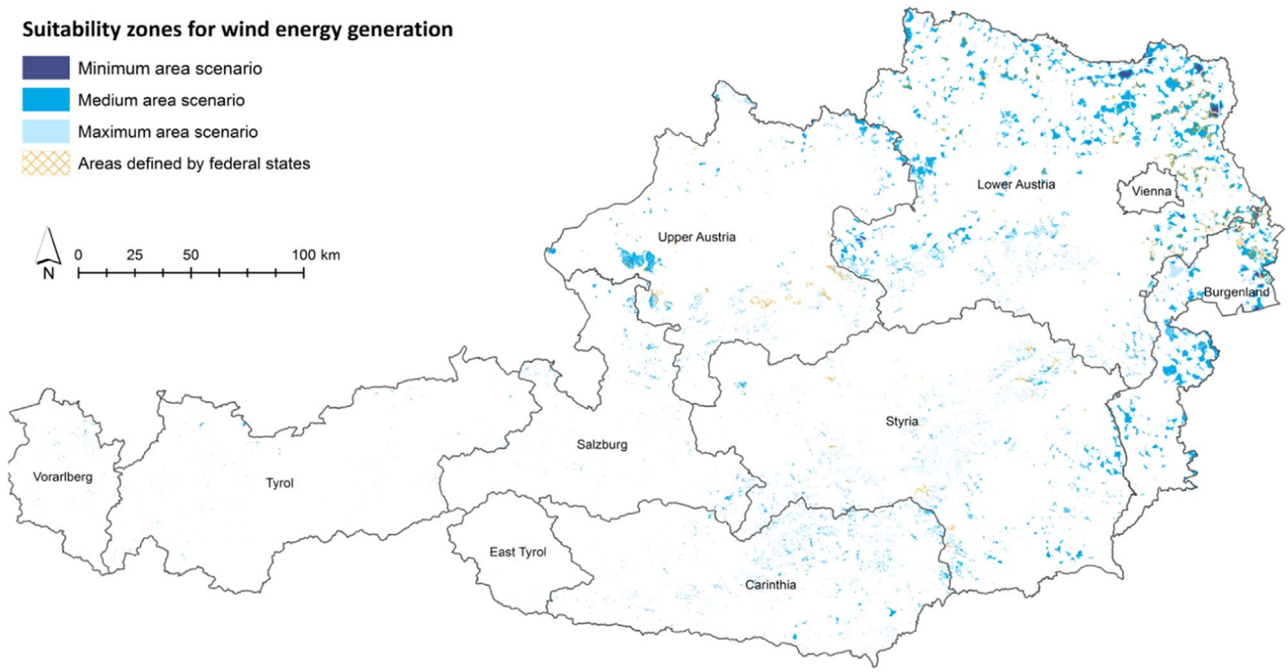

Fig. 2. Spatial distribution of potential areas for wind turbine in the four scenarios (min, med, max and federal suitability zones).

Table 4
Area for potentially suitable wind turbine sites in the four scenarios (min, med, max and federal suitability zones).

	Total area (km^2)	Max scenario (km^2)	Med scenario (km^2)	Min scenario (km^2)	Suitability zones (km^2)[a]
Burgenland	3,966	550	408	14	80
Carinthia	9,546	293	121	0	–
Lower Austria	19,199	1,497	1,258	59	282
Upper Austria	11,991	368	214	0	83
Salzburg	7,163	98	43	0	–
Styria	16,416	452	221	0	37
Tyrol	12,652	35	13	0	–
Vorarlberg	2,602	12	5	0	–
Vienna	415	0	0	0	–
Austria	83,949	3,305	2,285	74	482

[a] Currently only defined for four federal states.

setbacks to settlements and infrastructure. The available area in the Eastern lowland regions was considerably higher than in Western mountainous regions (Fig. 2).

The potential areas for wind turbine sites ranged from 74 km^2 in the min scenario up to 2285 km^2 and 3305 km^2 in the med and max scenarios, respectively (Table 4). This is equivalent to 0.1%, 2.7% and 3.9% of Austria's total area, respectively. In the min scenario, only Burgenland and Lower Austria offer potentially suitable sites.

In the med scenario, the Eastern federal states Lower Austria and Burgenland contributed 45% and 15% to Austria's area potential, followed by Upper Austria and Styria with approximately 10% each, and Carinthia and Salzburg with approximately 5% and 2%, respectively. The share of the other federal states was less than 1%. In the max scenario, the relative contribution of Burgenland and Lower Austria decreased slightly, as suitable areas in most of the other federal states were more than double when compared to the med scenario. The suitability zones of Burgenland, Lower Austria, Styria and Upper Austria (other federal states have not defined such zones yet) amounted to 482 km^2, or 0.57% of Austria's total area. Approximately 60% of the suitability zones are located in Lower Austria.

3.2. Technical wind energy potential

The technical potential describes the potential wind energy production assuming that all of the potentially suitable areas are

Table 5
Potential capacity (GW), wind energy generation (GWh) and generation per area (GWh km^{-2}) for all Austrian federal states in the four scenarios (min, med, max and federal suitability zones).

	Min scenario			**Med scenario**			**Max scenario**			**Suitability zones**[a]		
	GW	TWh	GWh km^{-2}	GW	TWh	GWh km^{-2}	GW	TWh	GWh km^{-2}	GW	TWh	GWh km^{-2}
Burgenland	0.7	1.9	0.5	4.9	10.9	2.8	6.1	13.5	3.4	1.4	3.6	0.9
Carinthia	0.0	0.0	0.0	3.2	4.9	0.5	5.5	8.3	0.9	–	–	–
Lower Austria	1.0	2.0	0.1	19.5	38.9	2.0	22.0	43.8	2.3	3.6	8.4	0.4
Upper Austria	0.0	0.0	0.0	4.4	6.8	0.6	6.4	9.8	0.8	0.9	1.4	0.1
Salzburg	0.0	0.0	0.0	1.2	1.6	0.2	2.2	2.7	0.4	–	–	–
Styria	0.0	0.0	0.0	5.0	7.8	0.5	8.4	13.1	0.8	0.5	0.9	0.1
Tyrol	0.0	0.0	0.0	0.4	0.5	0.0	0.9	1.0	0.1	–	–	–
Vorarlberg	0.0	0.0	0.0	0.2	0.3	0.1	0.4	0.4	0.2	–	–	–
Austria	1.7	3.8	0.0	38.8	71.6	0.9	51.8	92.8	1.1	6.3	14.3	0.2

[a] Currently only defined for four federal states.

utilized. The technical potential considers site specific wind conditions, turbine power curves and the minimum distances between two wind turbines. The maximum capacity was determined by the number of wind turbines that can be placed in suitable areas times the assumed average rated power of 3.05 MW. The scenarios, which were presented in the previous section, result in large variations of the technical potential that ranged from 1.76 GW in the min scenario to 38.79 GW in the med scenario and 51.82 GW in the max scenario (Table 5).

The potential wind energy generation for all of the federal states was calculated by multiplying the installed capacity by the average full load hours. It ranged from 3.89 TWh in the min-scenario to 71.59 TWh in the med-scenario and 92.78 TWh in the max-scenario. Lower Austria contributed to about half of Austria's technical wind energy potential (54% or 43.8 TWh in the med-scenario and 47% or 38.9 TWh in the max-scenario). Other federal states with considerable contributions to the technical wind energy potential in the med and max-scenario were Burgenland (15%), Styria (11–14%), Upper Austria (10–11%) and Carinthia (7–9%). The total technical wind energy potential of the Western mountainous federal states Salzburg, Tirol and Vorarlberg amounted to only 3–5% in the med and max-scenarios, respectively. The suitability zones defined by federal states allowed for an annual production of approximately 14.29 TWh with an installed capacity of 6.28 GW. The wind energy generation per federal state area in the med scenario ranged from 0.1 GWh km^{-2} in Vorarlberg to 2.8 GWh km^{-2} in Burgenland.

The site specific wind conditions varied considerably among Austrian federal states, so that a high area potential did not automatically translate into a high wind energy potential and vice versa. However, wind conditions were best in the two federal states with the highest area potential, Lower Austria and Burgenland (Fig. 3).

Depending on the scenario, the mean full load hours in those two federal states ranged between 1985–2020 h and 2215–2590 h, respectively. The mean for federal suitability zones was higher with 2355 and 2600 full load hours for Lower Austria and Burgenland, respectively. This indicates that the wind conditions have been considered in defining the suitability zones. The mean full load hours for the other federal states with considerable area potential, Carinthia, Styria and Upper Austria, were much lower, with 1230–1560 h.

3.3. Economic wind energy potential

In the previous section, we presented feasible estimates for the maximum wind energy potential in Austria. In this section, we further elaborate on the costs that are associated with expanding the share of wind energy. The LCOEs increase with the installed capacity, assuming that the best wind turbine locations are utilized first. The supply curves (Fig. 4) visualize the relationship between installed capacity and the marginal baseline LCOE for all scenarios of potentially suitable wind turbine sites.

As the potentially suitable wind turbine sites decrease, the corresponding supply curves become steeper. The economic wind energy potential at a given price level varies considerably between the different scenarios. The Austrian green electricity act of 2012 foresaw a wind energy production of approximately 6 TWh (3 GW installed capacity) for 2020. The marginal baseline LCOE for attaining this target ranges from 86.83 EUR MWh^{-1} in the max scenario and 87.82 EUR MWh^{-1} in the med scenario up to 91.20 EUR MWh^{-1} for federally defined suitability zones.

The light-colored areas (Fig. 4) indicate the uncertainty range for the marginal LCOE based on the different assumptions for investment and operation costs and the discount rate (Table 3). For the most optimistic assumptions (low investment and operational costs) the marginal LCOE was between 8% and 14% lower than the marginal baseline LCOE. Consequently, the wind energy potential in the med scenario could nearly triple from 9.46 to 25.75 TWh at

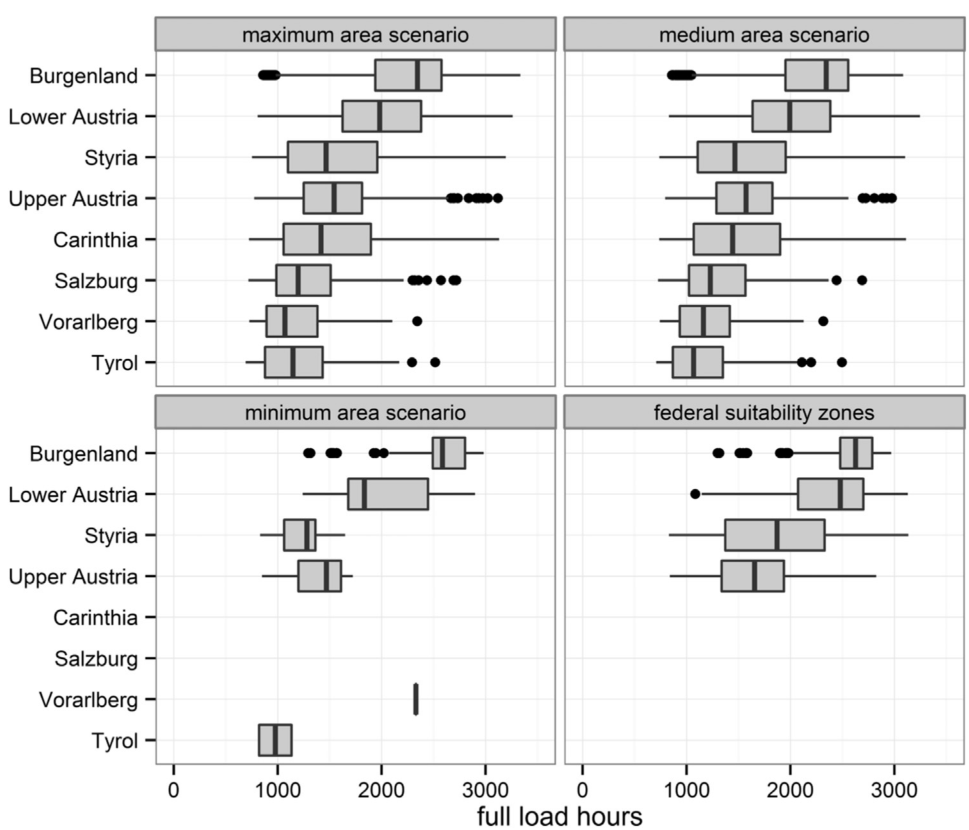

Fig. 3. Boxplots showing the distribution of full load hours for all scenarios (min, med, max, federal suitability zones).

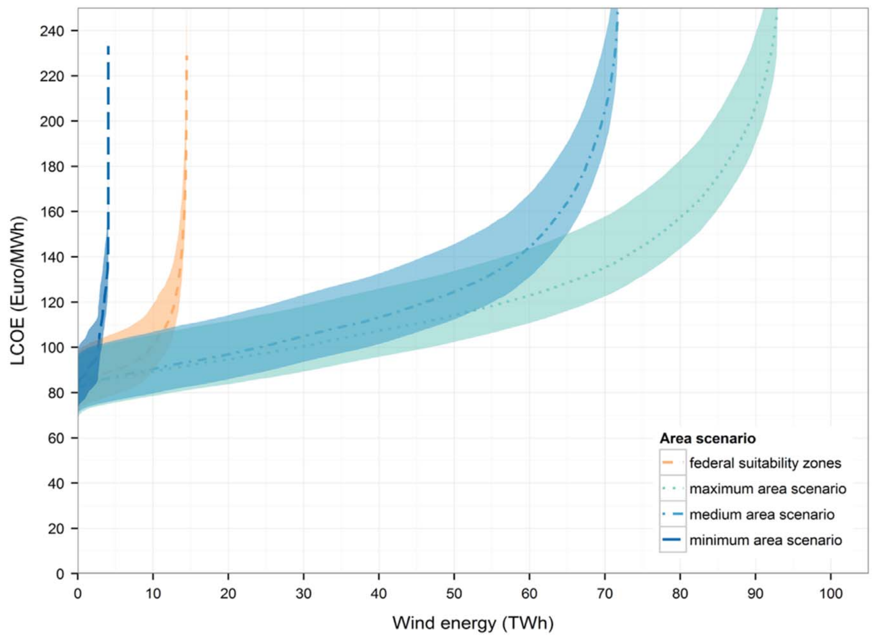

Fig. 4. Supply curves showing the economic wind energy potential for the four scenarios (min, med, max and federal suitability zones). The lines show the marginal baseline LCOE and the light-colored areas indicate the range between the minimum and maximum marginal LCOEs based on the input parameter assumptions (Table 3).

a marginal LCOE of 90 EUR MWh^{-1}. For the most pessimistic assumptions, the marginal LCOE was 16–20% higher than the marginal baseline LCOE. Thus, the marginal baseline LCOE for attaining Austria's renewable energy target could be as high as 102.75 EUR MWh^{-1} in the max scenario, 103.87 EUR MWh^{-1} in the med scenario and 107.71 EUR MWh^{-1} for federally defined suitability zones. The regional cost curves for all of the Austrian federal states are shown in Appendix A6.

Targets for wind energy expansion are often defined as a relative share of the final end energy demand. Thus, the development of the end energy demand determines the costs for attaining a certain wind energy share. To provide a feasible bandwidth for the end energy demand in 2030, we assume, that in the best case, the demand can be stabilized at the level it was in 2013, and in the worst case, the demand will continue to grow with the same annual rate of 1.5%, as observed on average in the last 10 years. This scenario would result in a final end energy demand for electricity between 62.0 and 80.5 TWh in 2030. For Austria, the EU reference scenario projected a demand of 68.0 TWh and a wind energy production of 13.4 TWh in 2030 (Capros et al., 2013).

At an end energy demand of 62.0 TWh, i.e., a stabilization of demand at 2013 levels, the marginal baseline LCOE for attaining the 10% target varied between 86.92 EUR MWh^{-1} in the max scenario and 87.95 EUR MWh^{-1} in the med scenario up to

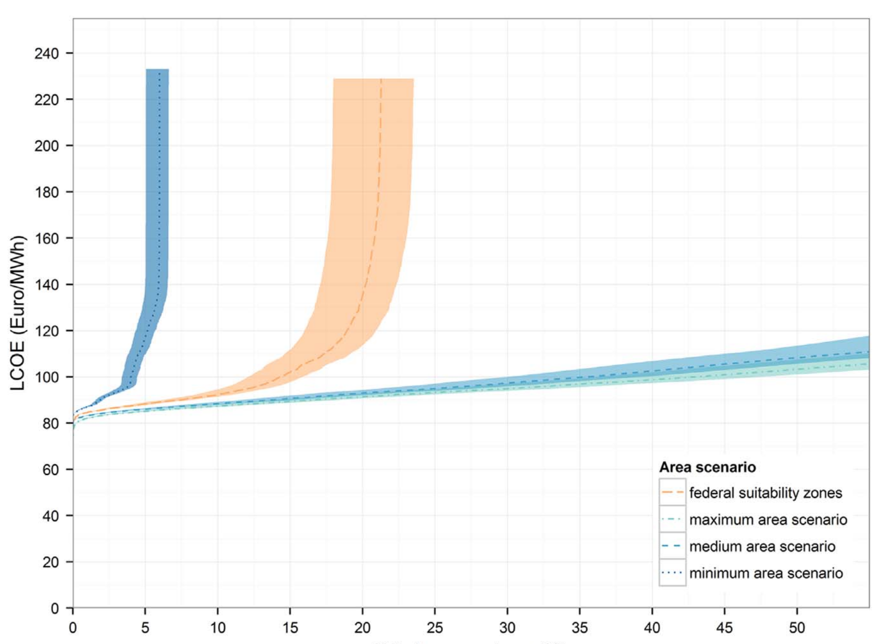

Fig. 5. Supply curves showing the marginal baseline LCOE for attaining a certain wind energy share. The colors represent the four scenarios (min, med, max and federal suitability zones). The lines show the marginal baseline LCOE for a final end energy demand of 68.0 TWh. The light-colored areas show the bandwidth of the marginal LCOE for an end-energy demand between 62 and 80.5 TWh.

91.45 EUR MWh^{-1} for the federal suitability areas (Fig. 5). Assuming that feed-in tariffs are calculated based on our LCOE calculation, the annual costs for reaching the 10% wind energy share under a feed-in tariff scheme are 3.8% and 4.9% (23.8 and 30.7 million EUR) lower for the med and max scenario compared to the federal suitability zones.

For a wind energy share of 20%, this cost difference increased to 19.6% and 20.8% (229.1 and 243.5 million EUR) in the max and med scenarios, respectively. With the suitable areas of the min scenario, the maximum wind energy share that can be reached was approximately 6%.

3.4. Sensitivity analysis

The impact of varying economic parameters (e.g., operational and investment costs) on the wind energy potential and the effect of different assumptions for the future electricity demand on the costs for attaining renewable energy targets were highlighted in the previous section. In this section, we explore the sensitivity of the wind energy potential to the inputs from the stakeholder group (e.g., varying assumptions for the criteria that are presented in Table 2 and applying an alternative wind turbine to consider the future technological development of wind turbines). The criteria catalogue represents the full bandwidth of stakeholder preferences with respect to the suitability of potential wind turbine sites. Fig. 6 shows the impact of applying an alternative wind turbine and more restrictive criteria for the distance to settlements, maximum slope, suitability of forests and a combination of all three. The impacts of these changes are compared with the wind energy potential of the maximum area potential.

Reducing the maximum feasible slope from 11.3° to 5.7° lowered the wind energy potential by 30%. Excluding forest areas or increasing the distance to settlement areas from 1000 to 2000 m resulted in an approximately 45% lower potential. All three restrictions combined reduced the wind energy potential by more than 80%, from 92.3 to 15.7 TWh. Assuming a larger wind turbine with a capacity of 4.20 MW (instead of 3.05 MW) and a rotor diameter of 126 m (instead of 101 m) increases the maximum wind potential by about 10% to 102 TWh. Differences in the LCOEs between the two turbine types occur only at high penetration rates in the different scenarios (e.g. above 40 TWh in the max area scenario). The effect on the costs for attaining 6 TWh of wind energy, as envisaged in the Austrian eco-electricity act, was moderate. The marginal baseline LCOE of 86.83 EUR MWh^{-1} in the max scenario would increase by 0.9%, 2.7% and 3.1% by reducing the maximum slope, excluding forest areas and increasing the minimum distance to settlement areas, respectively. Combining all three restrictions would increase the marginal baseline LCOE by 10.5%. For the more ambitious goal of 20% wind energy, the effect on the LCOE became much more pronounced. The marginal baseline LCOE in the max scenario ranged from 90.64 EUR MWh^{-1} for a stagnating electricity demand to 92.73 EUR MWh^{-1} if demand keeps rising by 1.5% p.a. The exclusion of forests and higher offset distances to settlements would then increase the marginal baseline LCOE by 3.9–5.1% and 6.2–8.5%, respectively.

4. Discussion

Previous studies on the social acceptance of wind energy have focused on public and community acceptance (Batel et al., 2013; Wolsink, 2007). Our assessment highlights that there is little consensus about the future of wind energy in Austria on the level of key stakeholders and decision-makers, a fact that is often not taken into account in other modeling studies. Therefore, wind power expansion should expect significant opposition – not only by communities but also by high-level stakeholders and policy makers. The consideration of social-political and market barriers in our participatory modeling approach and the resulting range for wind energy potential demonstrates that the realizable wind potential might be much lower than that suggested by other techno-economic studies.

The heterogeneity of stakeholders and their diverging opinions on the suitability of different land-use categories result in large variations of the scenarios for the area potential ranging between 0.1% of the total Austrian area in the min scenario and 3.9% in the max scenario. This finding is considerably less than in Germany, where previous studies reported values between 11.7% (McKenna

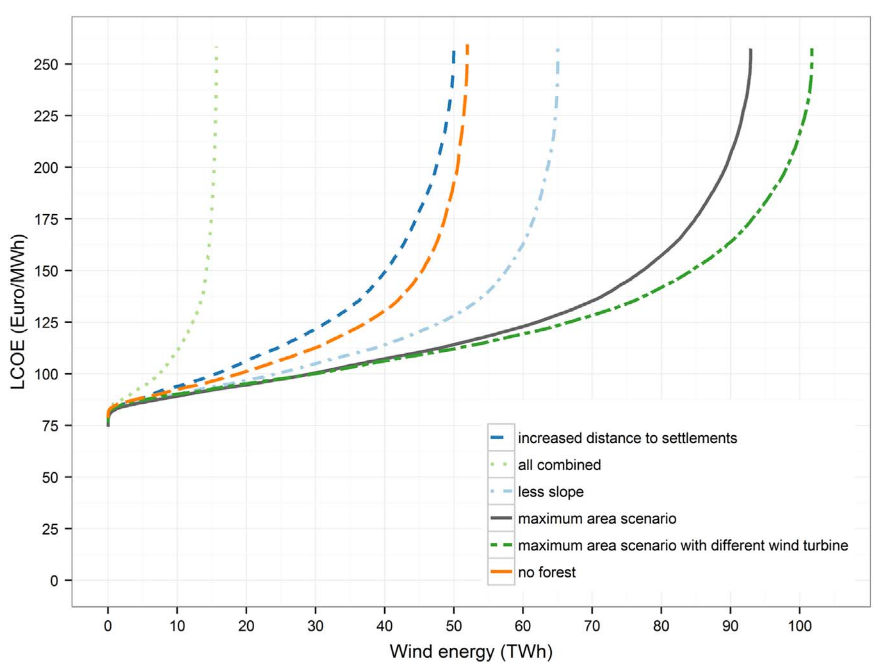

Fig. 6. Supply curves showing the impact on the marginal baseline LCOE of applying an alternative wind turbine and more restrictive assumptions for the maximum slope, distance to settlements and forest areas on the wind energy potential.

et al., 2014) and 13.8% (Lütkehus et al., 2013). The difference in our results can potentially be explained by the large share of mountainous regions in Western Austria that lower the Austrian average. The Eastern federal states of Lower Austria and Burgenland achieve similar shares of suitable areas in the max scenario of 7.8% and 13.9%, respectively. McKenna et al. (2015), who carried out a wind potential assessment on the European scale, found that 10% of the Austrian area is suitable for wind energy deployment. In our assessment, even the most progressive stakeholders – with respect to wind energy – do agree on a socially acceptable wind area potential of solely 3.9%, which is far lower. This finding demonstrates that the consideration of socio-political and market acceptance in modeling studies reduces the area potential significantly. Beyond that, the realizable potential is likely to be even lower as community acceptance, which can be hardly integrated in a modeling assessment on a national scale, is usually regarded as an additional barrier for wind energy deployment (Batel et al., 2013; Wolsink, 2007).

The diverging area potentials result in a wind energy potential that ranges from 3.89 TWh in the min scenario to 92.78 TWh in the max scenario. The min scenario excludes forest areas completely and defines large setbacks to protected and settlement areas. Consequently, the scenario allows for a wind energy generation of only 3.89 TWh, which is only slightly above the production in 2014 of 3.64 TWh (E-Control Austria, 2014). Other recent studies assessing the Austrian wind energy potential report similar results. Only the European Environment Agency found a much higher total potential of 466 TWh for Austria, of which 56 TWh are expected to become competitive until 2030 (EEA - European Environment Agency, 2009). Winkelmeier et al. (2014) estimate the technical potential to be 63.21 TWh (23.78 GW installed capacity). They assumed that with a feed-in tariff of 95 EUR MWh^{-1}, the annual rate of new installations would remain constant, so that 17.68 TWh, or 28%, of the wind energy potential could be realized until 2030. In a wind potential study for Europe, the technical potential for Austria was reported to be 95 TWh, with approximately 20 TWh available at costs below 90 EUR MWh^{-1} (McKenna et al., 2015). Our med scenario shows a lower potential of 9.46 and 17.19 TWh for marginal LCOEs of 90 and 95 EUR MWh^{-1}, respectively. However, the estimates between minimum and maximum marginal LCOEs range between 7.5 and 42.1 TWh. This is similar to the range that was presented by Gass et al. (2013), from 5.34 to 44.66 TWh (1.72–14.38 GW) at a feed-in tariff of 97 EUR MWh^{-1}. These uncertainties make it difficult to estimate the wind energy potential that can be realized at a certain price and thus to determine the appropriate height of a fixed feed-in tariff.

Our sensitivity analysis shows that forest areas and the recommended distance to settlement areas can have a significant impact on wind energy potential. Excluding the forest areas or increasing the required distance to settlement areas from 1000 to 2000 m reduces the wind energy potential by approximately 45%. For Germany, a similar GIS-based analysis assessing the wind potential on land shows that the available area decreases from 5.6% to 0.4% if the minimum distance to settlements is increased from 1000 to 2000 m (Lütkehus et al., 2013). Employing larger wind turbines increased the overall wind potential by about 10% but affected the marginal LCOE for expanding the wind energy share to 10% or 20% only moderately. The additional energy yields per turbine have been largely leveled out by the larger distances between turbines, which were necessary due to the larger rotor diameters. An assumption that leads to lower potential compared to other studies is the maximum feasible slope for wind sites, which is based on experiences of wind project developers in our stakeholder group. They estimated a range of 5.7° to 11.3° for the maximum feasible slope. For steeper locations, the costs for access roads and fundaments would render the project economically infeasible. However, other studies assume much higher slopes of 15° (Gass et al., 2013; Winkelmeier et al., 2014) to 20° (McKenna et al., 2014). As our sensitivity analysis confirms, the assumption on the maximum feasible slope leads to variations of the wind energy potential of up to 30%. We used SRTM DEM (Shuttle Radar Topography Mission digital elevation model) data, with a resolution of only 90 m, which leads to additional inaccuracy especially in the mountainous regions. Future assessments could reduce the uncertainty from this parameter by using digital elevation model (DEM) data with a higher resolution.

The presented wind energy supply curves are based on the marginal LCOE for all of the potential wind energy sites and do not consider the variability and integration costs of wind energy, which is considered in the system LCOE (Ueckerdt et al., 2013). System LCOE increases with higher shares of wind energy and can become as large as generation costs at high wind energy penetration rates. Supply curves that apply a system LCOE approach would therefore be steeper, in particular at higher shares of wind penetration.

The experience from our stakeholder workshops has shown that it is difficult to assess the socio-political and market acceptance of wind energy isolated from other renewable energies and energy efficiency measures. Furthermore, key stakeholders stressed the importance of including relevant infrastructure, such as new transmission lines in future analyses, as they also affect the socio-political and market acceptance of wind power. Future research could therefore contribute by applying an approach that uses electricity system models, integrating the electricity grid, different renewable energy sources and energy efficiency measures into the analysis. Assessing community acceptance in national or international modeling studies on renewable energy potentials is difficult due to the multitude and heterogeneity of factors that determine acceptance on a community level. However, case studies on the community level could provide greater insight into the acceptability of wind energy potentials and are therefore an important future research topic.

5. Conclusions and policy implications

Our paper presents an approach to assess scenarios for the socio-political and market acceptable wind potential for Austria. We included stakeholder knowledge from various interest groups to increase the legitimacy and plausibility of our assessment. The participatory modeling approach, which allows stakeholders to define criteria for suitable areas leads to more comprehensive and transparent results than the existing legislations of most federal states. However, including stakeholders from various interest groups makes it difficult to reach consensus and leads to large variations of the estimated wind energy potential in different scenarios. The large bandwidth of our scenarios demonstrates that there is no consensus about the future role of wind energy in Austria. Future expansion plans are likely to face opposition – not only on the community level but also by high-level stakeholders. This indicates that techno-economic assessments may overestimate the realizable potential significantly.

Our results demonstrate that the Austrian renewable energy target according to the Eco electricity act (2012) of 10% wind energy until 2020 can be met with the suitability zones that were defined by federal states at the current demand levels. However, if the transition to a low-carbon electricity system for Austria should be achieved, higher shares of wind energy may be required after 2020. Our scenarios illustrate that there is a significant trade-off between the acceptability of wind turbine expansion by key stakeholders' and generation costs. Future legislation (e.g., the required distances of wind turbines to settlement areas) can significantly affect the LCOE of wind energy. More restrictive criteria for wind turbine sites will therefore require higher feed-in tariffs - and more wind turbines - to achieve the same level of wind energy production. Those costs are passed on to the electricity end-consumers, who pay a levy for green electricity. Experiences from Germany show that higher electricity costs can further decrease the acceptance of expanding renewable energies. In Austria, up to now only four out of nine federal states have defined suitability zones for wind energy and employed wind turbines in on a larger scale. The medium area scenario demonstrates that harmonizing the legal framework conditions for defining suitable areas for wind energy and applying them for all federal states could avoid economic inefficiencies and reduce wind energy expansion costs. The challenge for policy makers will be to find the right balance between limiting wind production to sites with minimal negative effects on landscape scenery, human health and the environment and providing enough potential wind turbine sites to allow the deployment of wind energy at feasible costs. Minimizing expansion costs, which directly affect end consumer electricity rates, while ensuring that important land-use restrictions are taken into account to guarantee acceptability, is a delicate act and implies that future expansion targets may have to be adapted according to technological developments (which reduce costs), to changes in social acceptability and to alternative low-carbon technologies. We propose a continuous consultation process with important stakeholders on the national level to openly discuss these trade-offs.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2016.08.010.

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Appendix

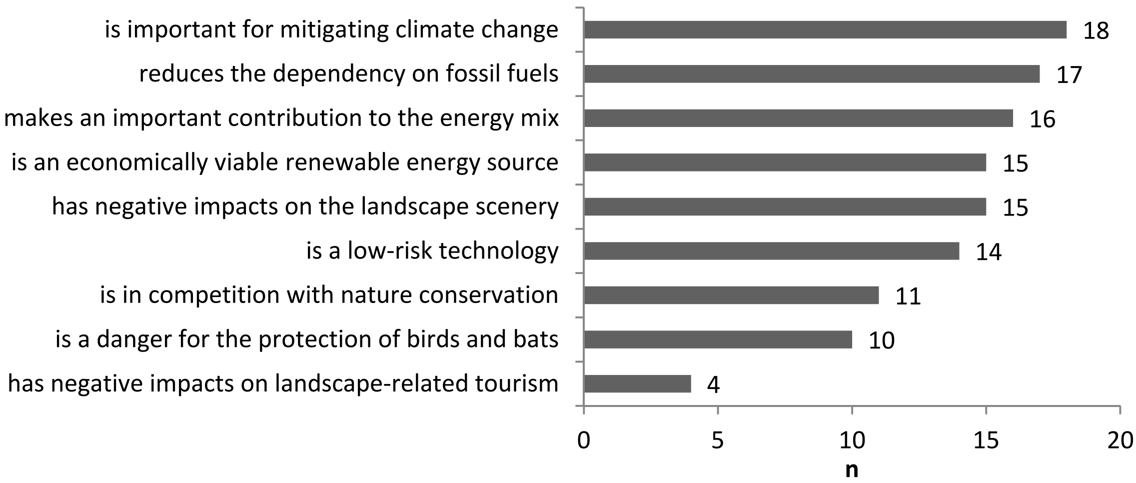
A1 Results of the online questionnaire

The online questionnaire was divided into two main sections: the first part on the general attitude toward wind energy and preferences for the future expansion and the second part on specific siting criteria for wind power plants and the suitability of various land use categories.

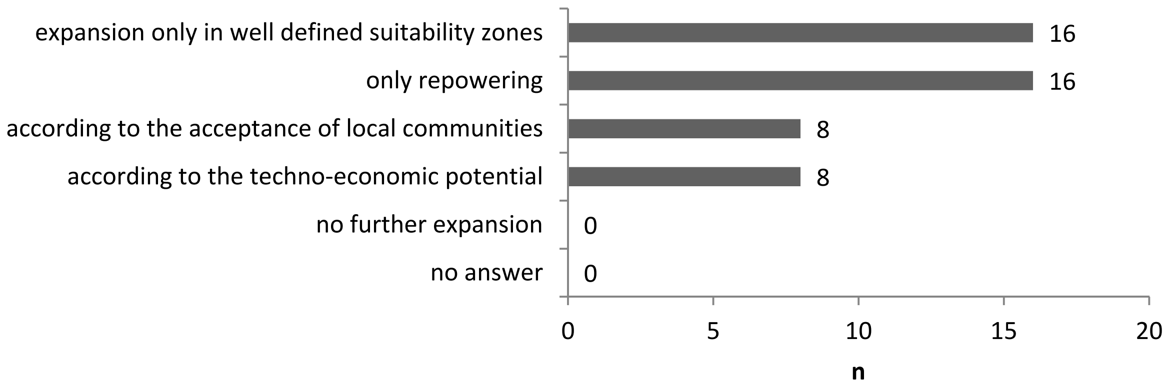
Part 1 – Attitudes toward wind energy and preferences for the future wind energy expansion

In this part, we assessed general attitudes of key stakeholders towards wind power generation and their preferences for the future expansion.

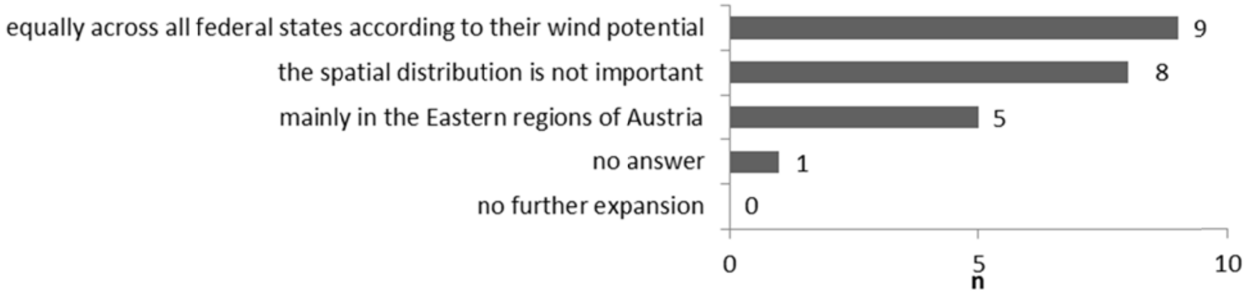
Q1: Do you agree that wind energy in Austria (n=23)



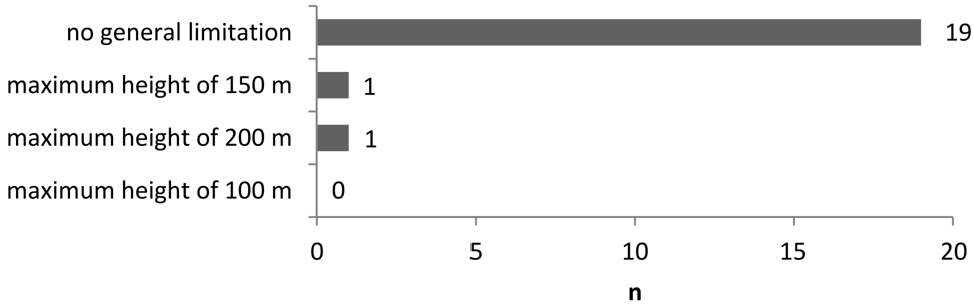
Q2: What is your preference for the expansion of wind energy in Austria? (n=23)



Q3: Where should the expansion of wind energy take place in Austria? (n=23)



Q4: In your opinion, should there be a general limitation for the height of wind power plants? (n=21)



Part 2 –Siting criteria for wind power plants and the suitability of land use categories

In this section, stakeholders were asked to rate the suitability of different land-use categories and protected areas for wind energy utilization (Figure A1). The suitability of different land-use categories was evaluated quite similarly by most stakeholders. However, the suitability of forests was seen very controversially with 12 respondents (52%) assessing forest areas as very suitable or suitable for wind energy and 11 respondents (48%) arguing that they are unsuitable or very unsuitable. Discussions in the stakeholder workshops revealed that the definition of potentially suitable wind turbine sites is a key issue that determines the acceptance of wind energy.

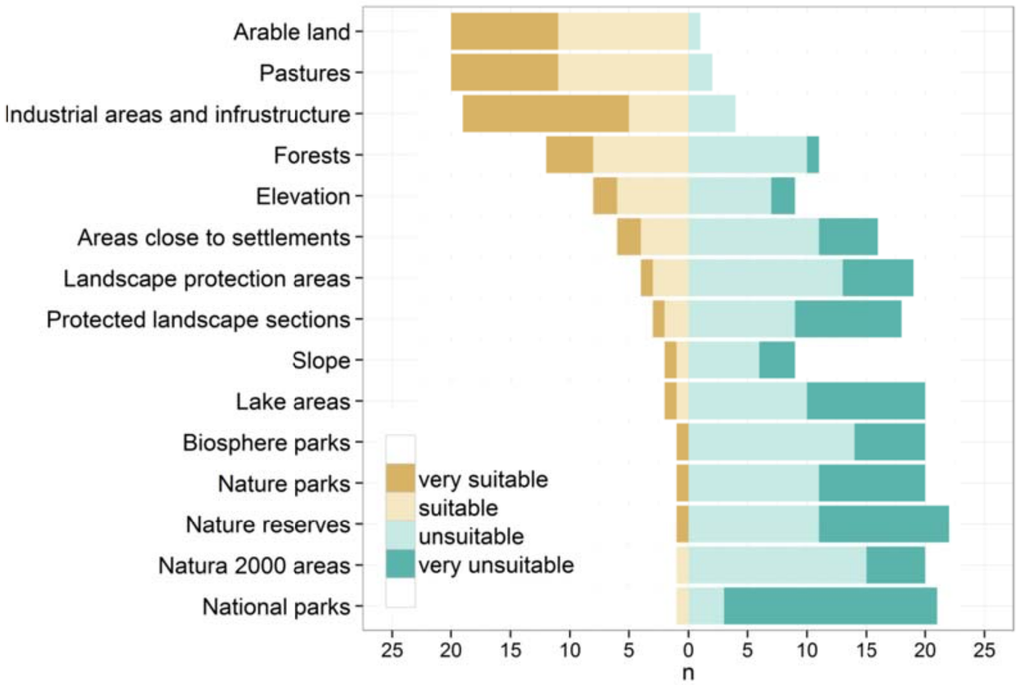


Figure A1: Suitability of different land use categories for the installation of wind turbines – results of the online questionnaire with stakeholders of different fields (n=23)

For those land-use categories and protected sites that were found to be unsuitable, the participants were asked to rate the relevance of the following arguments: impacts on the scenery of landscapes and villages, the protection of birds and bats, the protection of other wild animals, noise emission, shadow flicker and light reflections, negative impacts on landscape-related tourism, difficult technical realization and not economically feasible (Figure A2).

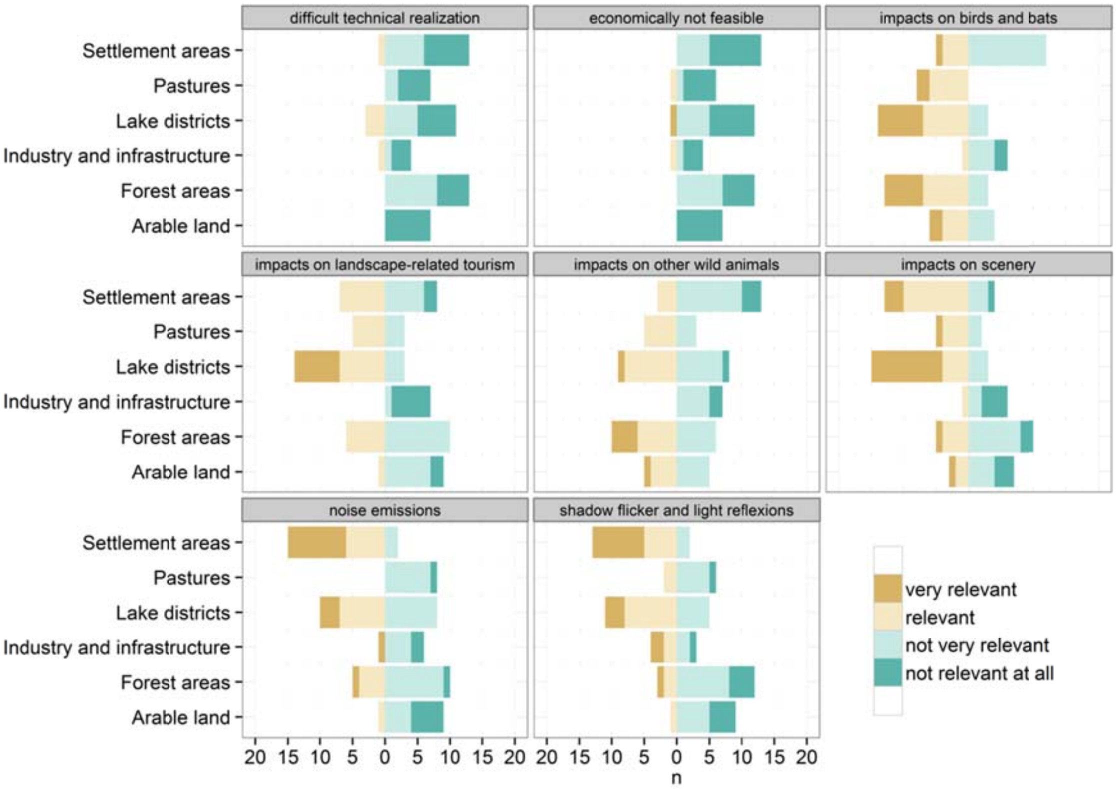


Figure A2: Relevance of arguments against wind energy for various sites (n=23)

For, in their opinion, unsuitable land use categories and protected sites participants defined the minimum distance to large wind turbines (Figure A3).

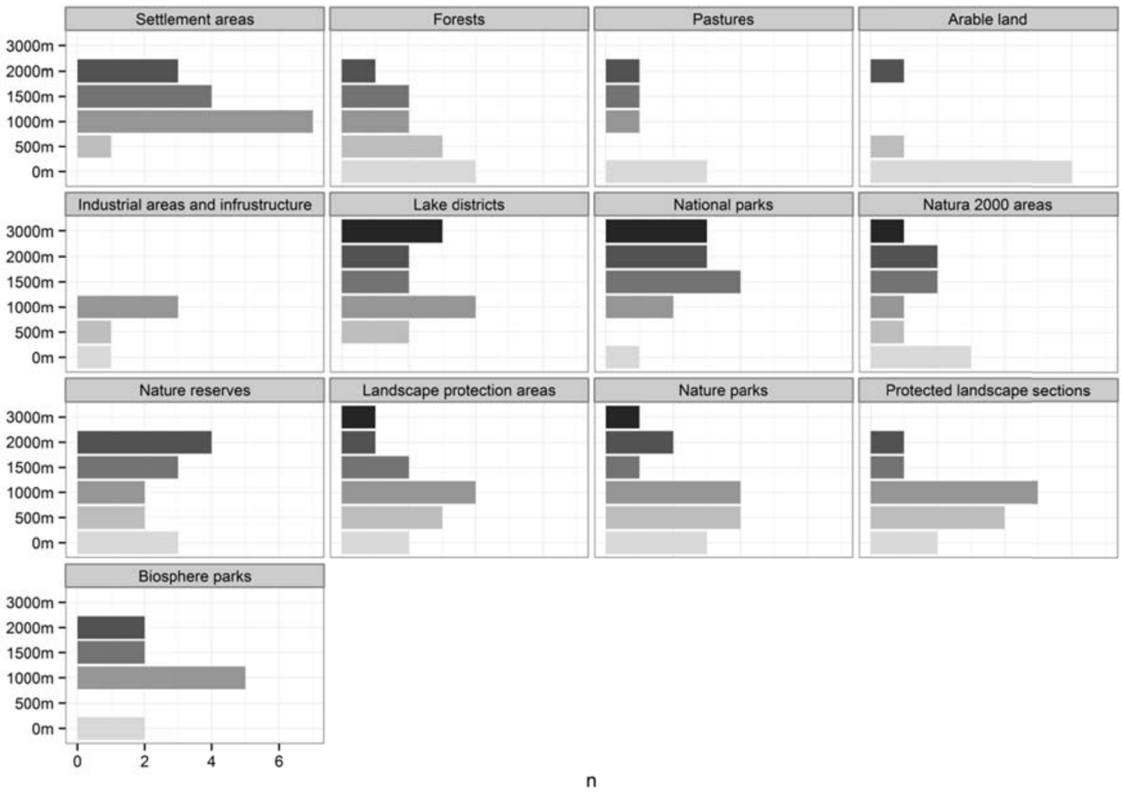


Figure A3: Suggested minimum distances to different land use categories and protected areas (n=22)

A2 Regression model for estimating rotor diameter and hub height

To predict the energy production of wind turbines at a specific site, we used information on the wind speeds from the Austrian wind atlas (Krenn et al., 2011), the rated power of the turbine, the rotor diameter and the hub height. As the last two parameters are not specified in the open street map dataset (available from http://download.geofabrik.de), we used a complete dataset of wind power plants from Lower Austria (available from https://de.wikipedia.org/w/index.php?title=Liste_von_Windkraftanlagen_in_Nieder%C3%B6sterreich&oldid=133977567) to estimate rotor diameter (RD) and hub height (HH) based on the rated power (KW) by means of two linear regression models:

$$RD = \beta_0 + \beta_1 * KW + \varepsilon$$

$$HH = \beta_0 + \beta_1 * KW + \varepsilon$$

where β_0 is the intercept, β_1 is the regression coefficient and ε is the error term. The ordinary least square estimator shows a good fit for both regression models with $R^2 = 0.93$ for the rotor diameter and $R^2 = 0.80$ for the hub height.

A3 Turbine power curve

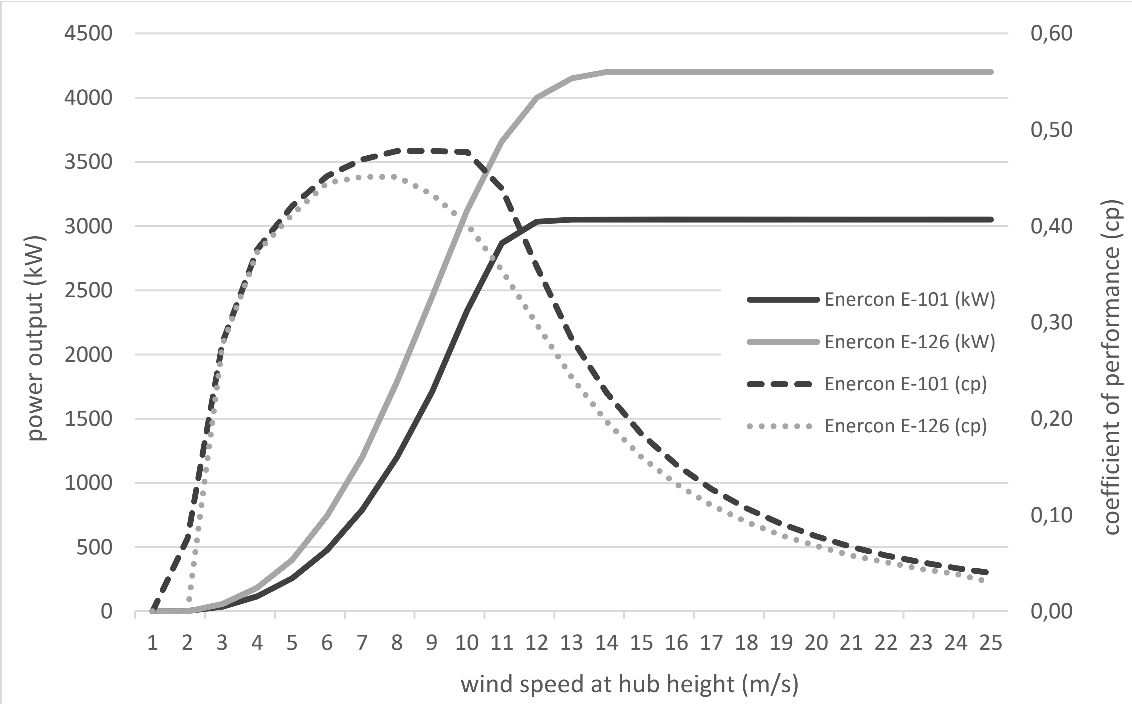


Figure A4: Turbine power curves and coefficients of performance of the Enercon E-101 3.05 MW and Enercon E-126 4.20 MW used for the calculating the wind energy yield in the baseline scenario and the sensitivity analysis (Enercon, 2015)

A4 Model validation

To validate our model, we compared the historic wind energy production from 2007-2010 with the simulated outputs of our model. The model used wind speed distributions as provided by the Austrian wind atlas (Krenn et al., 2011) and a spatial dataset of Austrian wind turbine locations that included rated power and estimated rotor diameter and hub height (see Appendix A3). For 2007, the simulated data matches the actual wind energy production very well with a deviation of only 0.1%. For the other years, our results slightly overestimated the actual production by 3.9% in 2008, 9.2% in 2009 and 3.5% in 2010. Some of these deviations can be explained by the varying installation dates of new turbines, as we assumed that all of the plants start production in the beginning of the year after installation. Furthermore, the annual variability of long-term mean wind speeds in Europe, which amounts to approximately 6% (Hassan, 2015), is not covered by our Monte Carlo simulations from the Weibull distributions.

A5 Economic assumptions for the LCOE calculation

The Austrian wind energy association (Hantsch et al., 2009) carried out a survey among wind turbine operators, reporting average total investment costs of 1.762 EUR kW^{-1} for wind projects in Austria. This figure was confirmed by the wind status report by the Joint Research Centre of the European Commission (EC, 2013), giving a range of 1600-1900 EUR KW^{-1} for wind turbines in Austria. Operational expenditures include operational and maintenance (O&M) costs and all other annual costs, such as insurance, land rental, taxes and administration. The JRC wind status report estimates O&M costs of 9.5 EUR MWh^{-1} and total operational expenditures of up to 14-19 EUR MWh^{-1} (European Commission, 2013). A comprehensive survey with wind turbine producers and wind project developers in Germany reported higher total operational expenditures from 18.5-34.2 EUR MWh^{-1} (Rehfeldt et al., 2013). The operational lifetime for wind turbines is usually assumed to be 20 years (Kost et al., 2013; Mai et al., 2014; McKenna et al., 2014). The discount rate reflects the opportunity cost for the capital investment and is determined by the investors' expected rate of return, the risk premium and interest rates. Those factors were included in the weighted average cost of capital (WACC), which differs for the various renewable energy technologies. For onshore wind energy projects, the share of equity is usually between 20% and 30% (Falkenberg et al., 2014; Rehfeldt et al., 2013). The return on equity is assumed to be 8-10% after tax, and interest rates on debt are currently low with approximately 3.8% (Falkenberg et al., 2014). The return on equity (R_e) and interest rates on debt (R_d) were weighted according to the share of equity (E) (Cleijne and Ruijgrok, 2004):

$$WACC = E * R_e + (1 - E) * R_d \tag{5}$$

These assumptions led to a WACC of approximately 5%. **Fehler! Verweisquelle konnte nicht gefunden werden.** summarizes all of the relevant values and parameter ranges for the LCOE calculation.

A6 Regional wind energy supply curves

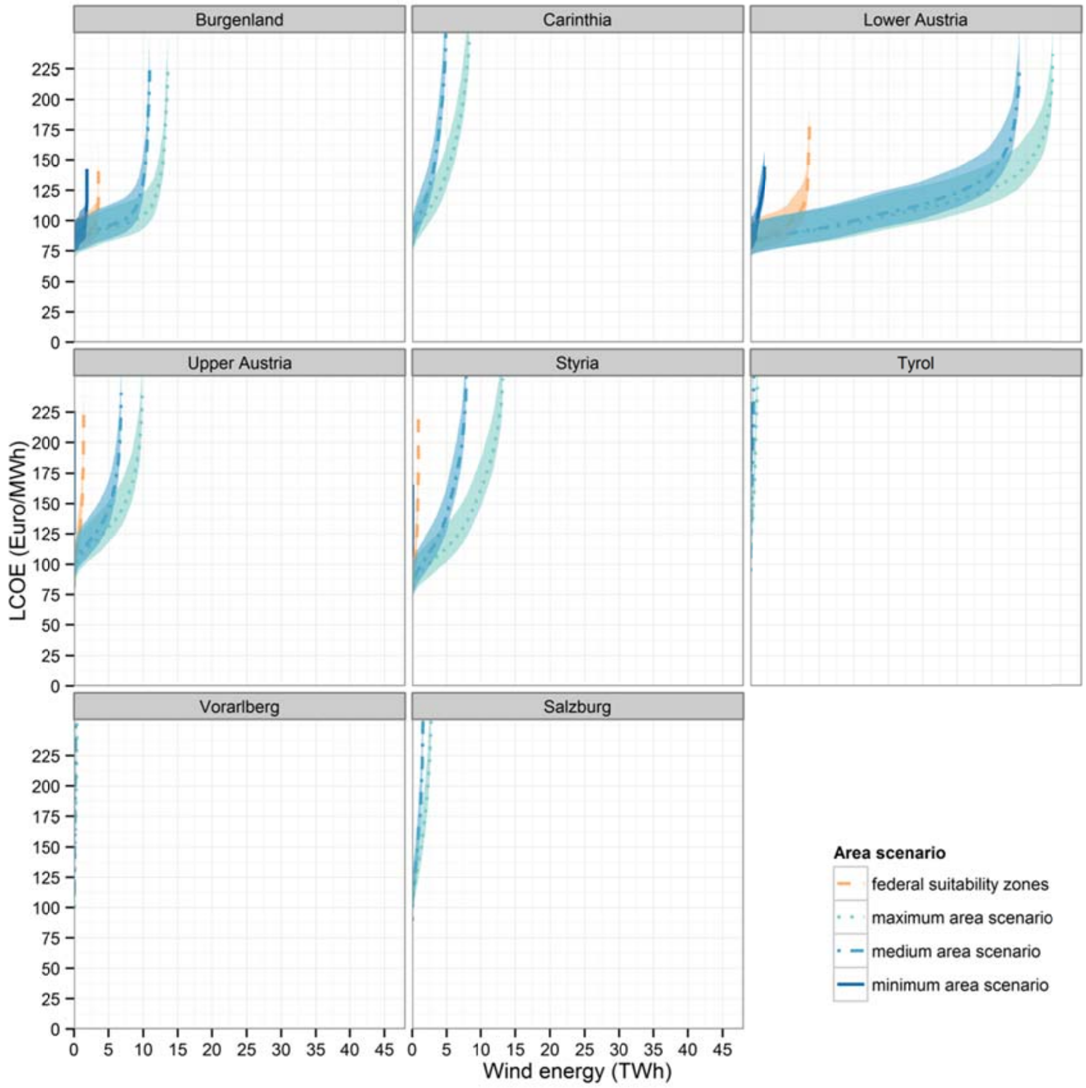


Figure A1: Regional wind energy supply curves showing the economic wind energy potential for all Austrian federal states with the exception of Vienna in the four scenarios (min, med, max and federal suitability zones). The lines show the marginal reference LCOE and the light-colored areas indicate the range between minimum and maximum marginal LCOE based on the input parameter assumptions (Fehler! Verweisquelle konnte nicht gefunden werden.**).**

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Article VII

Schmidt, J., Lehecka, G., Gass, V., Schmid, E.
Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines.

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Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines

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ABSTRACT

Feed-in tariffs (FIT) are among the most important policy instruments to promote renewable electricity production. The fixed-price FIT (FFIT), which guarantee a fixed price for every unit of produced electricity and the premium based FIT (PFIT), which pay a premium on top of the market price are commonly implemented in the EU. Costs for balancing intermittent electricity production may be significantly higher with FFIT than with PFIT, and FFIT do not provide any incentive to produce electricity when marginal production costs are high. In contrast, PFIT do provide strong incentives to better match renewable power output with marginal production costs in the system. The purpose of this article is to assess the effects of the two tariff schemes on the choice of wind turbine locations. In an analytical model, we show that both the covariance between wind power supply and demand as well as between the different wind power locations matter for investors in a PFIT scheme. High covariance with other intermittent producers causes a decrease in market prices and consequently in revenues for wind power investors. They are therefore incentivized to diversify the locations of wind turbines to decrease the covariance between different wind power production locations. In an empirical optimization model, we analyze the effects of these two different schemes in a policy experiment for Austria. The numerical results show that under a PFIT scheme, (1) spatial diversification is incentivized, (2) the covariance of wind power production with marginal electricity production costs increases, and (3) the variances of the wind power output and of residual load decrease if wind power deployment attains 10% of total national electricity consumption.

Nomenclature

Symbol	Description	Unit
Model parameters		
NPV_i^{FFIT}, NPV_i^{PFIT}	Net present value (NPV) under the FFIT and PFIT scheme for location *i*	€
$w_{i,t}$	Wind power production at location *i*, and hour *t*	MWh
NPV^{FFIT}, NPV^{PFIT}	Net present value (NPV) of the optimal solution under the FFIT and PFIT scheme	€
f^{FFIT}, f^{PFIT}	Fixed-price and premium-price feed in tariffs	€ MWh^{-1}
c_i^{dis}	Sum of discounted cash-outflows (investment, and operation and maintenance costs) at location *i*	€
dr_t	Discount factor from time *t* back to time 0	
$f_t^{dis}(w_{j,t};l_j)$	Discounted compensation for investors in a PFIT scheme consisting of market price plus premium	€ MWh^{-1}
p_t	Marginal production costs in system without additional wind power production	€ MWh^{-1}
$f_t^{mo}(w_{j,t};l_j)$	Function that determines the price decreasing effect of wind power production (i.e. the merit order effect)	€ MWh^{-1}
$w_{i,t}^s$	Simulated wind power production at location *i* and hour *t*	MWh
c_i^{sdis}	Simulated sum of cash out flows resulting from investment, operation and maintenance costs at location *i*	€
p_t^h	Historical electricity price at Austrian energy exchange in hour *t*	€ MWh^{-1}
d_t^h	Historical electricity demand in Austria at hour *t*	MWh
w_t^h	Historical measured wind power production in Austria at hour *t*	MWh
$dh_{t,k}$	Dummy for hours	
$wd_{t,h}$	Dummy for days	
$m_{t,u}$	Dummy for months	
ε_t	Error term	
Optimization model variables		
l_i	Decision variable in interval [0,1] on the deployment of the wind potential in location *i*	
Model indices		
i, j	Location and alias for location	
t	Time period	

1. Introduction

Feed-in tariffs (FIT) are among the most important policy instruments to promote renewable electricity production. Two types of tariff schemes are commonly implemented in the EU: fixed-price FIT (FFIT), which guarantee a fixed price for every unit of produced electricity, and premium based FIT (PFIT), which pay a premium on top of the market price. FFIT transfer price risks from investors to consumers,

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which can lead to high and stable growth rates of renewables and incentivize investments of risk-averse investors such as small municipalities and private households. However, FFIT do not provide any incentive to match electricity production with marginal costs of electricity production (Couture and Gagnon, 2010; Schallenberg-Rodriguez and Haas, 2012), and the costs for balancing intermittent electricity production may be lower with PFIT (Hiroux and Saguan, 2010; Klein, 2008). As shown by Lamont (2008), the market value of renewable electricity increases with the covariance between marginal electricity production costs and renewable electricity production. PFIT could provide an incentive to better match renewable power output with marginal production costs. Technically, there are various options to shift electricity production to times when prices are high. Fuel based renewables such as bio-electricity can directly adjust their output to market price signals. Maintenance of intermittent renewable technologies, such as wind power, can be scheduled in times of low prices to maximize output when prices are high (Schallenberg-Rodriguez and Haas, 2012). Furthermore, investors can, a priori to the investment, choose locations for intermittent production where production is correlated with marginal electricity costs.

In this article, we assess the effects of the two tariff schemes on the choice of wind turbine locations. We show that both the covariance between wind power supply and marginal production costs matter as well as the covariance between the different wind power locations. High covariance with other intermittent producers can cause a decrease in market prices and consequently a loss in revenues for the wind power investors. Spatial diversification allows decreasing the covariance between different wind power production locations. Consequently, lower covariance between different wind power production locations causes lower variance of total wind power production (Degeilh and Singh, 2011). This may decrease energy system costs caused by wind power due to less variability of the residual load, i.e. demand minus intermittent producers. In addition, spatial diversification may be beneficial to the grid operation because less transmission lines may be necessary and the visual impact of wind turbines is spread over a larger region. FFIT do not provide any incentives to diversify production locations. They lead to investments in high yielding locations that are often concentrated in one region.

Diversifying wind power production locations can reduce variability of total wind power output as shown in Degeilh and Singh (2011). Roques et al. (2010) apply portfolio optimization to analyze the potential of reducing the variance of joint output of European wind power production. Rombauts et al. (2011) also present a portfolio based approach on the optimal portfolio of wind power production locations under transmission constraints. However, both take the position of a social planner to optimally deploy wind turbines. They do not assess the effect of policies on the spatial distribution of wind power capacity. Recent assessments of FFIT and PFIT (Couture and Gagnon, 2010; Klein, 2008; Schallenberg-Rodriguez and Haas, 2012) argue that PFIT require more subsidies due to increased price risks for project developers. They also argue that incentives to match wind power production with marginal production costs are higher in PFIT than in FFIT such that wind integration costs can be reduced. However, no quantitative analysis is applied by any of the studies. Hence, we aim at assessing quantitatively the effect of the two tariff schemes on the spatial distribution of wind power deployment and associated co-benefits of reduced variance in wind power output.

This article is structured as follows. The analytical model for investors under FFIT and PFIT schemes is investigated in Section 2. Then, in Section 3, we apply the optimization models to analyze whether PFIT and FFIT lead to different location choices in the case of Austria. For this purpose, we create synthetic time series of wind power production, using data from the Austrian wind atlas and from meteorological stations, which are included in an optimization model that considers the effect of wind power production on market prices. The optimization model also employs price reducing effects of wind power derived from a regression analysis of hourly market prices from the Austrian Energy Exchange. The results are presented in Section 4 and discussed in Section 5. Finally, a summary and conclusions are given in Section 6.

2. Analytical model

We compute net present values (NPV) of investment options in the two different FIT support schemes. Investors can choose between different wind power locations that differ by their wind profile and associated investment, operation and maintenance (O&M) costs.

The NPV_i^{FFIT}, denoting the NPV of a fully deployed location i in the FFIT scheme is thus determined by

$$NPV_i^{FFIT} = f^{FFIT} \sum_t w_{i,t} dr_t - c_i^{dis} \tag{1}$$

where $w_{i,t}$ denotes the potential wind power production at location i and hour t, and f^{FFIT} is the fixed feed-in tariff. The factor dr_t is applied to discount the revenues to the present time. Also, the investor has to consider the sum of annually discounted cash outflows c_i^{dis} at location i, consisting of investment and O&M costs.

The wind power production at location i, and hour t, $w_{i,t}$, is considered to be a random variable with respect to index t, and thus, the NPV_i^{FFIT} in Eq. (1) can be rewritten in terms of the expected value in order to clarify the effect of correlations between the terms:

$$E\left(NPV_i^{FFIT}\right) = E\left(w_{i,t}\right) f^{FFIT} \sum_t dr_t - c_i^{dis}. \tag{2}$$

$E(\bullet)$ denotes the expected value of wind power production at the location. This implies that the NPV of a certain location is only determined by the expected discounted total revenue from selling wind power at the location minus the discounted total costs, assuming that the covariance between $w_{i,t}$ and dr_t is 0.

The investor under a FFIT scheme faces the following optimization problem:

$$\max_l \; NPV^{FFIT} = \sum_i NPV_i^{FFIT} l_i \tag{3}$$

$$\text{s.t.} \quad 0 \le l_i \le 1, \forall i. \tag{4}$$

The investor maximizes the net present value NPV^{FFIT} by choosing from different wind power locations i. The decision variable l_i indicates how much of a certain location is going to be built. Adding expectations to Eq. (3), and extending by Eq. (2), yields

$$E\left(NPV^{FFIT}\right) = \sum_i l_i \left(f^{FFIT} E\left(w_{i,t}\right) \sum_t dr_t - c_i^{dis}\right) \tag{5}$$

Since the net present value is independent of the covariance of locations with marginal production costs or with each other, the investor aims at investing in wind turbines at locations with high wind power production and low costs. Any location which NPV_i is greater than 0 is fully built while all other locations are not included at all in the optimal solution because covariance with other locations is not of interest (Schmidt et al., 2013).

In contrast, under a PFIT scheme, the NPV of a fully deployed location is given by

$$NPV_i^{PFIT} = \sum_t w_{i,t} f_t^{dis}\left(w_{j,t}; l_j\right) - c_i^{dis}. \tag{6}$$

At location i, the NPV consists of cash in-flows from the produced wind energy (i.e. $w_{i,t}$) times the compensation per unit $f_t^{dis}(w_{j,t};l_j)$, which consists of the discounted market price in hour t plus the discounted feed-in premium. The market price is dependent on the deployment of all other wind turbines; index j being an alias for i, the location. The market price of electricity is influenced by the deployment of wind power, regardless of whether a FFIT or a PFIT scheme is implemented, because wind power production shifts the supply curve outwards and therefore decreases the market price. This effect is known as merit order effect (Gelabert et al., 2011; Sensfuß et al., 2008). The function

$$f_t^{dis}\left(w_{j,t};l_j\right) = \left(p_t - f_t^{mo}\left(w_{j,t};l_j\right) + f^{PFIT}\right)dr_t \tag{7}$$

can therefore be disaggregated into three parts. Price p_t is the spot market price in hour t if no additional wind power turbines were deployed, i.e. it indicates the marginal production costs in the system without additional wind production. It depends on demand and the characteristics of the residual power generation system and is, at least in short to medium-term, independent of the deployment of wind turbines. The second part $f_t^{mo}(w_{j,t};l_j)$ describes the merit order effect, i.e. the price reducing effect of wind power production. It depends directly on the choice of all other wind power locations. The third part is the fixed premium on top of market prices.

Applying expectations and substituting Eq. (7) into Eq. (6) yields

$$E\left(NPV_i^{PFIT}\right) = E\left(w_{i,t}\left(p_t - f_t^{mo}\left(w_{j,t};l_j\right) + f^{PFIT}\right)\right)\sum_t dr_t - c_i^{dis}. \tag{8}$$

The following relation holds for the covariance of random variables:

$$Cov(A,B) = E(AB) - E(A)E(B) => E(AB) = Cov(A,B) + E(A)E(B). \tag{9}$$

Assuming p_t to be a random variable with respect to hours t, Eq. (8) can therefore be rewritten to

$$E\left(NPV_i^{PFIT}\right) = \begin{pmatrix} Cov\left(w_{i,t},p_t\right) + E\left(w_{i,t}\right)\left(E(p_t) + f^{PFIT}\right) \\ -Cov\left(w_{i,t},f_t^{mo}\left(w_{j,t};l_j\right)\right) - E\left(w_{i,t}\right)E\left(f_t^{mo}\left(w_{j,t};l_j\right)\right)\end{pmatrix}\sum_t dr_t - c_i^{dis}. \tag{10}$$

Consequently, the investor faces the following optimization problem

$$\max_l \; NPV^{PFIT} = \sum_i l_i \left(\sum_t w_{i,t} f_t^{dis}\left(w_{j,t};l_j\right) - c_i^{dis}\right), \tag{11}$$

$$\text{s.t.} \quad 0 \le l_i \le 1, \forall i. \tag{12}$$

Written in terms of expectations, the following objective function can be derived from Eq. (10):

$$E\left(NPV^{PFIT}\right) = \sum_i l_i \left(\begin{pmatrix} Cov\left(w_{i,t},p_t\right) + E\left(w_{i,t}\right)\left(E(p_t) + f^{PFIT}\right) \\ -Cov\left(w_{i,t},f_t^{mo}\left(w_{j,t};l_j\right)\right) - E\left(w_{i,t}\right)E\left(f_t^{mo}\left(w_{j,t};l_j\right)\right)\end{pmatrix}\sum_t dr_t - c_i^{dis}\right).$$

The expected NPV therefore increases

(i) If the covariance between wind power production at the chosen locations and marginal production costs in a system without wind deployment increases, which is similar to the result shown by Lamont (2008), and
(ii) If the revenues given by the expected wind power production at all chosen locations times expected market prices plus premium increases.

Furthermore, the expected NPV decreases

(i) If the covariance between the wind power production at different locations increases, as in that case market prices are lower (the detailed relation to wind speeds at other sites is outlined in the Online-Appendix Part 1, A),
(ii) If the expected production times the expected decline in price of the chosen locations increases, and
(iii) If investment and O&M costs at the chosen sites increase.

Both optimization models for FFIT and PFIT are solved using empirical data as shown in Sections 2 and 3.

3. Description of the empirical model

We apply the analytical models in a policy experiment for the case of Austria, which has currently implemented a FFIT scheme. Austria aims at increasing the wind power output to meet the EU 20/20/20 targets. The policy experiment assesses the spatial deployment of wind turbine locations in a PFIT and a FFIT scheme. Therefore, we create synthetic time series of wind power production at potential locations and calculate the location specific costs of wind power deployment in Austria. The approach is described in Section 3.1. In order to assess the influence of wind power production on market prices, we estimate a regression model, which is described in Section 3.2. The outcomes are subsequently fed into the two optimization models outlined in Section 3.3. The results are presented in Section 4.

3.1. Synthetic wind power production and production costs

Fig. 1 shows how time series of wind power production for potential wind turbine locations in Austria, i.e. how simulated realizations $w_{i,t}^s$ of $w_{i,t}$, are derived. In addition, simulated cash-outflows c_i^{sdis} are calculated. A detailed description of the applied methods can be found in Schmidt et al. (2012) and Gass et al. (2013).

We use the Austrian wind atlas (Energiewerkstatt et al., 2010), which provides the scale and shape parameters of the Weibull distribution of wind on a 100 m * 100 m grid for Austria. Additionally, we use hourly wind data from 265 meteorological stations to generate time series of wind. The hourly wind data is available from 2005 to 2010. The pre-processing of the wind atlas data includes the definition of feasible locations for placing wind turbines by using a geographic information system (GIS). The complete modeling steps are outlined in Gass et al. (2013) and involve the exclusion of areas such as forests, transportation networks, settlements, and bodies of water. The remaining locations are reduced further by filtering locations that are economically not feasible. For this purpose, wind power production is first estimated using the

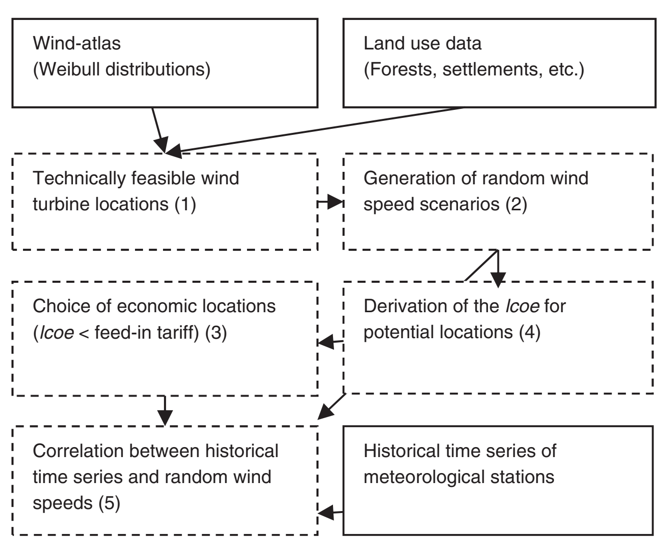

Fig. 1. Methodology to generate synthetic time series of hourly wind production at potential wind power locations. Note: Boxes with dashed lines indicate modeling steps while full lines indicate input data. Numbers indicate the step in the procedure.

Weibull shape and scale parameters of the potential wind turbine locations to generate hourly distributions of wind speeds by Monte Carlo simulation, i.e. by randomly drawing from the respective Weibull distributions.

Annual wind power production can be estimated for each location by the use of simulated wind speeds and a technical model of wind turbine production. Levelized costs of electricity (*lcoe*) are calculated for 2 MW wind turbines. The locations where *lcoe* are below the current feed-in tariff for wind energy (i.e. 97 € MWh^{-1}) are selected for further analysis. *Lcoe* are calculated for an investment period of 13 years and a return of investment of 7%. The assumptions used in this modeling process are also used to derive c_i^{sdis}, i.e. the costs of wind power deployment at a certain location.

The wind speeds generated by means of the Monte Carlo simulation in step (2) follow the Weibull distribution, which assumes that there is no auto-correlation in the distributions. To generate time series of wind power production that are consistent with historically observed time series of wind speeds, we apply the Iman Conover method (ICM) (Iman and Conover, 1982). Online-Appendix Part 1, B discusses in detail the applied methodology and the validation of the resulting data.

3.2. Econometric market model

A crucial element in the optimization models is an estimate of f_t^{no}, i.e. the function that determines the price decreasing effect depending on how much wind power is produced. Sensfuß et al. (2008) apply an agent based model to provide such an estimate while Neubarth et al. (2006) and Gelabert et al. (2011) use econometric analysis of historical spot market prices and wind power production data. We also perform an econometric analysis because historical data is available and reliable and the demand for input data in spot market simulation models is huge and involves numerous uncertainties. The drawback of our approach is, however, that long-term investment decisions, i.e. structural changes in the market, cannot be explored. Therefore, the estimated effect may be of rather short-term validity.

The dataset consists of hourly load d_t^h on the network as measured by the Austrian regulator (E-Control, 2012) and wind power w_t^h that is provided by the Austrian regulation entity for renewables (OeMAG, 2012). The hourly price data p_t^h is taken from the website of the Austrian Energy Exchange (www.exaa.at) and is available from the years 2005 through 2010. Eight data points are omitted due to missing values and different data references because of daylight-saving time. Both, demand and wind power production are taken as they were measured at the time of production. However, the Austrian Energy Exchange determines prices one day ahead at 10:00 o'clock in the morning. At that time, only forecasts of demand and wind power production are available. Therefore, forecast errors directly affect the market clearing price. Nevertheless, we assume that the measured realizations of demand and wind power production serve as valid proxies for the forecasts in the regression.

We also test for the existence of unit roots in the time series using the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979). Summary statistics of p_t^h, d_t^h, and w_t^h can be found in Table 1. The ADF test results indicate that the three time series are I(0), hence we estimate the econometric model in levels. Due to the well-known seasonalities of electricity prices, the econometric model includes, in addition to a constant, 23 dummy variables indicating the hour of the day (hour 2 to hour 24), six dummy variables indicating the day of the week (Tuesday to Sunday), and eleven dummy variables indicating the month of the year (February to December). These dummy variables, $dh_{t,k}$, $wd_{t,h}$, and $m_{t,u}$, are one in daily hour k, weekday h, and month u and zero otherwise, respectively.

The regression model

$$p_t^h = \beta_0 + \beta_1 d_t^h + \beta_2 w_t^h + \sum_{k=1}^{23} \gamma_k dh_{t,k} + \sum_{h=1}^{6} \delta_h wd_{t,h} + \sum_{u=1}^{11} \pi_u m_{t,u} + \varepsilon_t \tag{13}$$

is estimated by OLS for hourly electricity prices p_t^h, with hourly data on network load d_t^h and wind power production w_t^h. ε_t denotes the error term. The Durbin–Watson test (Durbin and Watson, 1950) is used to test for the existence of autocorrelation in the OLS residuals and the Breusch–Pagan test for heteroscedasticity (Breusch and Pagan, 1979). Since both the Durbin–Watson and the Breusch–Pagan tests reject significantly, we use heteroskedasticity and autocorrelation robust standard errors (Newey and West, 1987, 1994). Almost all coefficient estimates are highly significant and the model can explain 48% of hourly electricity price variation ($R^2 = 0.48$). Detailed results, showing all coefficient estimates, are reported in Table C1 in the Online-Appendix Part1, C. Most important, the coefficient estimate for wind power is −0.0075, implying that one additional MWh of wind power causes a decrease of 0.0075 € or 0.75 €Cent in prices. Neubarth et al. (2006) estimate this effect to be 0.19 €Cent for Germany and the years 2004–2005, while Gelabert et al. (2011) report similar numerical results for the Spanish electricity market and the years 2005–2010. The two results are within the order of magnitude of our estimate. The level of the merit order effect is a critical parameter in our optimization model. We therefore use a sensitivity analysis to test a wide range of values for the parameter (see Section 3.1).

3.3. Optimization model application

In the optimization model, we assume that one unit of additional production of wind-power will decrease prices by 0.75 €Cent. The following functional form for the determination of the price after integration of new wind energy plants is therefore assumed:

$$f_t^{dis}\left(w_{j,t}; l_j\right) = \left(p_t^h - 0.0075 \sum_j l_j w_{j,t}^s + f^{PFIT}\right) dr_t. \tag{14}$$

The discounted price plus premium is determined by the observed price minus the observed wind power production at all deployed locations times the merit order effect as calculated above. Additionally, the premium f^{PFIT} is paid. The factor dr_t is applied to discount the price back from time *t* to time *0*. We assume annual discounting, i.e. the hourly discount rates are constant for each year. We assume that the NPV is calculated over 13 years as producers receive the feed-in tariff for this period, and the interest rate r is set to 7%. For the optimization model, synthetic time series of prices and wind power production at potential locations for the whole period are generated by bootstrapping rows from the matrix $[p_t^h, w_{i,t}^s]$.

To restrict wind power deployment, we include an additional constraint to ensure an additional annual wind power production of

Table 1
Summary statistics of variables used in regression.

Variables	Mean	Standard deviation	Min	Max	ADF	Data points	Time span
p_t^h (€ MWh^{-1})	45.73	26.84	0.01	888	−43.78**	52,576	Hourly data
d_t^h (MW)	6590.74	1229.93	3576.25	9675.25	−42.04**		1/1/2005–31/12/2010
w_t^h (MW)	209.33	201.70	0.01	898.39	−35.63**		

Notes: ADF denotes the Augmented Dickey–Fuller test statistic on the null hypothesis that there is a unit root in the series. Tests are conducted with a constant, a linear trend and lags of order determined by BIC. Double asterisks (**) denote significance at the 1% level.

6 TWh, which is denoted as *target*. The value corresponds to 10% of Austrian power consumption and can be considered to be technically feasible when compared to other European countries where domestic wind production reaches 15% (Spain and Portugal) or even 25% of domestic electricity consumption (Denmark) (Wilkes et al., 2012). The total annual economic wind power potential in Austria is estimated to be 23 TWh. This includes the total wind power production at locations where levelized costs of electricity are lower than the current feed-in tariff. Therefore, many locations are available in our baseline scenario representing additional 6 TWh of annual wind power.

The following optimization model is applied for the FFIT scheme, using the current Austrian level of f^{FFIT} which amounts to 97 € MWh^{-1} at $t = 0$:

$$\max_{l} NPV^{FFIT} = \sum_i NPV_i l_i \tag{15}$$

$$\text{s.t.} \quad 0 \le l_i \le 1, \forall i \tag{16}$$

$$NPV_i = \left(f^{FFIT} \sum_t dr_t w^s_{i,t} - c^{sdis}_i \right), \forall i \tag{17}$$

$$\sum_{i,t} w^s_{i,t} l_i = target. \tag{18}$$

We aim to produce similar net present values in the two schemes to allow for a direct comparison of results. Therefore, we minimize the level of f^{PFIT} to achieve the same NPV in the PFIT as in the FFIT scheme:

$$\min f^{PFIT} \tag{19}$$

$$0 \le l_i \le 1, \forall i \tag{20}$$

$$\sum_{i,t} w^s_{i,t} l_i = target. \tag{21}$$

$$\text{s.t.} \quad NPV^{FFIT} = \sum_i l_i \left(\sum_t w^s_{i,t} \left(p^h_t - 0.0075 \sum_j l_j w^s_{j,t} + f^{PFIT} \right) dr_t \quad - c^{sdis}_i \right) \tag{22}$$

The models are implemented in the General Algebraic Modeling System GAMS (GAMS Development Corporation, 2009) using CPLEX 11 for solving the linear program and CONOPT 3 for solving the nonlinear program.

4. Results

Results of the optimization models are shown in Table 2 for FFIT and PFIT, respectively. First, the variance of wind power production decreases significantly and considerably for the PFIT model by about 26%. Secondly, the correlations of wind power production with prices and demand, respectively, increase significantly for the PFIT model. Since 70% more different locations are chosen in the PFIT than in the FFIT model, wind turbines are spatially much more diversified. The choice of locations is considerably different in the two models as shown in Fig. 2. With FFIT, wind power deployment is clustered in the East of Austria, while wind power deployment is spatially much more diversified with PFIT. This implies that even for a small country such as Austria premiums on top of market prices cause spatial diversification.

This decreases the covariance between wind power production locations and consequently causes lower variance of total wind power production. Thirdly, the variance of residual load (i.e. demand minus wind production) is significantly lower in the PFIT model, indicating that a positive effect can be gained for the operation of the electricity system.

Table 2
Model results.

	FFIT model	PFIT model	PFIT/FFIT ratio
Variance of wind power production	0.81	0.60	0.74**
Variance of residual load	5.78	5.59	0.97**
Number of chosen locations	18	30	1.70
Number of wind turbines	1146	1151	≈1.00
Average wind turbines per location	65.47	38.55	0.59
Subsidy costs (€ MWh^{-1})	55.62	55.17	0.99
NPV for wind investors FFIT strategy in PFIT scheme (Million €)[1]	508.14	230.10	1.04
			PFIT–FFIT
Correlation of wind power production and prices	−0.07	−0.03	0.04**
Correlation of wind power production and demand	0.24	0.28	0.04**

Notes: Variances are calculated based on wind power production and demand measured in GW. Variances are tested based on an F test on the null hypothesis that the ratio of the variances is equal. Correlations are tested with the null hypothesis that both correlations are equal using the Steiger test (Steiger, 1980) on the difference between two dependent correlations. Double asterisks (**) denote significance at the 1% level.

[1] Here, FFIT denotes the case that investors use FFIT optimal locations in the PFIT scheme.

Finally, the amount of subsidies is slightly lower in the PFIT by equal NPV. The strategic positioning of the turbines in the PFIT scheme leads to production at times of higher market prices. To test if investors have the incentive to behave differently in PFIT than in FFIT, we compare the difference in profits in case an investor would deploy wind turbines at FFIT optimal locations under a PFIT scheme. In that case, their net present value is decreased by about 4%. Overall, results strongly indicate that not only does the covariance between wind power supply and marginal production costs matter for an investor in a PFIT scheme but also between different production locations.

4.1. Sensitivity analysis

Results may be sensitive to the total amount of wind power deployed in the region and also to the estimate of the merit order effect in the optimization model. We therefore apply a sensitivity analysis to assess how model output changes with changing input parameters. In total, 20 different wind power production targets are combined with 7 different estimates of the merit order effect. The parameter variations are listed in Table 3. A full factorial design is used, implying 140 model runs. Fig. 3 shows ratios of wind power production variance and residual load variance for the FFIT and PFIT schemes, respectively. The ratios for wind power production variance first increase and then decrease with increasing production targets. The reason is that at very low production targets, the merit order effect is small and diversification is therefore less pronounced, while at very high production targets, total wind power production approaches the total economic potential of 23 TWh. Therefore, little choices are available for the investors on economic locations. The ratios for residual load variance start to increase by around 5 additional TWh and remain high.

Fig. 4 depicts the differences of correlations of wind power production and prices as well as of wind power production and demand. Similar to the patterns of the variance ratios, the differences of correlations first increase and then decrease with increasing production targets.

Fig. 5 compares the number of selected locations and the number of deployed turbines. The number of selected locations is considerably higher in almost all PFIT scenarios. It is even three times the amount of locations in the FFIT scenarios for the scenarios with 11 TWh of additional annual wind power production and the highest merit order effect. Consequently, the stronger the merit order effect, the more locations are chosen. Only slightly more turbines are deployed in a PFIT scheme, with a maximum of merely 1.3% more turbines in the PFIT scheme. This indicates that spatial diversification does not necessarily lead to an exploitation of significantly less windy locations.

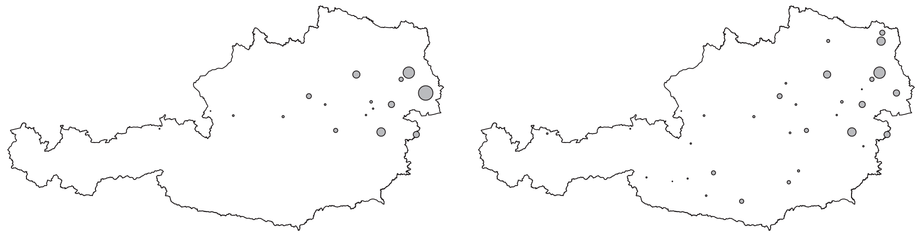

Fig. 2. Choice of locations in model FFIT (left) and model PFIT (right). Note: The circles show where and how many wind turbines are deployed in the two FIT schemes.

Fig. 6 shows ratios of total subsidies between the FFIT and PFIT schemes as well as the ratios of the net present value if the FFIT optimal locations were chosen in a PFIT scheme. Total subsidies are lower in almost all cases in the PFIT scheme. The ratios of the net present values by using the FFIT optimal locations under a PFIT scheme indicate that investors would have strong incentives to change their investment strategy. The reduction in net present values is even up to 30% with the highest merit order effect. In both cases, the ratios decrease with a stronger merit order effect.

Furthermore, the results show that a smaller merit order effect decreases the diversification effect, as the ratios for variances of wind power production and residual load are smaller in these cases. The differences in correlations between wind power production and prices as well as demand show a similar pattern. Note that the beneficial effects on variances and correlations of the PFIT scheme start at a production target of around additional 5 TWh, indicating that a fixed feed-in tariff scheme may be appropriate as long as wind power production is low. Finally, the results of the sensitivity analysis support the conclusions derived from the analytical model: in the case of a PFIT scheme, the variances of wind power output and of residual load are lower, and, in almost all cases, correlations between wind power production and market prices are higher.

5. Discussion

Although we have assessed only wind power production, the approach presented in this article can be extended to other intermittent power producers. There is an incentive to reduce covariance between the power production of different technologies, or of the same technology at different locations, if the PFIT scheme is implemented. The analysis can also be extended to larger regions or even continents. For instance, if there were a completely integrated European electricity market with harmonized subsidy schemes for renewables, the PFIT scheme would foster the development of renewable energy production that reduces system integration costs on the EU level. A wider geographical area and different intermittent technologies allow for many options of diversifying renewable energy production. Our results can therefore easily be extrapolated to a larger geographical area with different technologies. Smoothening effects should even be stronger on a larger scale (Degeilh and Singh, 2011). The analysis can also be extended to any other support mechanism that bases compensation of renewable electricity production partly on market prices. Such mechanisms include investment subsidies in combination with selling the produced electricity on spot markets.

Model results show that the positive effects of PFIT start to kick in at higher rates of wind power penetration, implying that a fixed feed-in tariff scheme, which is simpler to handle for investors, may be more appropriate when renewable energy penetration is low. However, when market penetration increases, a premium scheme seems to be a better choice in terms of incentivizing system compatible location choices of investors.

The application results strongly support the conclusions from the analytical model. However, there are a number of methodological limitations that have to be considered when interpreting the results. First, six years of historical wind power production and prices are used in this study. If correlation between prices and certain wind power locations was exceptionally high (low) in these years, the possibility to increase revenues in a PFIT may be overestimated (underestimated).

Second, the model to describe electricity prices is based on an econometric regression of historical prices. Short-term effects of the deployment of additional wind capacities may be well covered by such an approach. However, long-term structural changes induced by wind power deployment, i.e. the modification of the remaining power plant portfolio, cannot be captured. Structural effects increase with time and also with the amount of wind power deployed. We therefore consider our empirical levels to be valid in the short-time for lower levels of wind power production. Nevertheless, the analytical results remain valid independent of the adaptation of the power system such that reducing covariance between different wind power production locations is incentivized by a PFIT scheme. The merit order effect will be present as long as storage technologies and demand side management options do not completely flatten out the price curve.

Third, network connection costs are assumed to be uniform among all locations. They may differ reasonably, however, in reality. Also, networks may impose technical restrictions on where wind farms can be deployed. We did not test for the technical feasibility of the different results with respect to the electricity grid, therefore some of the location choices in the model may be currently unlikely from a technical point of view. Constraints in network capacities would translate to different zonal prices if nodal pricing were introduced to the Austrian/German electricity market design. In some of the regions, power prices may be increased in comparison to historical spot market prices on the current uniform market, and the profitability of locations would consequently be affected. Zones with high prices would be preferred by investors in a PFIT scheme. In case the FFIT is paid uniformly among all price zones, the spatial deployment of wind turbines would not differ from our analysis of FFIT. To provide an estimate of the economic importance of price differences among price zones, an analysis of power network flows and transmission constraints would be necessary. This, however, is left for future research.

Forth, the current model considers investment into wind power from the point of view of one single investor who undertakes all investments necessary to attain the Austrian wind power deployment targets. The investor is therefore able to optimize the complete wind power portfolio with respect to spatial diversification. However, in reality several competing investors share the market. In that case, investors may either decide sequentially where additional wind turbines are going to be built – or they may decide concurrently. If investors know the decisions of their predecessors, the incentive for spatial diversification exists similar to the one shown in this analysis. If investors decide concurrently without

Table 3
Parameter variations applied in sensitivity analysis.

Parameter	Value in baseline scenario	Range	Stepwise increase by
Production target (TWh)	6	[1;20]	1
Merit order effect (€ MWh_{wind} −1)	0.0075	[0.0020;0.0130]	0.0018

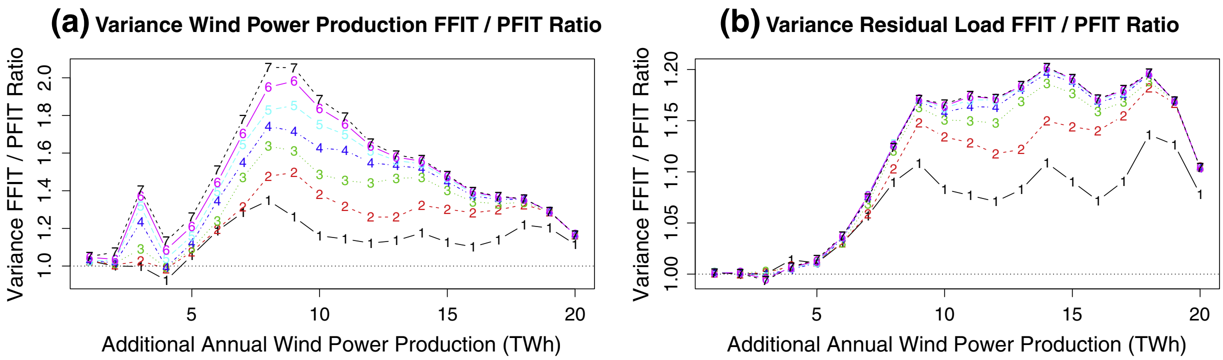

Fig. 3. Ratios of (a) wind power production variance, and (b) residual load variance for the FFIT and PFIT schemes, respectively. Note: The numbers indicate the scenario with respect to the merit order effect, i.e. 1 is the lowest effect while 7 is the highest.

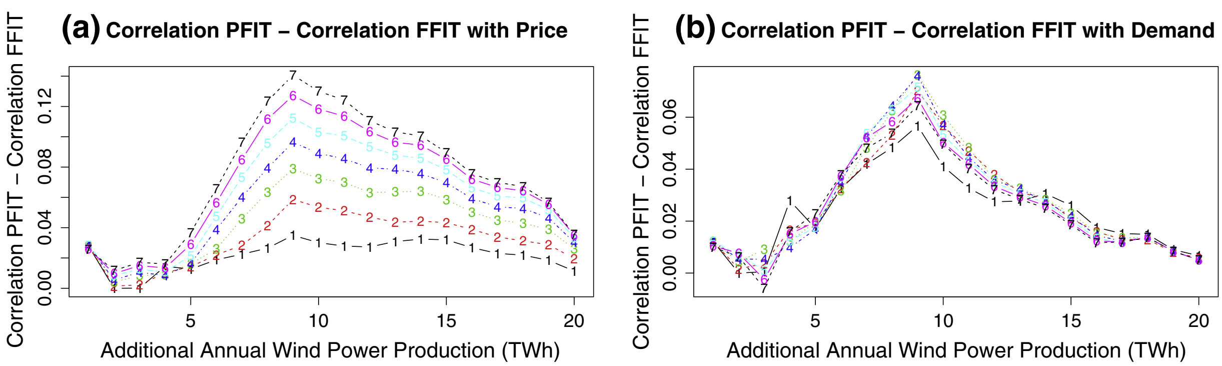

Fig. 4. Differences between the FFIT and PFIT schemes of (a) correlations of wind power production and price, and (b) correlations of wind power production and demand, respectively. Note: The numbers indicate the scenario with respect to the merit order effect, i.e. 1 is the lowest effect while 7 is the highest.

any information about the decisions of other investors, they face a prisoner's dilemma: investment in high productive locations is most profitable only, if others do not choose locations nearby. Future research may address these issues.

Finally, as discussed in the introduction, there are several issues that have to be regarded when comparing the FFIT and PFIT schemes. Other studies show that investors have to be compensated for higher price risks in the PFIT scheme, which are usually taken on by consumers in the FFIT scheme.[1] The necessary level of the risk premium as well as the assessment whether higher subsidies are compensated by lower overall costs for the electricity systems may also be the focus of future research.

6. Summary and conclusions

In this article, we present an analytical and an empirical analysis on the comparison between a premium based feed-in tariff scheme and a fixed feed-in tariff scheme with respect to the spatial diversification of wind turbines in Austria.

The analytical analysis shows that in a premium based scheme investors have incentives to find locations where (a) the wind power production potential and (b) the covariance between wind power production and prices is high as well as where (c) the covariance with other wind power generators is low. The latter results from the incentive to minimize the merit order effect in a premium based scheme. The empirical analysis strongly suggests that all three components can be influenced if investors choose locations for wind turbine deployment appropriately, even in a small country such as Austria. The empirical model is based on the simulation of wind speeds, using data from a wind atlas and from historical wind time series at meteorological stations. The development of prices at the electricity market under different wind power deployment scenarios are determined in the optimization model by assuming a merit order factor for wind power which was derived from a regression analysis of wind power production and market prices in Austria from the years 2005 to 2010.

Future research may determine the potential of a premium based FIT scheme to reduce system integration costs in comparison to a fixed-price FIT scheme. In addition, research should investigate on the level of the risk premium that has to be paid as the price risk is transferred from consumers to producers in such a scheme.

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[1] In most European feed-in tariff schemes, consumers bear the extra costs for feed-in tariffs through charges on network connection and charges on consumption (Klein et al., 2008). In Austria, for example, costs for feed-in tariffs are directly covered by electricity consumers who are obliged to pay a fixed amount per connection and a variable amount per consumed kWh of electricity. The costs for feed-in tariffs are determined ex-post by calculating the difference between the feed-in tariff and the average market-price of electricity (Federal Law, 2002).

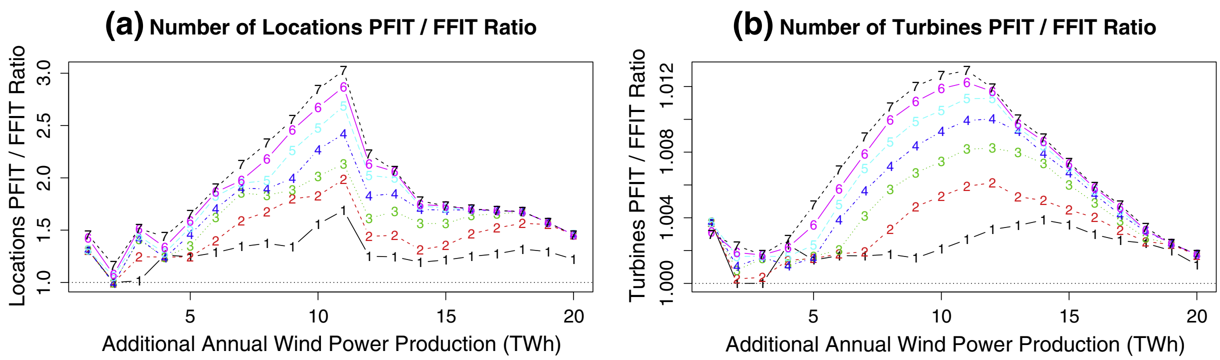

Fig. 5. Ratios of (a) number of locations, and (b) number of turbines for the FFIT and PFIT schemes, respectively. Note: The numbers indicate the scenario with respect to the merit order effect, i.e. 1 is the lowest effect while 7 is the highest.

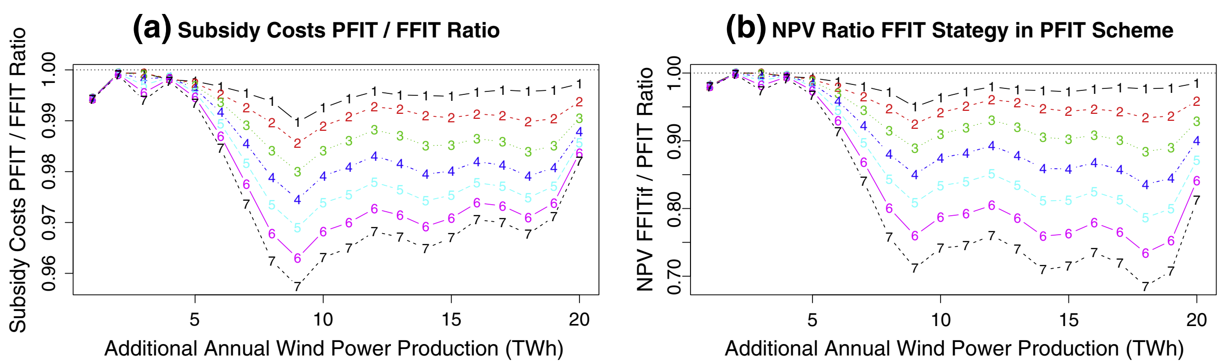

Fig. 6. Ratios of (a) subsidy costs for models FFIT and PFIT, and (b) the ratios of the NPV if FFIT optimal locations were used in a PFIT scheme. Note: The numbers indicate the scenario with respect to the merit order effect, i.e. 1 is the lowest effect while 7 is the highest.

Online-Appendix

The online appendix of this paper outlines in detail how different forms of the merit order impact our results, how the synthetic wind time series are constructed, and reports in detail on the results of the econometric model (Part 1). Also, the R-Code (Part 2) and the corresponding data (Part 3) for the econometric model can be found in the online appendix at http://dx.doi.org/10.1016/j.eneco.2013.07.004.

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Appendix A – The effect of correlation between wind speeds on the NPV of a location

The relation of the covariance of wind speeds at different sites and the effect on the NPV of a particular site depends on the assumption on the functional form of $f_t^{mo}\left(w_{j,t};l_j\right)$, as we have shown in section 2 that $Cov\left(w_{i,t}, f_t^{mo}\left(w_{j,t};l_j\right)\right)$ negatively impacts the NPV. If no nodal pricing is present, market prices are decreased by the joint output of all wind power plants, independent of their location. The price reducing effect $f_t^{mo}\left(w_{j,t};l_j\right)$ is therefore a function of the sum of production at all deployed locations in hour *t*. If we assume the function to be linear and not dependent on the current market price, i.e. $f_t^{mo}\left(w_{j,t};l_j\right)=a+b\sum_j w_{j,t}l_j$, a and b being constants, it follows directly that $\text{cov}\left(w_{i,t}, f_t^{mo}\left(w_{j,t};l_j\right)\right)=b\sum_j l_j \text{cov}\left(w_{i,t}, w_{j,t}\right)$. In that case, the higher the covariance between a particular location and the other chosen locations, the lower the NPV.

However, $f_t^{mo}\left(w_{j,t};l_j\right)$ may be a non-linear transformation of the sum of wind power production at all sites, and it may depend on the level of current market prices, i.e. $f_t^{mo}\left(w_{j,t};l_j\right)= f^{generic}\left(\sum_j w_{j,t};l_j;p_t\right)$. The reason is that the merit order curve may show strictly increasing marginal costs due to high variable costs of peak power plants – in times of high prices, the price reducing effect of wind power may therefore be higher than in times of baseload production. The influence of covariances between different wind power sites on the NPV cannot be derived easily analytically for any functional form. However, for the special functional form $f_t^{mo}\left(w_{j,t};l_j\right)=\varepsilon p_t\sum_j w_{j,t}l_j$, ε being some constant, indicative results can be generated. Bohrnstedt and Goldberger (1969, equation 11 and 14) show that an asymptotic approximation procedure of the covariance of products of random variables is

$Cov(AB,C) = E(A)Cov(B,C) + E(B)Cov(A,C)$, A, B, and C being random variables. Therefore,

$$\mathrm{Cov}\left(w_{i,t}, \varepsilon p_t \sum_j w_{j,t} l_j\right) = \varepsilon\left(E(p_t)Cov\left(w_{i,t}, \sum_j w_{j,t} l_j\right) + E\left(\sum_j w_{j,t} l_j\right)Cov(w_{i,t}, p_t)\right),$$

which indicates again that covariances between locations reduce the NPV while also the covariance between prices and wind may have a second-order price reducing effect. Very clearly, possible impacts on the NPV have to be assessed numerically as the term $Cov(w_{i,t}, p_t)$ is found to contribute positively to the NPV in equation (10).

Appendix B – Creation of Time Series and Validation of synthetic time series of wind power production

To generate time series that are consistent with observed time series of wind speeds, we choose the closest meteorological station as reference station. Figure B1 shows which meteorological stations (circles) are linked to which potential wind turbine locations. A location in the optimization model is associated with exactly one meteorological station, i.e. all potential wind power locations associated with the same meteorological station are assumed to belong to the same location i. The randomly drawn wind speeds are reordered to correlate with historical measured time series of wind speeds at the respective meteorological station using the Iman Conover method (ICM) (Iman and Conover, 1982). According to Feijoó et al. (2011), this is considered to be the most efficient method to construct correlation between previously uncorrelated data. The length of the time series that may be produced using this method is identical to the available length of the historical time series. The time series of the selected stations serve as reference time series for the potential wind locations. It can be expected that correlation of hourly wind data between meteorological stations in the East of Austria is high due to a rather flat topography. In contrast, the South and West of Austria are characterized by the Alps, which strongly interfere with wind patterns as confirmed in Figure B2. In the figure, a line between stations indicates a correlation coefficient higher than 0.7 (top) or 0.5 (bottom).

Clearly, wind in the East of Austria is highly correlated while the West and South of Austria show less correlation with other stations indicating that spatial diversification may be beneficial.

Figure B1: Selected wind turbine locations. Note: The circles show selected reference stations while the lines link reference stations with potential locations for the deployment of wind turbines.

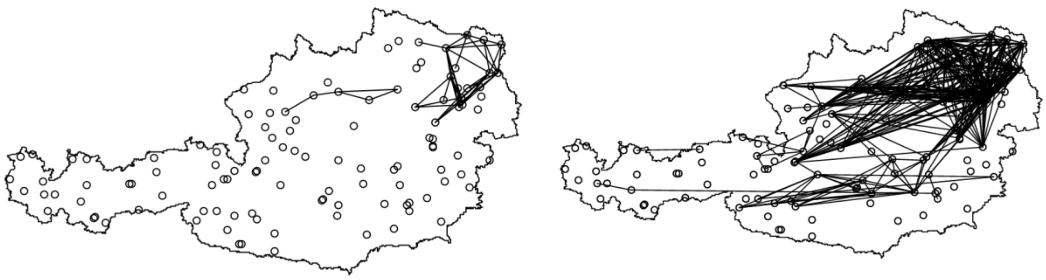

Figure B2: Correlation between hourly wind speeds of selected meteorological stations in Austria. Note: The circles show the locations of meteorological stations. Left map: Lines are drawn if correlation is >0.7. Right map: Lines are drawn if correlation is >0.5.

Historical wind power output in Austria is available in an interval of 15 minutes for the years 2003-2010 from the Regulator for Green Energy OeMAG (OeMAG, 2012). The presented methodology is validated by comparing the historical time series for one year (2008) with a modeled time series for the same year by aggregating OeMAG data to one hour to fit the synthetic time series. The year 2008 is chosen because locations as well as capacities of installed wind turbines (in total 980 MW) are known and installed wind turbines did not change significantly during the year. The wind atlas is used to derive shape and scale parameters for locations of existing wind turbines. Then, wind speeds are randomly drawn from the Weibull distribution and correlated with the closest meteorological station assuming a rank correlation coefficient of 0.99, leading to an average Pearson coefficient of correlation of 0.99. Wind power output is calculated using a technical model, including cut-in and cut-off speeds of wind turbines, size of swept area, and rated capacity (see Gass et al. (2013) for details). The hub heights of existing wind turbines are known. Wind speeds are adjusted from 100m height (as estimated by the wind atlas) to the real hub height using the formula presented in Hoogwijk et al. (2004). The final output of all locations is aggregated and compared to the aggregated Austrian wind power output. The left graph in Figure B3 shows a 720 hours (30 days) moving average plot of the results: overall performance of the methodology can be assumed to be satisfying. The right graph of Figure B3 shows the first 240 hours of the year 2008 without applying a moving average: The wind power production cannot be exactly reproduced, but similarities are visible. Statistical analysis shows that a linear regression of the simulated data on the historical data can explain 81% of the variability (i.e. R^2 of 0.81). Correlation of the two time series is 0.90. A t test suggests that the mean of the difference of the two time series is zero since the null-hypothesis of a zero mean cannot be rejected. There are two major uncertainties in the validation procedure, which may explain the difference in the outcome between simulated and observed data: First, the position and the type of existing wind turbines is not exactly known in every case as the database contains inaccuracies. The shape and scale parameters taken from the wind atlas may therefore reference to different locations than the actual location of the wind turbines. Second, as outlined above, correlation between reference stations and wind locations is unknown. The assumed correlation of 0.99 can therefore only be an approximation of real correlations.

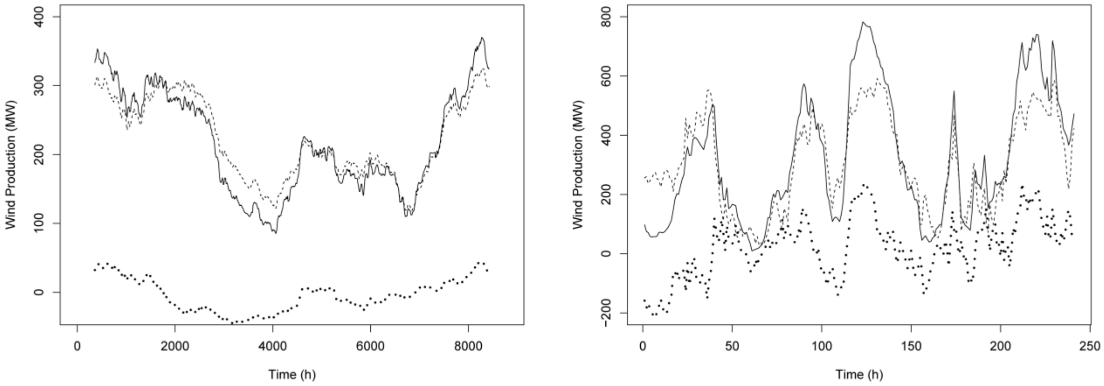

Figure B3: Comparison between historical wind power production and modeled production (dashed line). Left graph: moving average (720 hours) for the year 2008. Right graph: first 240 hours of the year 2008 (No moving average). Note: The dashed line represents the simulated data, the fat dashed line the difference between measured and simulated data.

Appendix C – Coefficient Estimates of regression model

Table C1: Results of regression

Variable	Coefficient estimate	t-value	Significance
Intercept	-83.68	-17.34	**
d_t^h	0.0185	27.04	**
w_t^h	-0.0075	-4.18	**
$dh_{t,2}$	1.04	5.12	**
$dh_{t,3}$	0.38	1.28	
$dh_{t,4}$	1.17	2.83	**
$dh_{t,5}$	0.61	1.62	
$dh_{t,6}$	-2.31	-15.41	**
$dh_{t,7}$	-8.34	-22.12	**
$dh_{t,8}$	-6.99	-10.18	**
$dh_{t,9}$	-7.78	-8.83	**
$dh_{t,10}$	-6.73	-6.95	**
$dh_{t,11}$	-6.45	-6.12	**
$dh_{t,12}$	-3.57	-2.87	**
$dh_{t,13}$	-4.87	-4.8	**
$dh_{t,14}$	-6.17	-6.55	**
$dh_{t,15}$	-7.40	-8.5	**
$dh_{t,16}$	-8.87	-10.69	**

$dh_{t,17}$	-9.33	-11.64	**
$dh_{t,18}$	-4.88	-5.49	**
$dh_{t,19}$	-1.88	-2.09	*
$dh_{t,20}$	-3.50	-4.24	**
$dh_{t,21}$	-3.96	-5.66	**
$dh_{t,22}$	-2.99	-5.9	**
$dh_{t,23}$	-3.76	-7.39	**
$dh_{t,24}$	-2.64	-10.26	**
$m_{t,2}$	0.84	0.44	
$m_{t,3}$	3.20	1.76	
$m_{t,4}$	14.61	7.59	**
$m_{t,5}$	17.14	9.22	**
$m_{t,6}$	21.22	9.63	**
$m_{t,7}$	26.10	9.48	**
$m_{t,8}$	21.49	10.72	**
$m_{t,9}$	22.59	9.02	**
$m_{t,10}$	23.14	10.82	**
$m_{t,11}$	15.44	6.8	**
$m_{t,12}$	6.33	3.33	**
$wd_{t,2}$	-1.07	-0.73	
$wd_{t,3}$	-1.73	-1.32	
$wd_{t,4}$	-0.99	-0.92	
$wd_{t,5}$	0.44	0.43	
$wd_{t,6}$	3.33	2.95	**
$wd_{t,7}$	5.10	4.25	**
	DW statistic	0.22	**
	BP statistic	697.41	**
	R^2	0.48	

Notes: DW and BP test statistics denote the Durbin-Watson test on autocorrelation (Durbin and Watson, 1950) and the Breusch-Pagan test for heteroscedasticity (Breusch and Pagan, 1979) in the residuals of the regression, respectively. Standard errors are robust to heteroscedasticity and autocorrelation (Newey and West, 1987; Newey and West, 1994). Single (*) and double (**) denote significance at the 5% and 1% levels, respectively.

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Article VIII

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Analysis

Ecosystem services and economic development in Austrian agricultural landscapes — The impact of policy and climate change scenarios on trade-offs and synergies

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ABSTRACT

We have developed an integrated modeling framework (IMF) to quantify indicators for ecosystem services (ES) and economic development (ED) in agricultural landscapes. Austria serves as a case study in which impacts, trade-offs, and synergies of ES and ED are assessed for different agricultural policy pathways and regional climate change scenarios. Agricultural intensification and incentivized use of *provisioning* ES (e.g. biomass production) lead to higher macro-economic output (e.g. GDP) but usually reduce ES related to *regulation and maintenance* (e.g. ecological integrity, climate regulation), as well as *cultural* services (landscape diversity). We revealed both synergies for certain ES (e.g. biomass production and soil organic carbon stocks) as well as large spatial deviations from the national mean across the heterogeneous agricultural landscapes in Austria. Climate change scenarios (i) lead to substantial variation in ES and ED indicators and (ii) usually amplify trade-offs by stimulating land use intensification. Our findings depict the complex relationship between different ES and ED indicators as well as the importance of considering spatial heterogeneity and regional climate change. This assessment can help to improve targeting of agri-environmental schemes in order to provide a more balanced and efficient supply of ES and to foster rural development.

1. Introduction

Land use choices in agriculture usually aim at producing biomass, which can be viewed as an ecosystem service (ES) from agricultural ecosystems. These services, by definition, contribute directly and indirectly to human well-being (MEA, 2003; TEEB, 2010) and are commonly categorized into (i) *provisioning services* such as supply of food, fodder, fiber and bioenergy, (ii) *regulation and maintenance services* such as local and global climate regulation, soil formation and fertility, and (iii) *cultural services* such as landscape esthetics and recreation (for a detailed overview on the different types of ES see MEA, 2003 and Haines-Yong and Potschin, 2013). Many of these ES represent characteristics of a public good (TEEB, 2010), degraded at an unprecedented rate in the past decades and are likely under-supplied today (MEA, 2005). Some ES such as climate regulation, nutrient cycling, as well as biodiversity are likely to have already moved beyond certain global biophysical threshold levels (Rockström et al., 2009). In addition, the supply of one ES may affect other ES negatively at spatial and temporal scales (MEA, 2005; TEEB, 2010) due to their interdependency and non-linear relationships (Rodriguez et al., 2006). For instance, the increase in agricultural production has become a dominant driving force in diminishing the potential of ecosystems to provide ES related to *regulation and maintenance* as well as *cultural* services (Tilman et al., 2002; Bennett and Balvanera, 2007; Power, 2010; Bryan, 2013; Schirpke et al., 2014).

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Two significant driving forces – agricultural policies and climate change – may stimulate or depress the supply of particular ES significantly in the future. Agricultural policies such as agri-environmental programs can account for a more balanced supply of ES from agriculture (Power, 2010; Pirard, 2012). They may foster *regulation and maintenance* ES such as increasing soil organic carbon (SOC) levels, and *cultural* ES such as maintaining permanent grasslands, hedgerows or other landscape elements (Barraquand and Martinet, 2011). This frequently comes at the cost of *provisioning* ES such as biomass production for human use (Schmid et al., 2004; Badgley et al., 2007; Pretty et al., 2006). Climate change as a driving force likely puts further pressure on ES supply in agricultural landscapes (Schröter et al., 2005). This can happen directly as an impact on ecosystem functions and processes that provide ES (e.g. sediment loss, see Mitter et al., 2014) and indirectly through autonomous adaptation strategies by farmers (Briner et al., 2012; Leclère et al., 2013; Schönhart et al., 2014). The impacts of these two driving forces will strongly depend on regional and local socio-economic, and biophysical characteristics like farmers' responses, resource endowments, and soil conditions, thereby making it paramount to account for spatial heterogeneity (Bateman et al., 2013).

Besides theoretical approaches (c.f. Barraquand and Martinet, 2011; Hussain and Tschirhart, 2013) a bulk of ES research applies geographic information systems (GIS) or spatial mapping based approaches (c.f. Goldstein et al., 2012), multi-criteria analysis (c.f. Fontana et al., 2013) or integrated modeling frameworks (IMFs) (c.f. Schönhart et al., 2011a; Briner et al., 2012) in order to provide policy support. The overarching objective of applied ES research is thereby to generate knowledge on the sustainable supply of ES by eliciting causal relationships, trade-offs as well as synergies (Carpenter et al., 2009).

For example, Jiang et al. (2013) mapped changes in production value of agricultural and forestry land use (*provisioning* ES), carbon storage, and biodiversity in a landscape in the UK for a time period of 70 years. They revealed increases in production values at the cost of biodiversity. However, carbon storage remained unchanged at the aggregated level despite considerable shifts among land use classes. Maskell et al. (2013) reveal severe trade-offs between carbon storage and provisioning services for particular observed land uses. These authors suggest intermediate land use intensities to benefit from synergies among multiple ES. Maes et al. (2012) provide a GIS-based analysis at a spatial resolution of 10 km on ES and biodiversity at European scale. They confirm trade-offs between *provisioning* ES from agro-ecosystems, *regulation and maintenance* ES, and biodiversity but emphasize synergies at the local management scale by diversifying cropping plans and planting of buffer strips and cover crops.

GIS based and spatial mapping analyses on observed and scenario-based land use changes are well prepared to provide detailed information on ES indicators, and reveal potential trade-offs, synergies, impacts or vulnerabilities. Nonetheless, there are some shortcomings. First, some of the studies assess a wide range of ES indicators (c.f. Raudsepp-Hearne et al., 2010) but only few focus on biodiversity (Bateman et al., 2013; Bryan and Crossman, 2013; Nelson et al., 2009) or landscape amenities (Bateman et al., 2013; Reyers et al., 2009). Second, national or supranational analyses are still uncommon (c.f. Metzger et al., 2006; Lorencová et al., 2013) and regional case studies remain a dominant approach. Third, detailed bottom-up economic modeling of land use and management choices such us land use intensities or crop rotations are rare, although the opportunity costs of alternative land uses (Goldstein et al., 2012; Swallow et al., 2009) and monetary valuation of non-market ES (Bateman et al., 2013; Bryan et al., 2010; Bryan and Crossman, 2013; Naidoo and Ricketts, 2006; Nelson et al., 2009) are often accounted for. This could be an important shortcoming as different management measures can have substantially different impacts on ES supply (Syswerda and Robertson, 2014). The GIS mapping study by Koschke et al. (2013) emphasizes on the importance of detailed data on both land use change and management to reveal trade-offs among different ES and to provide spatially explicit policy recommendations.

In contrast to the widely applied GIS based and spatial mapping analyses for ES assessments, integrated modeling frameworks (IMFs) can overcome some of the shortcomings raised above. IMFs depict impact chains by linking disciplinary data and models (e.g. from climatology, soil sciences, agronomy, animal husbandry, and economics) and are thus suitable to disentangle the complex interactions between the human system and the environment (Falloon and Betts, 2010; Zuazo et al., 2011; Laniak et al., 2013). This enables the quantification of ES impacts (Rounsevell et al., 2012) and helps to derive better recommendations on mitigating ES trade-offs and supporting ES synergies. Despite the advances in IMFs (Janssen et al., 2011; Laniak et al., 2013), multi-regional IMFs at a high spatial resolution with focus on ES supply, trade-offs, and supporting synergies are still rare but required to derive robust conclusions under regional heterogeneities (Crossman et al., 2013).

Current state-of-the-art IMFs with explicit or implicit consideration of ES all share a focus on land use modeling but they differ greatly with respect to indicator selection, scenarios, scale, model linkages, and model types considered. Regarding indicator selection most studies do not cover the full range of ES categories, usually focusing on *provisioning* and *regulation and maintenance* ES (Barthel et al., 2012; Briner et al., 2012; Leclère et al., 2013), and only rarely also on *cultural* ES (Schönhart et al., 2011a). In recent years some large scale projects such as SEAMLESS-IF (van Ittersum et al., 2008; Ewert et al., 2009) and SIAT (Helming et al., 2011a,b; Sieber et al., 2013) have been initiated to pursue the development and use of IMFs in land use science. Both SIAT and the regional IMF GLOWA (Barthel et al., 2012) provide the same high spatial resolution as our IMF (i.e. 1 km), although some local case studies provide even finer spatial analyses at the field or sub-field level (Briner et al., 2012; Schönhart et al., 2011a). SEAMLESS-IF can provide spatial resolution at field level, however, most results are reported at farm or regional level. Except for SIAT, which does not assess climate change impacts and employs the land use allocation model DYNA-CLUE, a common denominator in the various model linkages is the use of bio-physical process models or statistical crop models in order to account for changes in climate, which then provide input to various types of farm models, either optimization models (SEAMLESS-IF, GLOWA, Briner et al., 2012; Schönhart et al., 2011a, b) and/or agent-based models (GLOWA, Leclère et al., 2013). Further linkages include forest growth models (SIAT, Briner et al., 2012), hydrological models (GLOWA), agronomic models (Schönhart et al., 2011a), partial equilibrium models (SEAMLESS-IF, SIAT), macro-economic models (SIAT), and econometric meta-models (SEAMLESS-IF, SIAT).

This article aims at providing scientific support for policy interventions by exploring trade-offs and synergies between indicators for ES and economic development (ED) in Austrian agricultural landscapes. We therefore apply a state-of-the-art IMF that reveals and assesses the interlinkages between ES and key system drivers such as regional climate change and policies (Carpenter et al., 2009), agricultural land use and management measures (Swift et al., 2004; Horrocks et al., 2014) as well as biophysical processes (Swinton et al., 2007). Our analysis considers most aspects required by state-of-the-art ES research, such as an *interdisciplinary* approach (Carpenter et al., 2009; Rounsevell et al., 2012), high spatial *heterogeneity* (Metzger et al., 2006; TEEB, 2010; Rounsevell et al., 2012), multiple *drivers* (Carpenter et al., 2009; Crossman et al., 2013), integration of key *stakeholders* (Rounsevell et al., 2012; TEEB, 2010), an unusually *wide range of ES indicators* (Tallis et al., 2008; TEEB, 2010; Kinzig et al., 2011), and, in contrast to most studies, *macro-economic* effects (Bryan, 2013).

2. Method

2.1. Integrated Modeling Framework (IMF)

Fig. 1 illustrates the models and linkages of our IMF. The IMF has been designed to explore the interfaces between climate, biophysical, and economic factors in land use management at a high spatial resolution of 1 km. We first provide a description of the individual models, which is followed by a short elaboration on important model interfaces.

2.1.1. Stand-alone Models

The Austrian Climate model based on Linear Regression Methods *ACLiReM* applies regression and bootstrapping procedures to observed data sets from 1975–2007 in order to project temperature trends and different possible precipitation patterns until 2040 (Strauss et al., 2013). The result is a variety of different climate change scenarios for Austria in the form of daily time series of solar radiation, maximum and minimum temperatures, precipitation, relative humidity and wind speed at a 1 km grid.

Caldis vâtis is a forest growth model that simulates potential forest growth productivity (i.e. incremental growth rate) at a spatial resolution of 3.89 km (Kindermann, 2010). The model is based on observed data from the Austrian National Forest Inventory and uses climate and soil variables as regressors. It can therefore consider climate changes for a certain extent.

The *CropRota* model derives typical crop rotations at municipality level considering observed crop shares, suitable crop sequences, and agronomic constraints (Schönhart et al., 2011b). It supports the design of land use management practices.

The biophysical process model *EPIC* (Izaurralde et al., 2006; Williams, 1995) provides information on the level and variability of crop yields and environmental outcomes (e.g. soil organic carbon stocks — SOC) of alternative crop management practices. It takes topography, soil characteristics, weather, and crop management (e.g. fertilization intensity) into account. *EPIC* outputs are differentiated at a spatial resolution of 1 km.

Land use choices are depicted by $PASMA_{[grid]}$ which is a spatially explicit version of the bottom-up economic land use model *PASMA* (Schmid et al., 2007; Schmid and Sinabell, 2007). It derives optimal management and production portfolios for agricultural and forestry land use by maximizing regional producer surplus (RPS) for each NUTS3 region subject to natural, structural and regional resource endowments, technical restrictions, and observed mixes for livestock, crops, and other land use types. $PASMA_{[grid]}$ represents the structural and environmental heterogeneity of the agricultural sector in Austria at a spatial resolution of 1 km for cropland, grassland, and permanent crops (i.e. wine, fruit orchards). We account for the emergence of land use types that have not yet been observed in the past, e.g. short rotation coppice or afforestation measures, but do not allow conversions between grassland, cropland and permanent crops. Afforestation can take place on any agricultural land, whereas short rotation coppice can only be planted on cropland. Livestock production is modeled at NUTS3 level. In this study, we consider four distinct management intensities including rainfed agriculture with (1) high, (2) medium, and (3) low fertilization intensity and (4) irrigated agriculture with high fertilization intensity (the latter is only available on cropland). $PASMA_{[grid]}$ is an optimization model suitable for comparative static scenario analysis. In this analysis, it is solved for the last point of an assumed period (e.g. 2040 for the period 2025–2040) while using average values with regard to bio-physical data (see Section 2.1.2). $PASMA_{[grid]}$ has already been applied in a regional case study (Schmidt et al., 2012). This article provides a first application of $PASMA_{[grid]}$ at national scale. The model results for land use correspond well to IACS data for the reference year 2008.

BeWhere is a spatially explicit energy system model (Leduc et al., 2009; Schmidt et al., 2011) that minimizes the costs of supplying regions with fuel, electricity, and heat considering fossil (gas combined heat and power, gasoline, diesel, fuel oil furnaces, gas furnaces) and

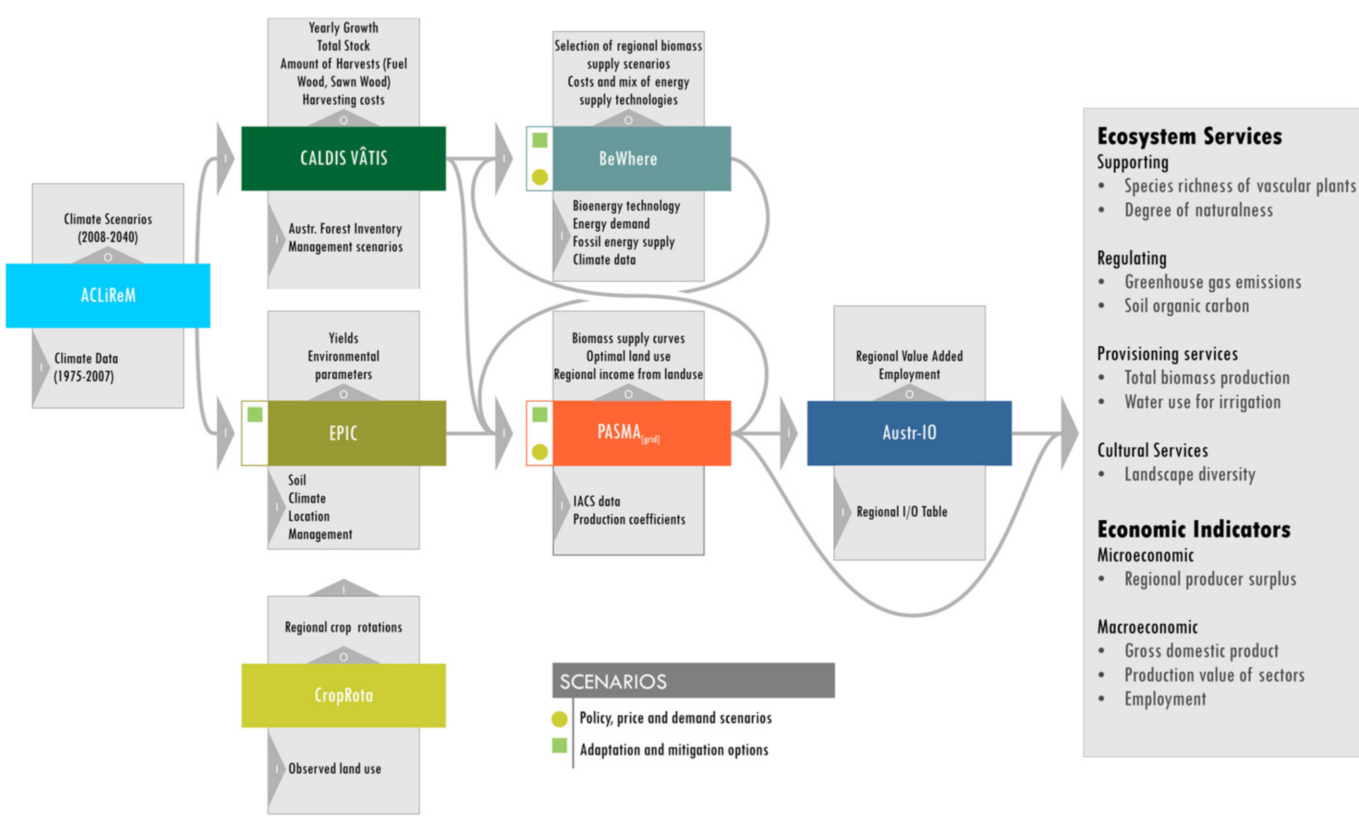

Fig. 1. The integrated modeling framework (IMF).

biomass technologies (biomass and biogas combined heat and power with and without gasification, pellets production facilities and furnaces, 1st and 2nd generation biofuels). *BeWhere* models the whole bioenergy supply chain from supply points over energy conversion to end use, including the competition with forestry based industries such as pulp and paper mills, and particleboard industry. Residuals from saw mills are taken into account as possible feedstock for material and energy uses. Fossil energy conversion chains are modeled with less detail of logistics. The spatial resolution of the model in this study is at the level of NUTS3 regions.

AUSTR-IO is a dynamic multiregional input output model of Austria and applied to assess the macroeconomic and sectoral impacts. The main model structure and parameterization are based on Fritz et al. (2003) and follow the traditional input–output framework of demand driven behavior (c.f. Miller and Blair, 2009). However, the model goes beyond traditional input output modeling approaches by using, e.g. translog cost functions and auto-distributed lag functions of production and demand (Kratena and Streicher, 2009; Kratena et al., 2013). The model is calibrated to the base year 2008 and solves recursively until 2040 (see Kulmer, 2013). The model uses regional supply and use tables of Austria and comprises 41 economic sectors which produce 59 commodities. In addition, the model is of the multi-regional type (NUTS2-level) and considers all nine federal states of Austria. Thus, trade and demand between the regions are determined endogenously. We follow the small open economy assumption and do not explicitly consider other countries in the model.

2.1.2. Model Interfaces

Daily climate data at a 1 km grid resolution from *ACLiReM* feeds into *EPIC* and *Caldis vâtis*. This allows assessing climate change impacts on crop and forage yields as well as forest growth. Pre-defined crop management choices in *EPIC* include crop rotations, provided by *CropRota*, as well as alternative cropping intensities and irrigation. Forest growth data from *Caldis vâtis* is used in $PASMA_{[grid]}$ for potential afforestation measures on agricultural land. Both, the *EPIC* biophysical and *Caldis vâtis* forest growth data are integrated into $PASMA_{[grid]}$ by the means of homogenous response units (HRUs) (Schmid et al., 2005; Stürmer et al., 2013). An HRU shares similar natural characteristics such as elevation, slope and soil type. Optimal land use and management choices are then derived for each spatial HRU considering the opportunity costs of agricultural and forestry production. The HRU concept saves computational resources and supports consistent integration of large biophysical data sets while maintaining its regional heterogeneity. With respect to temporal scales, $PASMA_{[grid]}$ uses average estimates for the simulated periods in EPIC (i.e. ø 1990–2005 and ø 2025–2040) as well as incremental growth rates from *Caldis vâtis* for calculating gross margin annuities.

$PASMA_{[grid]}$ is used to compute biomass supply curves for *BeWhere* to determine optimal bioenergy utilization pathways. The supply curves consist of price–quantity relationships for all NUTS3 regions. *BeWhere* selects for all regions an optimal point on the supply curve taking into account biomass transportation costs and thus different intensities of biomass production and prices in the NUTS3 regions. While $PASMA_{[grid]}$ output includes supply curves for forestry wood on afforested agricultural land, wood harvests in existing forests are provided to *BeWhere* by *Caldis vâtis*. The quantities harvested are fixed to the respective results of *Caldis vâtis* instead of modeling supply curves based on biomass costs (see discussion in Section 4.2 for more information). Once optimal bioenergy utilization pathways have been determined for each NUTS3 region by *BeWhere* it provides this information back to $PASMA_{[grid]}$ where the corresponding model solutions are selected for the final analysis.

The dynamic multiregional input output model *AUSTR-IO* incorporates the representation of the production and input demand structure of the agricultural and forestry sector in $PASMA_{[grid]}$. In particular, factor (e.g. labor input in production) and intermediate demand (e.g. consumption of intermediate goods such as energy and chemicals) as well as output levels and revenues of agriculture and forestry are provided by $PASMA_{[grid]}$. Furthermore, *AUSTR-IO* uses $PASMA_{[grid]}$ output on relevant policy parameters such as taxes and subsidies. Data is delivered on the spatial aggregation level of NUTS2.

Finally, land use data from $PASMA_{[grid]}$ at 1 km grid resolution provides the basis for spatial data processing and GIS analysis (see Section 2.2).

2.2. Ecosystem Service Assessment

On the basis of expert interviews (Haida et al., submitted for publication) and former studies (Fontana et al., 2013; Tasser et al., 2008, 2012) an ES indicator set was chosen for a detailed evaluation of the scenario results (see Section 2.3). Landscape functions (c.f. Haines-Young and Potschin, 2009) and resulting ES depend to a large extent on the integrity of ecosystems. Biodiversity and ecological integrity are usually not only an important precondition for many ES but can also be seen as a 'storage' for potential future ES. Therefore biodiversity relevant environmental indicators, such as *Naturalness of habitats* and *Area weighted mean species richness of vascular plants* were included in the analysis (Rüdisser et al., 2012).

In addition, we use landscape metrics (*Shannon Diversity Index*) to measure landscape structure and scenic beauty (Frank et al., 2013; Palmer, 2004; Uuemaa et al., 2009). As the model results from $PASMA_{[grid]}$ at 1 km are too rough for the calculation of landscape metrics, we downscaled the data according to a spatially implicit land cover model with an increased spatial resolution. For that purpose, two existing landcover maps (Rüdisser and Tasser, 2011; Wrbka, 2003) were combined and merged with slopes from a digital elevation model and the road and water network from Open Street Maps to receive a more detailed Austrian land cover map for the year 2008. The result is a raster layer at 25 m resolution containing information about topology and land use for each grid. The water and road network divides the landscape into feasible homogenous units. As landscape-based indicators rely on the analysis of a larger area, analysis units at a 10 km grid are extracted (INSPIRE, 2009).

The final selection of spatially applicable indicators (Table 1) covers all types of ES groups using a classification according to MEA (2003) and the Common International Classification of Ecosystem Goods and Services (CICES) (Haines-Young and Potschin, 2010) and includes many important ES relevant in agricultural landscapes. In addition, we also provide a quantitative assessment of economic impacts due to changes in *provisioning* ES such as food, timber, and biomass-based energy production. For that purpose, we report traditional ED indicators for regional development such as regional producer surplus (RPS), agricultural policy payments, agricultural sector output, employment, and gross domestic product (GDP).

2.3. Scenarios

Our analysis considers two dominant drivers, namely climate change and agricultural policy pathways up to the year 2040 (see Fig. 2). The scenario development has been facilitated by stakeholders from public administration and research institutes.[1] In total, 16 different scenarios are compared with a reference scenario (*REF*), which encompasses a future business as usual (*BAU*) policy pathway for the period 2025–2040 (i.e. the new CAP reform 2014) under the current climate. Biophysical data for the reference period is thus based on current climate data (ø 1990–2005). Using these settings for the reference scenario allows us to separate policy and climate impacts from market and other socio-economic developments such as technological progress and population growth.

[1] More information on the workshops and meetings are available on request.

Table 1
Overview of ES indicators in the assessment.

MEA	CICES			Indicator	Measurement	Data source[a]
Category	Category	Sub-category	Service(s)			
Provisioning	Provisioning	Biomass	Nutrition materials energy	Total biomass production on agricultural land	Dry matter tons	*Crops, forage and short rotation coppice:* EPIC *Afforestation:* Caldis vâtis
Regulating	Regulation and maintenance	Soil formation and composition	Decomposition and fixing processes	Soil organic carbon (SOC) in top-soil layer	t	*Agriculture:* EPIC *Afforestation:* regional estimates (Anderl et al., 2013)
		Climate regulation	Global climate regulation	GHG emissions from agriculture	t CO^2_{eq}	Emissions factors from Anderl et al. (2013)
Supporting		Gene pool protection (ecological integrity)	Naturalness	Degree of naturalness	1 — natural to 7 — artificial	Rüdisser et al. (2012) Tasser et al. (2012)
			Biodiversity	Area weighted mean species richness of vascular plants	Number of species	Fontana et al. (2013)
Cultural	Cultural	Intellectual and representative interactions	Landscape esthetic	Shannon Diversity Index	Without unit	Frank et al. (2013) Uuemaa et al. (2009) Palmer (2004)

[a] Final results all depend on the respective changes in $PASMA_{[grid]}$ activities on agricultural land (including afforestation) in the scenario analyses.

The climate change scenarios of *ACLiReM* differ with respect to changes in precipitation but have in common a temperature trend increase of +1.5 °C from 2008 to 2040. Uncertainties in future precipitation developments are framed by the following scenarios, i.e. (i) *High*: assuming an increase of 20% in mean annual precipitation sums, (ii) *Similar*: assuming similar distributions of precipitation sums compared to the past, (iii) *Shift*: seasonal precipitation sums in winter are increased by 20% with an respective decrease of precipitation sums in the summer, and (iv) *Low*: assuming a decrease of 20% in mean annual precipitation sums.

Table 2 provides details on the policy pathways. Policies in the business as usual pathway (*BAU*) are identical to *REF*. It is anticipated that less funding will be devoted to the current Austrian agri-environmental program. We also take into account new requirements for direct payments (i.e. the greening measures) by requiring farmers to set-aside at least 3% of their arable land as ecological focus areas (EFA) such as fallow and buffer strips that shall increase biodiversity. In the stakeholder process we decided on a percentage for EFA of 3% instead of the current 5% (European Commission, 2013), as it was a more likely and politically feasible assumption at the time of the stakeholder meeting in March 2013.

In addition to *BAU*, we developed three alternative pathways that differ with respect to their focus on ES categories. First, the provisioning pathway (*PRO*) assumes that policy makers aim at increasing the supply of *provisioning* ES, i.e. agricultural and forestry production. Hence, agri-environmental schemes are not funded as they would facilitate more extensive management methods. Furthermore, farmers are not required to set aside agricultural land for EFAs. Second, we also implement a provisioning pathway that focuses on the additional utilization of fuel wood and short rotation coppice for renewable energy production (*PRO_Energy*). This policy pathway is driven by assuming high fossil fuel prices in the energy system model *BeWhere*. Third, a balanced ecosystem pathway (*BAL*) is introduced with the aim to increase the level of ecosystem services other than *provisioning*. Hence, it increases funding of payments for low fertilizer intensity at the cost of payments for medium fertilizer input (i.e. the equivalent measures in the Austrian agri-environmental program 2007–2013 would be 'renunciation of agro-chemical inputs' and 'environmentally friendly management',

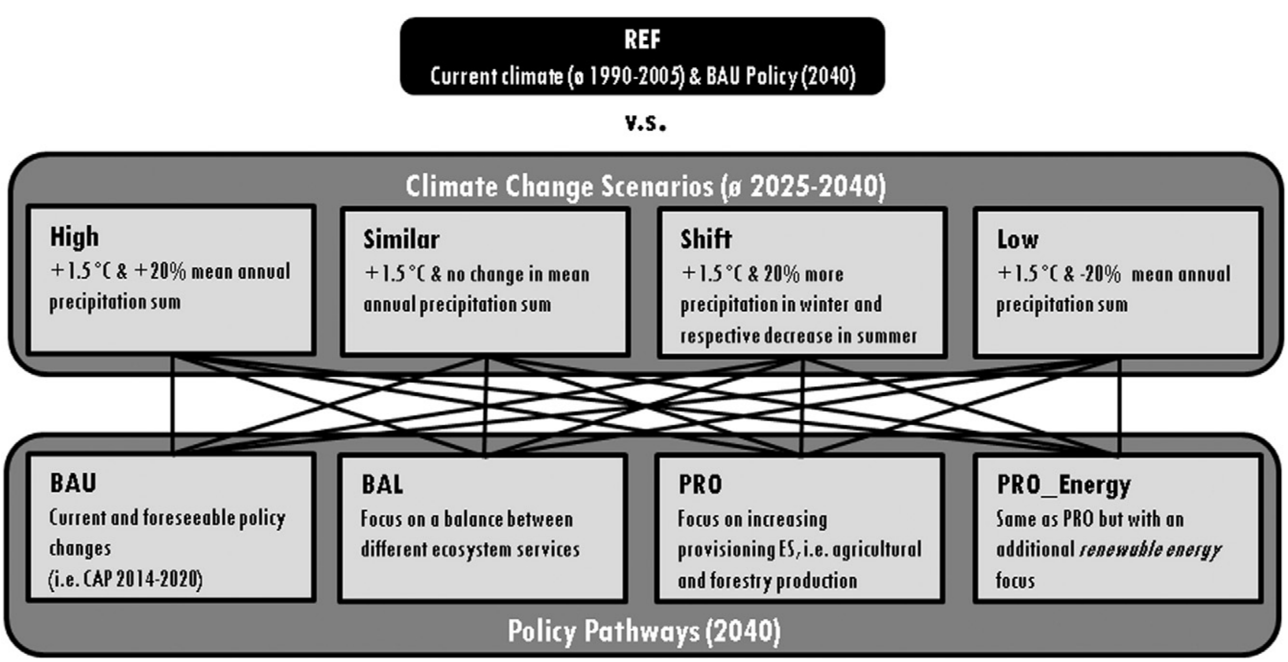

Fig. 2. Climate change scenarios and policy pathways until 2040 (own source).

Table 2
Policy pathways and the particular changes with respect to the year 2008.

Category	Model parameter	Scenarios			
		BAU	BAL	PRO	PRO_Energy
Market measures & direct payments	Price & cost development	OECD-FAO forecast to 2022[a]			
	Sealing of cropland	3% for each grid in 2040			
	Milk quota	Abolished			
	Suckler cow premium	Abolished			
	Payments for less favored areas	−15%			
	Ecological focus areas	+3%	+10%	0%	
Agri-environmental schemes	Payment for medium fertilizer intensity	Abolished	−50%	Abolished	
	Payment for low fertilizer intensity	No change	+100%	Abolished	
	Payment for extensive grassland management (one-cut)	No change	+25%	Abolished	
Renewable energy focus	Forcing biomass production for energy uses by implementing high oil prices in *BeWhere*.	No	No	No	Yes

[a] Prices and costs are kept constant from 2022 to 2040.

respectively), thereby clearly favoring the supply of non-market ES. The requirements for EFAs are set to 10%.

3. Results

3.1. National Level

Fig. 3 summarizes the results for all scenarios and most indicators on agricultural landscapes at national level for the period 2025–2040 (for detailed information see Table A-1 in the online appendix). The final results refer to the respective changes in $PASMA_{[grid]}$ activities on agricultural land (including afforestation) in the course of the scenario analysis. All values relate to percentage changes from the *REF* scenario. As prices and costs are kept constant between all scenarios (see Table 2) the changes indicate policy and/or climate change impacts only.

3.1.1. Business as Usual Pathway (BAU)

Changes in the *BAU* pathway depict changes in regional climate only. The climate change scenarios have positive impacts on overall agricultural yields at national level. Farmers are assumed to autonomously adapt to these impacts by increasing fertilizer application rates due to an increasing marginal productivity of fertilizer input. Positive climate change impacts, amplified by land use intensification, increase average total biomass production in all climate change scenarios between +3% and +9% in *Low* and *High*, respectively. Most of these gains come from large increases in forage yields on grassland and Alpine meadows (from +24% in *Low* to +27% in *High*). In contrast, crop production seems to be somewhat vulnerable to our climate change scenarios with decreases in most scenarios (−2% in *Similar* to −8% in *Low*) and a small increase in *High* (+1%).

The intensification of land use deteriorates the *mean species richness of vascular plants* (between −1.1% and −1.5%). Further, increases in the

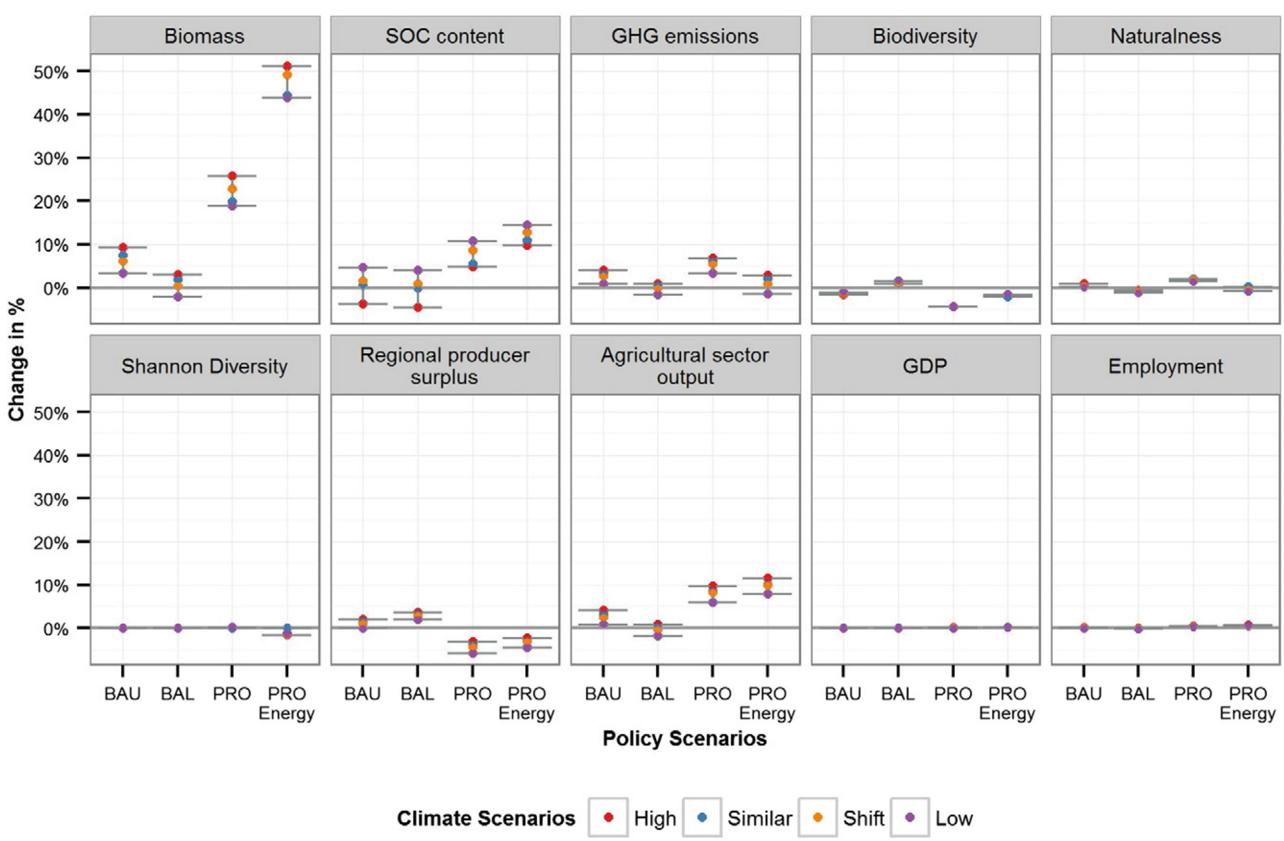

Fig. 3. Impacts on ES and ED indicators in Austrian agricultural landscapes at national level (changes in % compared to *REF*). Note: Degree of naturalness is higher the lower the indicator, i.e. negative changes indicate an increase in naturalness and vice versa. Abbreviations: SOC — topsoil organic carbon; GHG — greenhouse gas; GDP — gross domestic product.

indicator *degree of naturalness* from +0.3% to +0.9% indicate more anthropogenic interference on ecosystems. As the *degree of naturalness* values range from 1 (natural) to 7 (artificial), an increasing indicator value means decreased naturalness. More fertilizer use usually causes higher direct and indirect soil emissions from agricultural land use. The net increases in GHG emissions range between +1% in *Low* and +4% in *High*. The SOC content increases in all but the *High* scenario. The additional C input due to higher biomass and thus residue production dominates the effect of higher mineralization from increasing temperatures in *Low* (+5%), *Shift* (+2%) and *Similar* (+1%). The positive net impact declines with more precipitation as this leads to both (i) higher soil moisture which further amplifies mineralization rates and (ii) more soil erosion. Ultimately, the negative impacts prevail in the *High* scenario (−4%). Negligible impact has been detected for landscape diversity (i.e. Shannon Diversity), as changes in land use from climate change remain small.

The increase in productivity in all climate change scenarios positively affects the ED indicators, whereby *High* has the most positive impact and *Low* the lowest. The rising revenues of the agriculture sector lead to higher RPS (from +0% to +2%) and production value of the agricultural sector (between +1% and +4%). Agricultural payments decrease (from −1% to −2%) as some farmers opt out of agri-environmental schemes and intensify their land use management. Due to linkages in the economy, the production value of most other sectors in the economy increases (indirect effect; e.g. sectors such as energy and water, chemical, machinery; see Fig. A-1 in the online appendix), and thus GDP (+0.1%) and employment (from +0.1% to +0.3%). The latter two indicators are inclined to small changes as the agricultural sector only contributes about 1.4% to national GDP.

3.1.2. Balanced Pathway (BAL)

Higher agri-environmental payments in *BAL* lead to the adoption of more extensive management measures compared to *REF*. In addition, ecological focus areas increase by about 57,000 ha (+70%) in all climate scenarios. Total biomass production still increases slightly in *High* (+3%) and *Similar* (+2%), stagnates in *Shift* and declines in *Low* by 2%. This indicates that climate change induced yield increases and land use intensification can outweigh the increase of extensification measures of *BAL*. Nonetheless, changes in total biomass production are the lowest compared to the other policy pathways.

As intended by implementing *BAL* policy measures, less intensive land use in *BAL* improves the *mean species richness of vascular plants* (from +0.9% to +1.6%) as well as moves the *degree of naturalness* (from −0.6% to −1.0%) closer to a natural state. Further, changes in GHG emissions are the lowest for all policy pathways. They decrease slightly in *Low* (−2%), remain constant in *Shift* and marginally increase in *Similar* (+1%) and *High* (+1%). The SOC content increases in *Low* (+4%) and *Shift* (+1%), is not affected in *Similar* and declines significantly in *High* (−5%). Lower and partly negative SOC content values in *BAL* can be explained by less C input as a result of the relatively lower biomass and thus residue production in *BAL*. Significant changes in landscape diversity at national level are not detected.

The economic impacts of *BAL* are mixed. On the one hand, RPS increases by +2% (*Low*) to +4% (*High*) due to higher agri-environmental payments that farmers receive. Total agricultural payments thereby increase by 13%. On the other hand, less intensive land use decreases productivity and hence the production value declines. *BAL* thus shows the lowest and, depending on the climate change scenario, also the only negative changes in the production value of the agricultural sector. While the positive climate change impacts on yields can offset policy induced decreases in productivity in *High* (+1.0%) and *Similar* (+0.4%), the production value declines in *Shift* (−0.2%) and *Low* (−1.7%). GDP increases due to positive indirect effects on sectors such as energy and water, construction and services, but these impacts are negligible (between +0.01% and +0.06%). Changes in employment are marginally positive for all climate change scenarios (between +0.04% and +0.10%), except for *Low* (−0.02%).

3.1.3. Provisioning Pathway (PRO)

The decline of agri-environmental payments in *PRO* leads to intensification of agricultural land use. Fertilizer application increases, ecological focus areas nearly disappear and large scale afforestation (between 184,000 ha in *Similar* and 274,000 ha in *High*) takes place mainly on marginal areas in the Alps. This markedly increases total biomass production (from +19% to +26%).

Intensive management and high fertilizer use lead to higher pressures on ecosystems by deteriorating the *mean species richness of vascular plants* (between −4.3% and −4.4%) and by moving the *degree of naturalness* towards a state of higher anthropogenic influence (from +1.6% to +2.1%). GHG emissions also increase between +4% (*Low*) and +7% (*High*). The SOC content increases under *PRO* between +5% (*High*) and +11% (*Low*) due to higher C input from biomass production and afforestation. Changes in landscape diversity at national level are insignificant, but regional impacts can be substantial (e.g. afforestation on Alpine meadows leads to substantially reduced structural richness in the landscape).

RPS declines significantly due the elimination of the agri-environmental payments (from −3% to −6%). As agri-environmental payments make up a substantial amount of total policy payments, the latter decrease by around 37%. *PRO* positively affects the other ED indicators, as intensification of land use increases the output of the agricultural sector. Hence, the direct production value of the agricultural sector increases between +6% (*Low*) and +10% (*High*). Moreover, the rise in the output of the agricultural sector also implies a rise in intermediate and factor demand. This leads to GDP increases (about +0.2%) as well as raises employment rates by +0.4% (*Low*) to +0.6% (*High*).

3.1.4. Energy Provisioning Pathway (PRO_Energy)

The expansion of bioenergy production in *PRO_Energy* leads to large increases in both short rotation coppice plantations (between 177,000 ha in *High* and 219,000 ha in *Low*) as well as afforestation (between 376,000 ha in *Similar* and 429,000 ha in *Low*). This results in the highest total biomass output between +44% and +51% among all policy pathways.

Depending on the plantation size and landscape composition, the increase in short rotation coppice on cropland could improve landscape heterogeneity and biodiversity. Hence, the *degree of naturalness* improves towards more naturalness at national level in some climate change scenarios (−0.3% and −0.7% in *Shift* and *Low*, respectively). The *mean species richness of vascular plants* is still negatively affected (between −1.5% and −2.1%) but much lower compared to *PRO*. Short rotation coppice plantations require less fertilization than most other crops such that *PRO_Energy* has fewer GHG emissions than *BAU* and *PRO*, but still increase in all (from +1% to +3%) except the *Low* scenario (−1%). However, increasing above-ground biomass C stocks are not taken into account. The large increases in biomass production lead to higher SOC content (from +10% in *High* to +14% in *Low*). The impacts on landscape diversity are negative at national level in most climate scenarios (−1.2%, −1.6% and −1.4% in *High*, *Shift* and *Low*, respectively, as well as +0.1% in *Similar*), mainly due to a more monotonous landscape structure caused by large scale afforestation on Alpine meadows and some marginal grassland in the Alps. Notably, large regional differences exist as is shown in Section 3.2.3.

The economic impacts are comparable to *PRO* with declines of RPS (between −2% and −4%), large decreases in agricultural policy payments (−40%), and increases in the direct production value of the agricultural sector (between +8% and +12%), GDP (between +0.2% and +0.3%), and employment (between +0.5% and +0.7%). Slightly higher economic output in *PRO_Energy* than compared to *PRO* are due to regional price increases for fuel wood and short rotation coppice products, which are the results of meeting higher regional bioenergy demands.

3.2. Regional and Spatial Impacts

Aggregated results at national level hide important regional differences. These usually deviate in both sign and magnitude as exemplified in the following sections.

3.2.1. Biomass Production

Spatial impacts of climate change on total agricultural biomass production (dry matter from crops, forage, short rotation coppice and afforestation) are shown in Fig. 4. Grassland areas, especially those situated in and at the borders of the Alps, experience strong production increases as forage yields can gain from temperature increases in all precipitation scenarios until 2040. In contrast, crop yields are more exposed to changes in temperatures and precipitation as major cropland areas are located in warmer and drier flatlands in the North-East of Austria. This is most evident in the *Low* scenario, where decreases in mean annual precipitation sums lead to considerable yield losses in the North-East across all policy pathways (see Fig. A-2 in the online appendix).

3.2.2. Ecological Integrity

Analysis of ecological integrity is most meaningful at high spatial resolution. Spatial variation of the *mean species richness of vascular plants* among the four policy pathways for the climate change scenario *Shift* is displayed in Fig. 5. The importance of spatial differences is best represented in *BAL*. Although the national net impact is positive (Fig. 3), large areas are negatively affected. On the one hand, there is an increase in the *mean species richness of vascular plants* in the Alpine foreland of Lower Austria due to extensification and on some cropland (dark green patches) due to increases in ecological focus areas. On the other hand, many grassland areas (e.g. major Alpine valleys, northern Salzburg and in the South) are intensively utilized. This indicates that the opportunity costs for extensification are higher in these areas, and probably amplified due to climate change, than in the East. The *PRO_Energy* pathway is a counterpart example to *BAL* with a decrease of *mean species richness of vascular plants* at national level despite regional increase in species. Short rotation coppice plantations provide a higher *mean species richness of vascular plants* than most other crops. This leads to positive changes along major cropland areas where most of the short rotation coppice plantations take place (e.g. Danube flatlands in Upper and Lower Austria, north-western Lower Austria, southern Burgenland as well as south-eastern Styria). Intensification in almost all areas can be observed in the *BAU* and *PRO* policy pathways, although the respective impacts differ in their magnitude. Large local differences in the East are mainly the result of choices in crop rotations with varying effects on *mean species richness of vascular plants*.

As shown in Section 3.1.4, the national aggregated results on the *degree of naturalness* are somewhat mixed for *PRO_Energy*. Fig. A-3 (in the online appendix) illustrates these impacts at a 1 km grid resolution. It depicts gains in naturalness for afforested areas along the Alpine ridges in the West (bright green color) and increases in cropland areas with a high share of short rotation coppice (dark green color), most of them situated in flatlands around the Danube in Upper Austria, in the western part of Lower Austria, southern Burgenland and south-eastern Styria. The remaining area (cropland and intensively managed grassland) is mostly negatively affected due to more intensive land use. Fig. A-3 further reveals some local increases in naturalness in the North-East of Austria in *Low* and *Shift*. In these semi-arid areas, farmers are assumed to adapt to adverse climate change impacts on crop yields by lowering

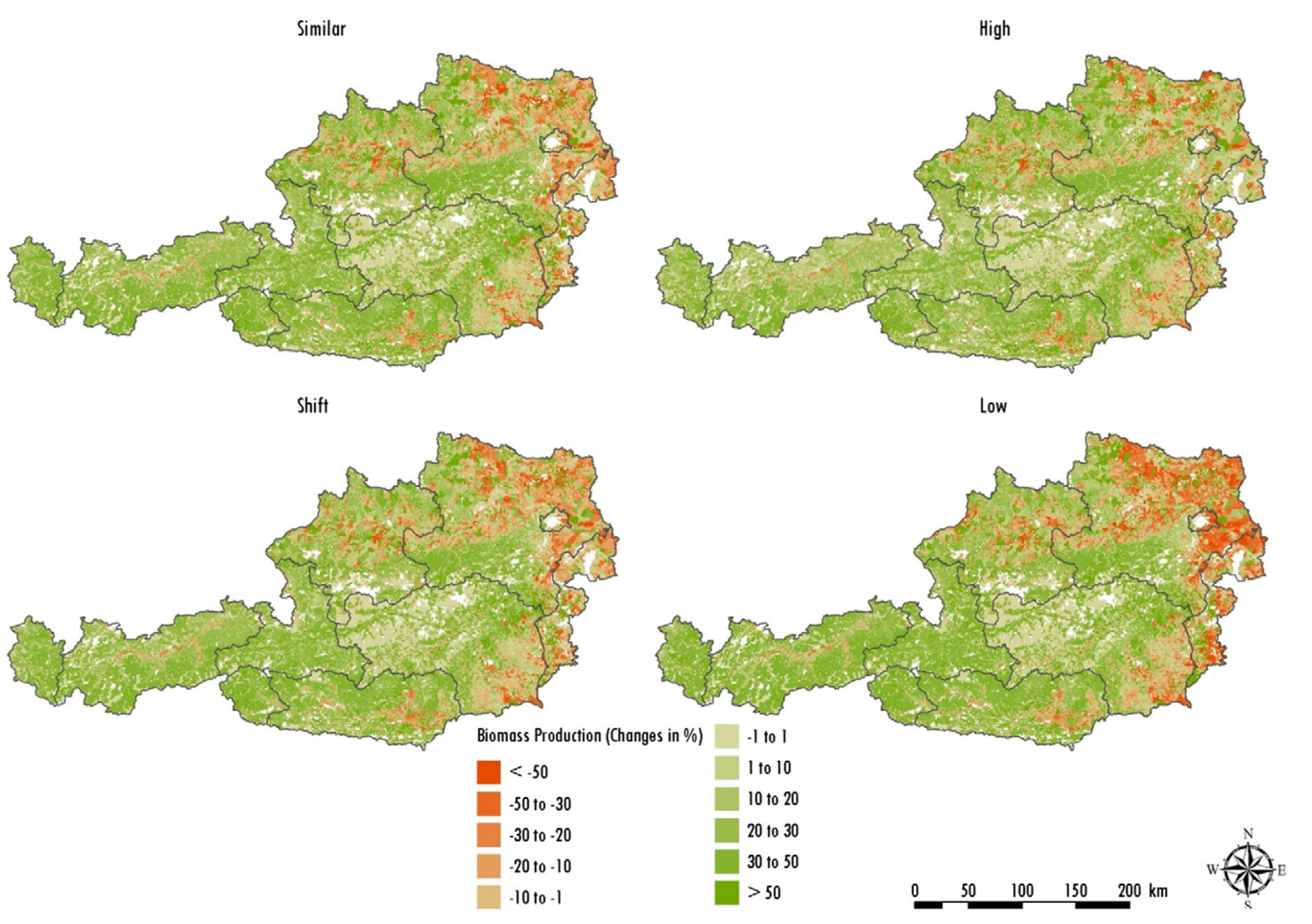

Fig. 4. Percent changes in total biomass production on agricultural land including afforestation in *BAU* for all climate change scenarios at 1 km grid resolution (compared to *REF*).

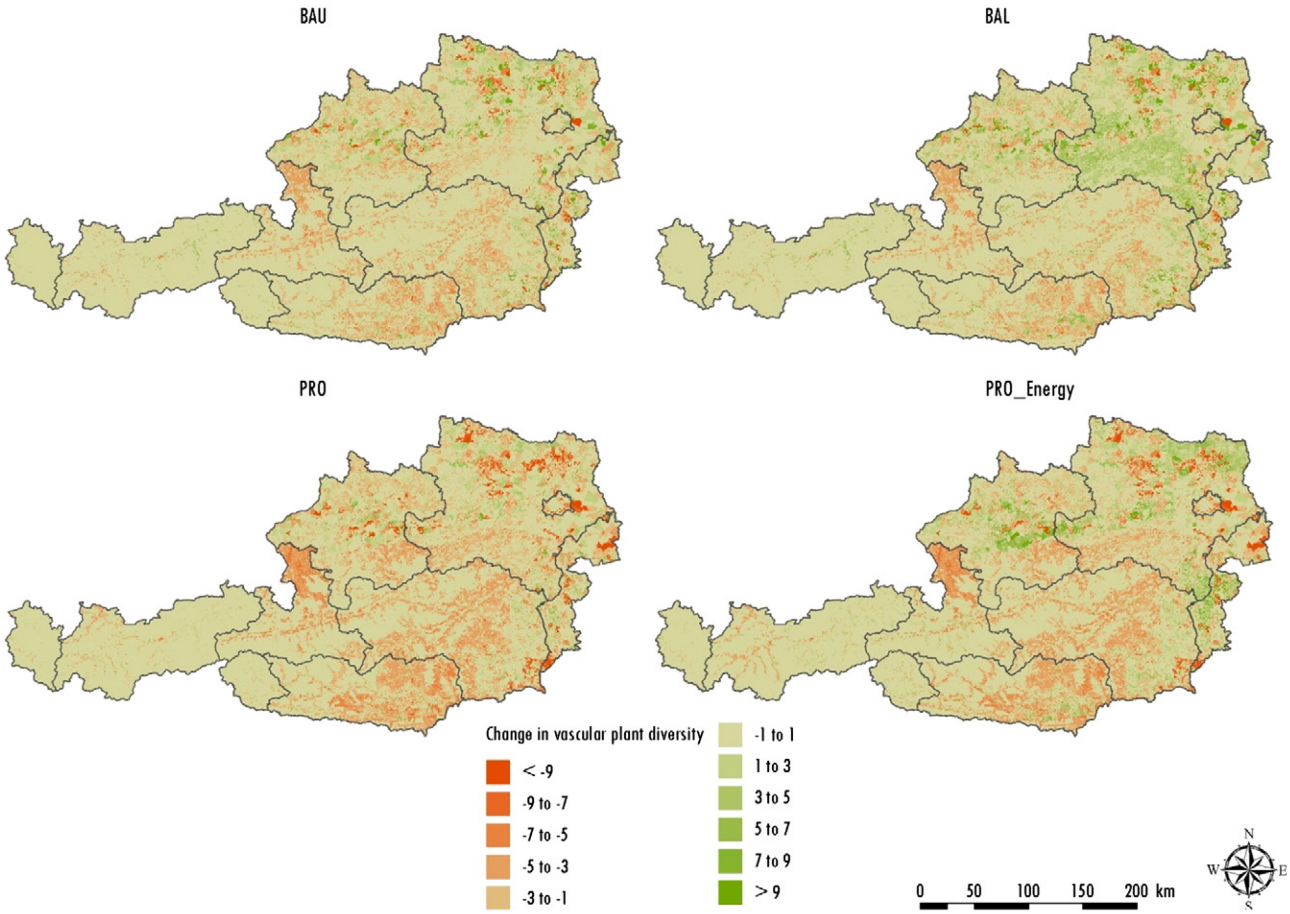

Fig. 5. Absolute changes in the mean species richness of vascular plants in the *Shift* climate change scenario for all policy pathways at 1 km grid resolution (compared to *REF*).

fertilizer inputs as well as by increasing the share of short rotation coppice plantations. This explains why *PRO_Energy* increases the amount of area closer to a natural state in *Low* and *Shift*.

3.2.3. Landscape Diversity

Landscape diversity is measured using the Shannon Diversity Index on $PASMA_{[grid]}$ results. Little effects are identified at the national level (see Fig. 3), but there are significant regional differences, as exemplified for *PRO_Energy* (Fig. 6). Changes in the Alpine regions are mainly affected by afforestation on Alpine meadows. Traditional management systems diminish the ecological and scenic value of Alpine landscapes. In the Alpine foothills as well as in the flat plains, the landscape quality benefits from the establishment of short rotation coppice. This can increase the structural richness especially in large-scale agricultural landscapes, but can also affect traditional structures like extensive meadows, hedges or orchards, especially when short rotation coppice areas increase substantially.

Attention should also be paid on the achievable level of detail for the analysis. An analysis raster of 25 m contains detailed information on land use, field sizes, and structures but omits many details like hedges or orchards that play an important role for the visual diversity of a landscape. Therefore, changes in landscape diversity need to be discussed regionally depending on specific site conditions and with spatially explicit indicators such as patch density or edge density (McGarigal and Marks, 1995).

3.2.4. Economic Impacts

Regional differences in economic impacts from climate change and policy pathways are due to heterogeneities in resource endowments, production conditions, sector composition, and trade opportunities. Fig. A-4 (in the online appendix) shows the results on regional GDP from the *AUSTR-IO* model. For instance, the federal state of Burgenland is most dependent on agriculture and forestry among all NUTS-2 regions and therefore shows the highest impacts on regional GDP. In contrast, the federal state of Vienna is hardly affected at all.

The policy pathways *PRO* and *PRO_Energy* incur the highest positive impacts in all federal states, while in *BAL* regional GDP is lowest and even negative in Burgenland, Lower Austria and Styria. The climate change scenarios hardly impact GDP in most federal states, except for Burgenland and Lower Austria. These two federal states are vulnerable to precipitation changes as most crop production is located in semi-arid regions with annual precipitation sums of about 500 mm. Hence, crop yield differences between *Low* and *High* and their consequential impact on GDP can be – relative to the other changes – considerable.

3.3. Trade-offs and Synergies

Trade-offs at national scale between biodiversity and other selected indicators are shown in Fig. 7 (for the relationship between all relevant indicators see Fig. A-5 in the online appendix). These figures reveal both trade-offs (i.e. negative relationships) and synergies (i.e. positive relationships) between our indicators. Note, that these figures represent the results of our particular scenario runs and not generalizable relationships between the indicators. Introducing other scenarios and/or different parameter settings may lead to significantly different relationships (see also the discussion in Section 4.2 on the limitations of applying sensitivity analyses in our IMF).

In the example of biodiversity (Fig. 7), we find strong and rather linear synergies with regard to naturalness, RPS, and GHG mitigation (i.e. naturalness and GHG emissions at 1 represent the best value, i.e. the

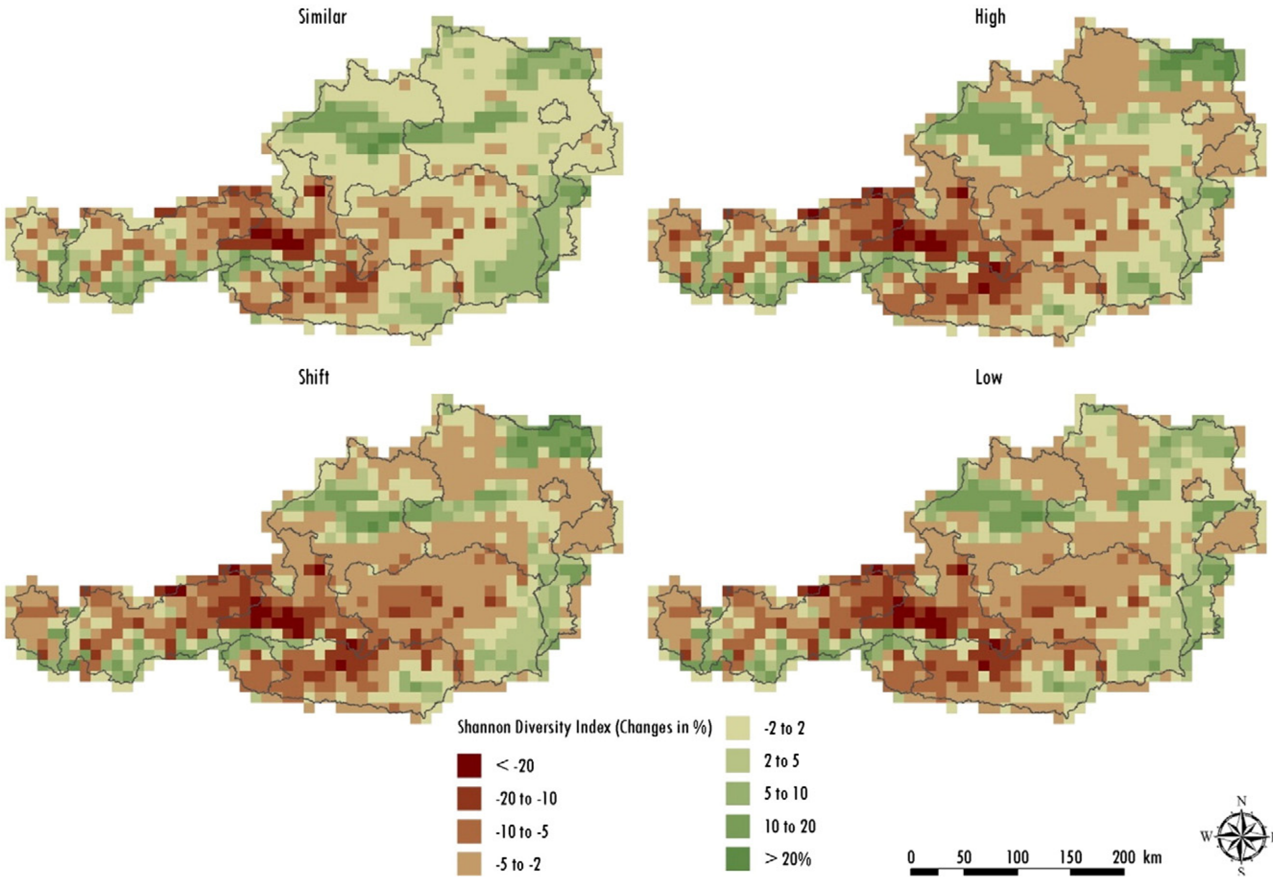

Fig. 6. Percent changes in the Shannon Diversity Index in *PRO_Energy* for all climate change scenarios at 10 km grid resolution (compared to *REF*).

most natural state and the lowest GHG emissions observed in the scenarios, respectively). This is not surprising, since (1) naturalness and biodiversity are closely linked conceptually, (2) farmers receive subsidies for adopting measures that are supposed to improve *regulation and maintenance* and *cultural* ES, which increases RPS, and (3) both biodiversity and GHG emissions are substantially driven by fertilizer rates (which decrease with higher agri-environmental payments).

Trade-offs seem to occur between biodiversity and biomass as well as biodiversity and macro-economic impacts (as normalized changes in GDP, agricultural sector output, and employment are almost the same in most scenario outcomes, they are not shown separately). In both cases the relationships are non-linear. This is due to the special case of scenario *PRO_Energy* (PRO_E in the graph) where gains in biomass production and macro-economic output are not only achieved by intensification but also by large scale afforestation and short rotation coppice plantations. This helps to decrease the impact on biodiversity in comparison to scenario *PRO*.

No clear relationship in our scenario runs can be identified between biodiversity and SOC content, although there seems to be a slight trade-off. This is due to the strong synergy between SOC content and biomass production (see Fig. A-5), as higher biomass production can increase crop residues and thus higher SOC content.

Regarding the remaining indicators (see Fig. A-5) we see that trade-offs and synergies between naturalness and other indicators are very similar to biodiversity. However, the largely positive impact of both afforestation and short rotation coppice plantations on naturalness in *PRO_Energy* further pronounces the complex relationship. GHG emissions generally increase with higher macro-economic output and biomass production, albeit the relationship is, again, non-linear due the positive impact of afforestation and short rotation coppice on fertilizer rates in *PRO_Energy*. Finally, within our scenario results SOC content shows no considerable interaction with other indicators, except for biomass production.

4. Discussion

4.1. Results

Our regional climate change impacts are similar to many other studies, e.g. intensification of agricultural land use (van Meijl et al., 2006; Leclère et al., 2013; Schönhart et al., 2014), regional differences with intensification in favorable areas and extensification in marginal areas (Audsley et al., 2006; Henseler et al., 2009), the vulnerability of crop production regions in the North-East (Alexandrov et al., 2002; Kirchner et al., 2012; Strauss et al., 2012; Thaler et al., 2012), increases in forage yields on Alpine grassland (Smith et al., 2005; Henseler et al., 2009; Briner et al., 2012; Schönhart et al., 2014), and the positive impact of increased biomass output on SOC content in Alpine grasslands (Smith et al., 2005) have been observed in other studies as well. Positive RPS impacts are more moderate than in Schönhart et al. (2014) and Leclère et al. (2013), but confirm the magnitude and direction of change.

At national level, the alternative policy pathways have a stronger impact on most indicators than the regional climate change scenarios for the investigated period (2025–2040) (see Fig. 3 and Table A-2 in the online appendix). This is also a very common finding among global change studies (c.f. Audsley et al., 2006; Metzger et al., 2006; Lehmann et al., 2013; Schönhart et al., 2014). Nevertheless, the regional climate change scenarios lead to substantial spatial variation in many indicators and in some cases also influence the direction of impacts at national scale (i.e. sector value and biomass production in *BAL*; GHG emissions in *BAL* and *PRO_Energy*; SOC content in *BAU* and *BAL*; see Figs. 3 and A-2).

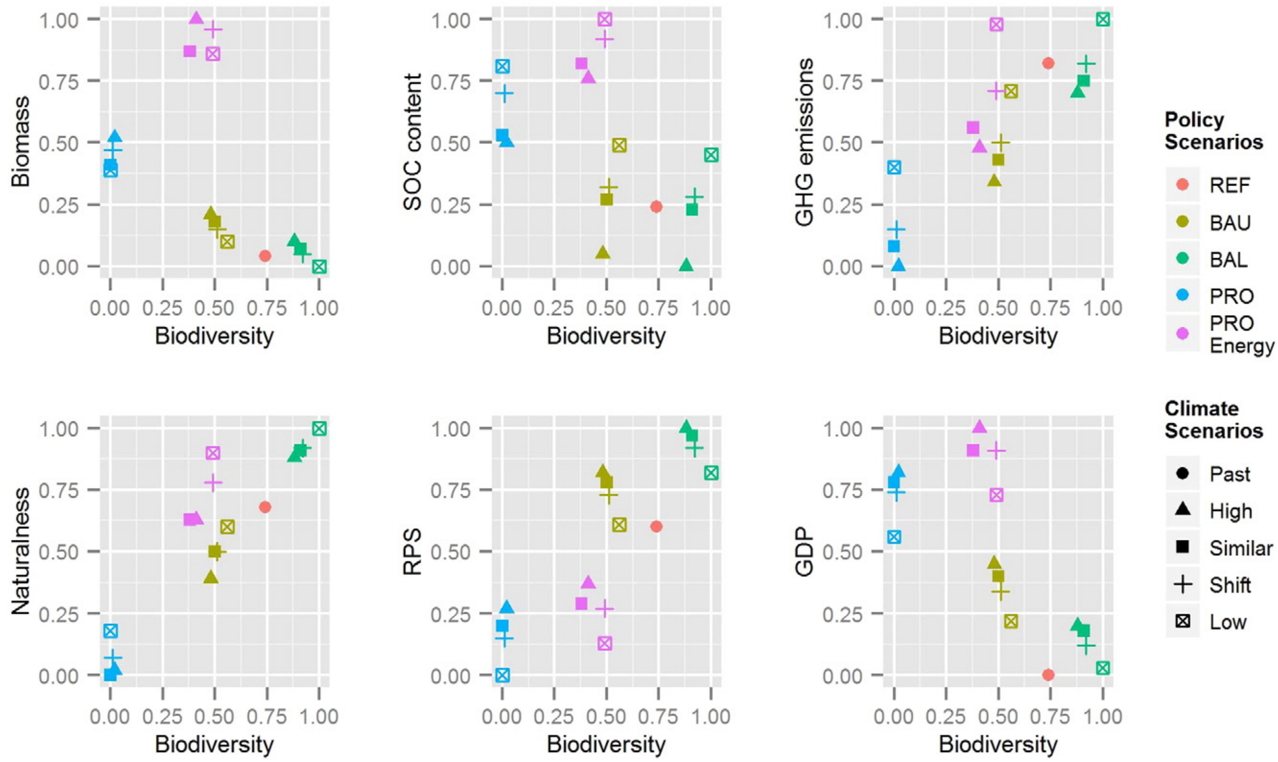

Fig. 7. Trade-offs and synergies between biodiversity (x-axis), i.e. area weighted mean species richness of vascular plants, and selected indicators (y-axis). Note: The absolute values from the scenario results have been normalized to 1 (best value) and 0 (worst value), e.g.: 1 for naturalness and GHG emissions refers to the most natural state and lowest GHG emissions observed in all scenarios, respectively (and vice versa). Hence, trade-offs are characterized by points being distributed along a downward slope, whereas synergies are characterized by points being distributed along an upward slope. The different values for the same policy scenarios represent the four climate change scenarios. Abbreviations: RPS — regional producer surplus; SOC — soil organic carbon; GDP — gross domestic product.

Moreover, there are also many instances in which the magnitude of climate change scenario impacts shown in *BAU* outweighs alternative policy impacts. Climate change is a dominant factor particularly in regions and sectors vulnerable to changes in temperatures and precipitation. The negative impacts on biomass production in the North-East of Lower Austria and in the North of Burgenland occur across all policy pathways, even in *PRO_Energy* (see Fig. A-2). This demonstrates that climate change impacts and uncertainty assessments need to consider spatial and regional heterogeneities and should account for future policy pathways.

The results emphasize the importance of capturing spatial heterogeneity. Although near-future climate change is expected to increase total biomass production at the cost of *mean species richness of vascular plants* in most areas, opposite trade-offs are visible for semi-arid croplands in the East, especially in *Shift* and *Low* (compare Figs. A-2 and 5). In addition, increases in afforestation measures and short rotation coppice plantations in *PRO* and *PRO_Energy* indicate that local synergies between many ES and ED indicators can be achieved. These two land use options can increase both biomass and macro-economic output and can improve naturalness at landscape level (see Fig. A-3 in the online appendix). Short rotation coppice plantations can – in adequate size – further raise the *mean species richness of vascular plants* (see Fig. 5), provide more landscape diversity (see Fig. 6), as well as decrease GHG emissions due to less fertilizer application. However, short rotation coppice plantations and afforestation provide a completely different type of biomass than traditional agricultural crops, i.e. woody biomass cannot be used as food or feed but is destined to energy, pulp and paper, and paperboard industries. Possible indirect land use change effects and related impacts on biodiversity and greenhouse gas emissions due to lower food and feed production in Austria may more than offset the positive regional impacts. This also applies to the *BAL* pathway which has lower overall biomass production. Accounting for these leakages might be overcome by linking $PASMA_{[grid]}$ with a global bottom-up partial-equilibrium model for agriculture and forestry such as *GLOBIOM* (Havlík et al., 2011).

Trade-offs identified in our study often follow the common pattern of increasing *provisioning* ES and economic output leads to declining *regulation and maintenance* ES and vice versa — a very prevailing finding in both empirical (Jiang et al., 2013; Raudsepp-Hearne et al., 2010; Tilman et al., 2002) and scenario based (Goldstein et al., 2012; Nelson et al., 2009) studies. These trade-offs become especially apparent in *PRO* and *BAL*, as the results for these scenarios are mainly concentrated in the extreme opposite corners of the scatterplots (see Figs. 7 and A-5 in the online appendix). Climate change (*BAU*) amplifies these trade-offs, where it leads to an intensification of land use. *PRO_Energy*, however, reveals some potential synergies between biomass production, macro-economic outputs, and *regulation and maintenance* ES (e.g. naturalness and GHG emissions). It underlines, in accordance with other studies (Badgley et al., 2007; Bryan and Crossman, 2013; Helming et al., 2011b; Pretty et al., 2006; Swallow et al., 2009), that the relationships between ES, as well as ES and ED indicators, are complex and that synergies between *provisioning* and the other ES categories are possible. Hence, while we did not reveal policy pathways without any trade-offs (and find this to be a very unlikely case), there seems to be potential to both alleviating trade-offs and fostering synergies between ES and ED (Koschke et al., 2013; Maes et al., 2012; Maskell et al., 2013).

4.2. Integrated Modeling Framework (IMF)

Our IMF has some weaknesses that are worth to be discussed. For example, it mainly allows for comparative static impact analysis (although EPIC and *Caldis vâtis* are able to simulate processes in a dynamic manner). We could not consider dynamics in biodiversity, e.g. the legacy effects of intensive agriculture (Horrocks et al., 2014). Positive impacts on biodiversity and naturalness have therefore to be viewed with caution as it may take decades for ecosystems to develop to a status that resembles low anthropogenic pressure (Tasser et al., 2008; Dullinger et al., 2013).

Furthermore, the static nature of $PASMA_{[grid]}$ is not fully compatible with the dynamic nature of forest management and thus forest growth models such as *Caldis vâtis*. To overcome this shortcoming, we decided to use forest growth data from *Caldis vâtis* only for afforestation measures on agricultural land by discounting net present values for different rotation periods and forest types using the concept of HRUs (see Section 2.1.2). *Caldis vâtis* is better equipped to account for climate change impacts on biomass output from currently observed managed forest land. Notably, *Caldis vâtis* output data for forestry land are only used in the policy pathway with a renewable energy focus, i.e. *PRO_Energy*, as the main focus of this analysis was on agricultural landscapes.

The scenario outcomes in *PRO_Energy* may be scrutinized as the coupling *of* $PASMA_{[grid]}$ and *BeWhere* does not consider market feedbacks between food, feed, and energy crops as is often assumed for a small open economy such as Austria. The high levels of short rotation coppice production and afforestation as observed in *PRO_Energy* may only be achieved if policy makers guarantee high subsidies to the producers of bioenergy crops. As already mentioned in Section 4.1, the inclusion of partial or general equilibrium models could help to account for market feedbacks and would also reveal whether the small open economy assumption is justified for our setting.

The scale of the modeling linkages in the IMF and the accompanying large data sets impede large scale sensitivity analyses of our and additional drivers to ES and ED indicator outcomes (c.f. Bryan and Crossman, 2013) as well as the inclusion of a larger set of land use measures that could produce better synergies among the ES and ED indicators (e.g. conservation tillage). Such assessments are crucial, given that uncertainties are high with regard to climate change, policy changes, market developments as well as the linkages between land use activities and ES provisioning. Moreover, these uncertainties are likely to increase with each element added to the model chain (Wilby and Dessai, 2010). While scenario analysis is a recommended tool to explore possible future pathways and thus uncertainty ranges (Metzger et al., 2006), it could be worthwhile to provide a more extensive analysis of sensitive parameters with high uncertainty and impact (e.g. food and energy prices). This might be overcome in future assessments when more efficient model linkages and a permanent software structure are established, similar to the technical integration approach (i.e. common graphical user interface and data storage) of SEAMLESS-IF (Janssen et al., 2011) or the econometric meta-modeling approach of SIAT (Helming et al., 2011a,b).

Finally, it remains crucial to link trade-offs and synergies in the supply of ES to their impacts on human well-being (TEEB, 2010). Many benefits and costs are difficult to assess due to limitations of monetary valuation methods on non-market ES (Turner et al., 2003; Zhang et al., 2007; Pirard, 2012). Therefore, studies often refrain from an economic valuation of non-market ES (Helming et al., 2011a). Instead, they quantify the impacts on non-market ES via biophysical indicators and value only the benefits of marketed goods from *provisioning* ES (c.f. Swallow et al., 2009; Schönhart et al., 2011a; Goldstein et al., 2012; Briner et al., 2012). Our integrated assessment follows this approach.

5. Conclusion

Our findings confirm the prevalence of the typical trade-off between *provisioning* and other ES categories. Consequently, supply of non-market ES generally decreases with higher macro-economic outputs (e.g. GDP). Nevertheless, we identify exceptions (e.g. biomass and SOC content), particularly for certain land use activities at landscape level (e.g. short rotation coppice). Hence, our analysis illustrates the complex relationships between different ES and ED indicators in agricultural landscapes, and emphasizes the importance of eliciting spatial heterogeneity as well as the impact chains of different policy pathways. In addition, considerable climate change impacts on many indicators emphasize the necessity to account for regional climate change uncertainty.

Our findings provide an extensive foundation on which agri-environmental schemes can be improved in order to provide a more balanced and efficient supply of ES. Policy makers should take into account spatial heterogeneity in agri-environmental policies in order to promote synergies and target extensification measures in areas with high intensification. In addition, regions where synergies of short rotation coppice plantations can be utilized (e.g. intensive cropland) should be another focus of policy interventions. High resolution data sets should be developed, continuously updated, and made available to researchers. Furthermore, intensification pressure from climate change should be considered in order to foster policies that maintain extensive land use on permanent grassland and to allow for a dynamic adjustment of agri-environmental payments to changes in opportunity costs. The adoption of mitigation measures should be incentivized as intensification usually increases GHG emissions. Finally, focus should be put on developing technologies and land use systems that supply multiple ecosystem benefits (e.g. short rotation coppice, crop rotation systems, conservation tillage).

In further research, multi-criteria analysis could help to prioritize policy pathways, the efficiency of spatial targeting of agri-environmental payments could be assessed, and additional IMF applications could reveal the trade-offs between “land sparing”, i.e. focusing on intensive land use and natural reserve patches, and “land sharing”, i.e. focusing on more heterogeneous and generally less intensively used land, developments.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2014.11.005.

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Article IX

Schmidt, J., Schönhart, M., Biberacher, M., Guggenberger, T., Hausl, S., Kalt, G., Leduc, S., Schardinger, I., Schmid, E.
Regional energy autarky: Potentials, costs and consequences for an Austrian region.

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Regional energy autarky: Potentials, costs and consequences for an Austrian region

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HIGHLIGHTS

- ▸ Energy autarky strong vision for many regional actors.
- ▸ Assessment of consequences of energy autarky for a rural region in Austria.
- ▸ Novel modeling approach coupling energy system model with land use model.
- ▸ Power and heat autarky causes high costs and decline in regional food and feed production.
- ▸ Heat autarky achievable at lower costs by utilizing regional forestry and agricultural biomass.

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ABSTRACT

Local actors at community level often thrive for energy autarky to decrease the dependence on imported energy resources. We assess the potentials and trade-offs between benefits and costs of increasing levels of energy autarky for a small rural region of around 21,000 inhabitants in Austria. We use a novel modeling approach which couples a regional energy system model with a regional land use optimization model. We have collected and processed data on the spatial distribution of energy demand and potentials of biomass, photovoltaics and solar thermal resources. The impacts of increasing biomass production on the agricultural sector are assessed with a land-use optimization model that allows deriving regional biomass supply curves. An energy system model is subsequently applied to find the least cost solution for supplying the region with energy resources. Model results indicate that fossil fuel use for heating can be replaced at low costs by increasing forestry and agricultural biomass production. However, autarky in the electricity and the heating sector would significantly increase biomass production and require a full use of the potentials of photovoltaics on roof tops. Attaining energy autarky implies high costs to consumers and a decline in the local production of food and feed.

1. Introduction

Local actors at community level as well as politicians on regional and national level often thrive for energy autarky.[1] Instead of importing energy resources, they assume that producing energy locally will bring along positive economic or environmental effects. The concept of absolute energy autarky does not allow any balancing thus implying that no energy resources are imported at all. Relative autarky allows for the balancing of energy needs between sectors (e.g. surplus production of

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[1] In a regional and national context, proponents of the concept include e.g. the Austrian minister of agriculture, forestry, environment and water management, Nikolaus Berlakovich, who stated that "Energy autarky is the answer." (Auer, 2011), the mayor of St. Georgen (Austria) Franz Augustin, who says that, "the main target is to achieve energy independence until 2036." (Eichinger, 2012) or the German mayor and representative of a provincial government Gabriele Theiss who thinks that "An autark energy supply with participation of citizens is a very important topic" (Wieduwilt, 2012). All translations from German to English are by the authors. On a larger geographical scale, elements of the idea of energy autarky are reproduced in the discussions on energy independence (USA) and security of supply (Europe).

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electricity for substituting imports of transportation fuel) or between different seasons (e.g. surplus production in the summer and imports in the winter season). Another framework definition of energy autarky includes the different energy sectors to be considered in the assessment: gray energy embedded in imported products as well as some useful energy sectors (such as heat or power or transportation) may be included or excluded from the analysis (Müller et al., 2011).

Proponents of energy autarky argue that local energy production may generate benefits such as decreased transportation distances of energy resources, increased local added-value, maintenance of cultural landscapes, insurance against future higher energy prices (Müller et al., 2011), creation of local jobs (Berndes and Hansson, 2007), increasing tourism (Jiricka et al., 2010), and strengthening of regional identity (Abegg, 2011). Frequently, regional autarky is considered to be achieved with renewable energies only (no locally available fossil fuels may contribute to the target) in order to contribute to a more sustainable renewable energy system. There are, however, serious challenges attached to the idea of regional energy autarky. From the perspective of neoclassical trade theory, restrictions in extra-regional (energy) trade lead to less efficient outcomes due to foregone benefits from comparative cost advantages in other regions. Other obstacles may limit the utilization of the regional renewable energy potentials such as the high costs induced by a significant shift in the energy system, eventual social disruptions due to regional losers and winners of an energy autarky strategy, and consequences for food and feed production or for security of energy supply (Abegg, 2011). The public debate on regional energy autarky appears similar to those about local food systems. One can observe unreserved proponents of regional production and marketing, who may be captured in a "local trap" by ignoring economic efficiency gains through trade as well as social and environmental disadvantages (Born and Purcell, 2006). However, fundamental critics of energy autarky concepts may argue from a too narrow economic perspective ignoring market failures such as external effects of energy production systems or oligopolistic market power. What seems necessary – as it can be observed in the debate on local food systems (Schönhart et al., 2009) – is a third perspective that analyses the feasibility of regional energy autarky. The feasibility analysis should be based on a detailed regional energy demand analysis and estimates of physical resource potentials for renewable energies. Such analysis should assess consequences for land use, costs of a new energy system and transfers of income between economic agents in and outside the region.

Studies in the field of regional energy analysis mainly focus on assessing technical and economic potentials, optimal plant locations and biomass logistics in the region (Leduc et al., 2009; van der Hilst et al., 2010; Kim et al., 2011; Kocoloski et al., 2011), compare various bioenergy conversion chains regionally (Mabee and Mirck, 2011) or conduct country or European wide analysis for the assessment of the potentials and the optimization of biomass conversion chains (Berndes and Hansson, 2007; König, 2011; Kalt and Kranzl, 2011). Until now, numerous studies on regional or countrywide renewable energy potentials have been published (Beccali et al., 2009; Stocker et al., 2011). However, only few publications take economic implications of energy autarky on regional production and consumption into account. Streicher et al. (2010) assessed the technical rather than economic feasibility of energy autarky for Austria until 2050. Burgess et al. (2011) modeled renewable energy supply potentials and energy demand for a small English region, explicitly addressing the trade-offs between food, feed and bioenergy production in physical units. However, their model did not consider economic effects in attaining energy autarky. Bryan et al. (2010) have assessed the trade-offs between food, feed, energy, and fiber production at a regional level and considered economic conditions of agricultural production. However, they did neither model the demand side nor assess the potentials of renewables besides bioenergy.

The Austrian Climate fund sponsored a series of projects to address some of these issues. We will report on the results of the research project BioSpaceOpt, conducted in the Sauwald region in Upper Austria. The agriculturally dominated rural region is inhabited by around 21,000 people. Within the project, we have assessed regional energy demand and economic potentials of renewable energy production from bioenergy with a particular focus on the competition between bioenergy and food production and the potentials for photovoltaic (PV), solar thermal and heat pumps. We apply a novel modeling approach that couples the agricultural land use optimization model PASMA with the energy system optimization model BeWhere to assess different scenarios of energy autarky in the region and depict consequences for local agricultural production as well as imports and exports of energy, food and livestock feed.

The article is structured as follows: in Section 2, methods and data are presented, while Section 3 reports on the results and Section 4 discusses the results and draws final conclusions.

2. Methodology and data

2.1. Case study region and project

The case study region Sauwald is a rural region in Upper Austria next to the German border (see Fig. 1). It encompasses 12 municipalities with a total of 20,619 inhabitants and an area of 302 km^2. The population density of 68 persons km^{-2} is below the national average of 100 persons km^{-2}. Agriculture and forestry are important economic sectors in the region: while nationally, only 4.4% of all jobholders work in the agriculture and forestry sector, this proportion reaches 10% in the Sauwald region. Sauwald is member of the municipality-level climate alliance network and is participating in the European regional development program LEADER+. Current land use patterns show the rural character of the region and were determined by combining satellite images with calibrated measurement points (Bauerhansl et al., n.d.) and data from the Integrated Administration and Control System (IACS) of the Common Agricultural Policy (CAP) (Federal Ministry of Agriculture, Forestry, Environment and Water Management, 2011). Deciduous forests cover 3980 ha (i.e. 13% of total regional land resource), which corresponds to a biomass stock of 10^6 m^3 while coniferous forests cover 8,700 ha (29%) corresponding to $3.2 \cdot 10^6$ m^3 of standing biomass. Agricultural land use dominates with 8,300 ha (27%) of grass lands and 6,040 ha (20%) crop lands. The remaining 11% can be associated with settlements, sealed areas, water bodies and undefined vegetation. Land covers are evenly distributed, with the exception of some hilly regions and the northern areas along the Danube being dominated by forests (see Fig. 2).

2.2. Energy demand and current supply structure

All public authorities, private businesses, and operators of district heating plants and networks have been asked for data on their energy demand and fuel consumption. While a high share of public authorities responded (90% response rate), feedback from district heating operators (57% response rate) and of business establishments (1% response rate) was significantly lower. Total demand for heat and warm water by public authorities was estimated based on the provided information. Heating demand of households and businesses was estimated with a heat demand

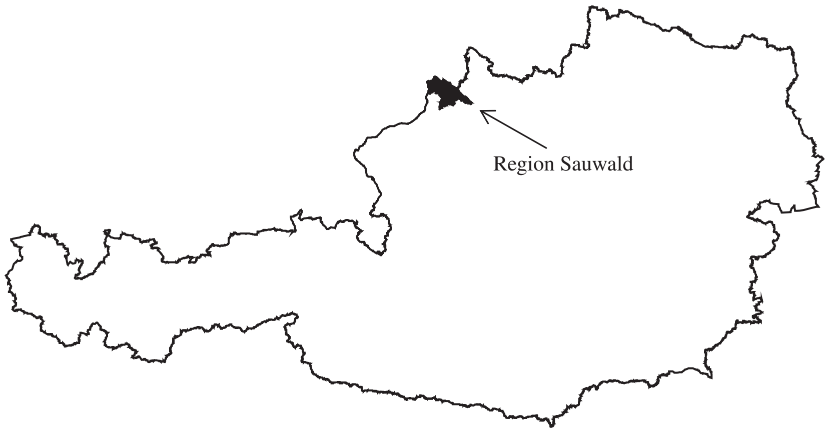

Fig. 1. Map of Austria with the case study region Sauwald in Upper Austria.

Fig. 2. Spatial distribution of main landcover classes.

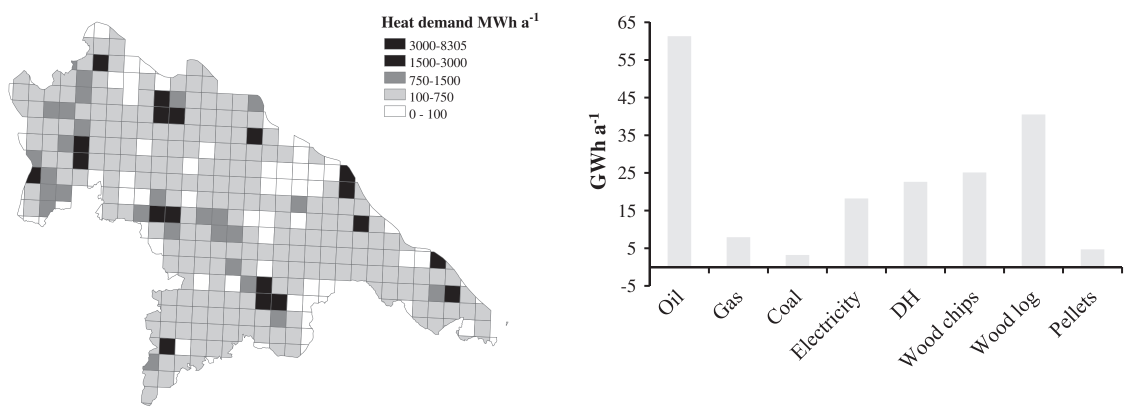

Fig. 3. Spatial distribution of modeled annual heat demand in MWh a^{-1}(left) and annual primary energy consumption for heating by fuel type in GWh a^{-1} (right) in the Sauwald region for the year 2010. DH is biomass district heating.

model based on the size and age of buildings and on the number of employees in a certain sector (see Schmidt et al., 2010 for details). Heat demand was estimated spatially explicitly for the Sauwald region at a spatial resolution of 1 km^2. It has been separately estimated for the winter and summer seasons based on the observed regional heating degree days. The model yields a total demand of 159 GWh_{heat} a^{-1}, which corresponds to 8.50 MWh_{heat} $person^{-1}$ a^{-1}. It consists of 6.89 MWh_{heat} $person^{-1}$ a^{-1} for heating and warm water in dwellings, 1.38 MWh_{heat} $person^{-1}$ a^{-1} for businesses, and 0.23 MWh_{heat} $person^{-1}$ a^{-1} for public buildings. Fig. 3 (left) shows the spatial distribution of the heat demand in the region, indicating that some of the settlements have rather high heat densities which may make district heating solutions economically feasible.

Fig. 3 (right) shows the results of the heat demand estimation model. Around 56% of the heat is supplied by fossil fuels (including electricity). The figure also indicates substantial potential for substitution of oil fired boilers by biomass boilers or other renewable heating options. Biomass district heating is available in the region with 11 plants supplying 11 district heating networks. Power demand is estimated from the average load in the regional network, which has been provided by the local network operator. The average load is 8 MW, the total demand is therefore 70 GWh_{power} a^{-1}. The demand includes all regional households, businesses, and public authorities. Due to the absence of electricity intensive industries, the average regional demand of 3.4 MWh_{power} $person^{-1}$ a^{-1} is below the national average (in 2010: 6.52 MWh_{power} $person^{-1}$ a^{-1}). Consequently, there may be a considerable gap between regional consumption of electricity and (gray) energy demand induced by imports of products to the region. Regional electricity production is currently close to zero apart from some PV facilities. Demand for transportation fuel was estimated to 172 GWh_{fuel} a^{-1} (8.20 MWh_{fuel} $person^{-1}$ a^{-1}) from national average data, including cargo transportation. However, transportation fuel is not considered to be supplied regionally with the exemption that

10% of transportation is provided by electric cars in 2020 in one of the scenarios. This yields an extra demand for electricity of 7 GWh a^{-1} (0.34 MWh_{power} $person^{-1}$ a^{-1}).

2.3. The energy system model BeWhere

We are using the existing energy system model BeWhere (Leduc et al., 2009; Schmidt et al., 2010, 2011) to optimize utilization of local renewable energy resources for heat and electricity supply. The mixed integer programming model minimizes costs of annual heat and electricity supply by considering two seasons (winter/summer). The spatial distribution of heat demand as well as renewable energy potentials are used as input at a resolution of 1 km^2. Electricity demand is aggregated to the Sauwald region neglecting effects on distribution and transmission grids. The model is spatially explicit, i.e. seeks to find optimal biomass plant positions, supply locations and transportation routes as well as optimal choices on the production of bioenergy products (i.e. plant oil and pellets) and the construction of district heating networks. Transportation distances between the grid cells are calculated on the basis of the existing road network. Only road transportation is available in the region. Biomass, PV, solar thermal and fossil fuels may be used to supply the region as shown in Fig. 4. The costs include the production costs of biomass, transportation costs of biomass from the production site to the plant or end-consumer, plant investment, operation and maintenance (O&M) costs, investment costs for district heating networks, transportation costs of pellets and plant oil to consumers, investment costs for heating infrastructure at the consumer such as biomass or heating oil boilers, heat exchangers, and PV and solar thermal installations and costs for heating oil and grid electricity. Certain technologies can be scaled to different sizes (such as biomass plants). The model may therefore select between different plant sizes. A plant of the same technology but with a different size may have different investment costs, O&M costs and conversion efficiencies as outlined in Kalt and Kranzl (2011). Additional investments in renewable energy technologies are annualized assuming an interest rate of 5% and a lifetime of 20 years. We have assumed an interest rate of 5% because investments in energy conversion technologies are capital intensive and will have to be financed mainly by risk capital provided by banks or other investors and will not be, to the greater part, provided by local savings. A rate of 5% can be considered low in this context therefore.

2.3.1. Model structure

The model, including the handling of biomass logistics and the integration of biomass supply curves and district heating, is well documented in Schmidt et al. (2011), however, balancing of electric power is modeled in more detail in this model version:

$$p_t^{grid} + \sum_i (p_{i,t}^{bio} + p_{i,t}^{pv}) = \overline{d}_t^{pow} + \eta_t^{heatpump} \sum_i h_{i,t}^{heatpump}, \forall t$$

where power taken from the national grid p_t^{grid} in season t and power produced in local renewable biomass plants $p_{i,t}^{bio}$ and from PV $p_{i,t}^{pv}$ in season t at locations i has to balance the total power demand in the season which is given by the sum of modeled power demand $\overline{d}_t^{pow}$ plus the power consumed by heat pumps installed in the region $\eta_t^{heatpump} \sum_i h_{t,i}^{heatpump}$. Balancing of heat demand and supply is, due to the availability of additional heating technologies, also slightly different to previous model versions:

$$\eta_{i,t}^{dh} \left(\sum_j \eta_{j,i,t}^{trans} h_{j,i,t}^{dh} \right) + \sum_k h_{i,k,t}^{biomass} + h_{i,t}^{fossil} + h_{i,t}^{heatpump} + h_{i,t}^{st} = \overline{d}_{i,t}^{heat}, \forall i,t$$

District heating heat supply $h_{j,i,t}^{dh}$, factoring in losses of transporting heat from plant to the grid cell $\eta_{j,i,t}^{trans}$ and losses in the distribution network within the gridcell $\eta_{i,t}^{dh}$ plus the sum of all biomass utilization in different types of single-dwelling boilers k (i.e. pellets, wood chips) in the region $h_{i,k,t}^{biomass}$ plus heat generated by heating oil $h_{i,t}^{fossil}$ plus heat generated by heat pumps $h_{i,t}^{heatpump}$ and heat generated by solar thermal production $h_{i,t}^{st}$ has to meet the demand given by parameter $\overline{d}_t^{heat}$.

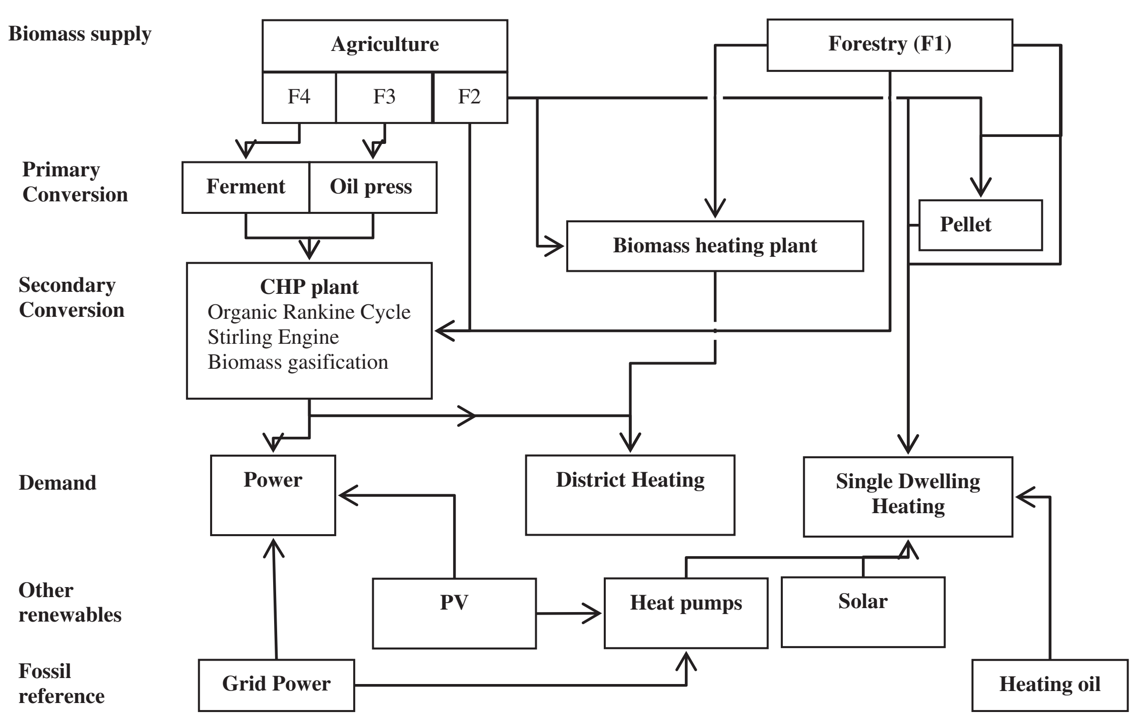

Fig. 4. Conversion chains in the model.

PV and solar thermal heat production compete for the same roof top areas which is modeled by

$$a_i^{PV}+a_i^{ST} \leq \overline{a}_i^{roof}, \forall i$$

where a_i^{PV} is the variable denoting the area dedicated to PV while a_i^{ST} is the area dedicated to solar thermal heat production. Parameter $\overline{a}_i^{roof}$ denotes the roof area available in a grid cell (all in m^2). The final production of power $p_{i,t}^{pv}$and heat $h_{i,t}^{st}$ in each period is calculated by multiplying the dedicated area with an indicator of production per m^2, denoted $pr_{i,t}^{PV}$ in the case of PV

$$a_i^{PV} pr_{i,t}^{PV} = p_{i,t}^{pv}, \forall i,t$$

and denoted $pr_{i,t}^{ST}$ in the case of solar thermal production

$$a_i^{ST} pr_{i,t}^{ST} = h_{i,t}^{st}, \forall i,t.$$

2.4. Technologies

The research project focused mainly on bioenergy, PV, solar thermal heat and heat pumps. There are no major hydro-potentials in the region besides the Danube River which is at the border of the region and not considered due to its supra-regional character. Wind power has been rejected on various occasions by the regional population due to concerns of esthetics in the cultural landscape and therefore excluded from our analysis as well. Fossil reference technologies are single-dwelling boilers fueled by heating oil and electricity from the grid. Technology and cost data, representing typical values for the case of Austria, are based on current market prices and data collected within different studies with a focus on energy supply. Data for bioenergy technologies have been adopted from Kalt and Kranzl (2011). Data for solar thermal systems, heat pumps and PV are primarily based on current market prices published in Biermayr et al. (2011). Forecasts for cost developments and additional data have been obtained from Kranzl et al. (2011) and Müller et al. (2010).

2.4.1. Bioenergy technologies

We consider bioenergy technologies for heat production in boilers for single-dwelling buildings, for heat production in district heating plants and for combined heat and power production. The feedstock for bioenergy production consists of forest wood, short rotation coppice, corn and oil crops from cropland as well as forage products from cropland and permanent grassland such as maize silage or grass silage. The full set of feedstock is depicted in Table 1 while Fig. 4 shows the full set of conversion chains. Biomass feedstock groups F3 (oil crops) and F4 (biogas crops) may be used for food, feed or for energy production. Only small-scale biomass Combined Heat and Power (CHP) technologies (up to 2 $MW_{biomass}$) are considered due to the comparatively low heat demand in the region. Most technologies are well known and currently used in Austria, but some are not commercially available yet such as integrated biomass gasification CHP plants. Uncertainties are therefore associated with the cost-estimates and conversion efficiencies for the modeled year 2020. Significant amounts of manure may be available in the region for the production of biogas. However, potential supply quantities are distributed over the whole region and the economic viability of biogas production from manure is considered unlikely for this setting. Therefore, we did not assess this option in detail.

Table 1
Biomass feedstock.

Category	Feedstock
F1-Forestry biomass	Wood logs, wood chips
F2-Short rotation coppice	Wood chips from poplar (3 year rotation)
F3-Oil crops	Rapeseeds, sunflower
F4–Biogas	Silage maize, grass silage (temporary and permanent grassland)

2.4.2. PV and solar thermal potentials

We have calculated potentials for solar thermal and PV production on roofs to reduce land-use competition – currently roof tops are not used for any other purpose. Solar potential calculations are therefore based on available roof areas for solar technologies, solar irradiation of the region and assumed efficiencies of the conversion technologies. In order to calculate potential areas for establishing roof top solar thermal or PV installations, roof areas are linked to known building areas and multiplied with corresponding regional irradiation values (PVGIS home, 2012). To distinguish between solar thermal potential – based on direct irradiation and relevant for covering heat demand – and potential for PV panels – based on global irradiation and relevant for covering electricity demand – the following assumptions are made: the direct irradiation on planes at 60° inclination angle (581 kWh m^{-2} a^{-1}) is calculated for solar thermal production since solar thermal panels contribute most to the system in the transition phase of spring and autumn when the highest irradiation is gained at a 60° inclination. For PV panels, the global irradiation on planes at 45° inclination angle (1,298 kWh m^{-2} a^{-1}) is calculated since that inclination guarantees the highest energy gain over a year. Efficiencies have been assumed to be 70% for solar thermal systems and 11.5% for PV-systems. The potentials have been determined for each building and aggregated to 1 km^2 raster grid cells as input to the optimization model. Thus, the total solar thermal potential is calculated to be 158 GWh_{therm} a^{-1}, corresponding to 7.7 MWh_{therm} $person^{-1}$ a^{-1}, while the PV potential is at 57.9 GWh_{power} a^{-1} corresponding to 2.8 MWh_{power} $person^{-1}$ a^{-1}. One of the most dynamic developments of costs is observed in the PV sector. From a household's perspective, the returns from PV are determined by the proportion of auto-consumption. The reason is that prices for grid electricity paid by consumers are higher than tariffs earned when feeding into the network due to network fees that accrue for grid electricity. We assume a network fee of 60 € MWh_{power}^{-1} for power fed to the public network and an auto-consumption rate of PV electricity of 50%, resulting in an additional network fee of 30 € MWh_{power}^{-1} for PV production. Biomass plants are assumed to feed all of their production into the network. They are therefore charged the full network fee of 60 € MWh_{power}^{-1}. These network costs are also fully considered for power that is bought from the grid.

2.4.3. Ambient heat potentials

Ambient heat utilized with heat pumps has to be considered an add-on technology for achieving regional energy autarky. It can reduce primary energy demand but still relies on electricity to work. Ambient heat systems are restricted by the existing building structure. Heat pumps may only rarely substitute other heating systems in existing buildings, because of restrictive technical prerequisites (applicable only in heating systems with low supply temperatures) and various other barriers such as restricted space and existing underground pipes. Therefore, ambient heat potentials have only been estimated for newly constructed buildings or potential developing areas detected through GIS-methods. Two types of ambient heat systems are considered: brine/water systems using heat in shallow water (horizontal collectors) and in deep water (vertical collectors), both in combination with heat pumps (full load hours 2400 h, coefficient of performance 3.8). Geological circumstances and available areas are also taken into account. The potentials for ambient heat systems are estimated to 10.6 GWh_{therm} a^{-1} or 0.5 MWh_{therm} $person^{-1}$ a^{-1} for shallow water systems and 32.3 GWh_{therm} a^{-1} or 1.6 MWh_{therm} $person^{-1}$ a^{-1} for deep water systems.

2.5. Biomass supply curves

The supply of biomass for energy purposes in a region is variable over space and time. It depends on (1) natural production conditions, (2) the land use and crop management choices by farmers and (3) their marketing choices for agricultural and forestry products. To attain energy autarky, additional biomass resources have to be produced regionally either by (1) increasing land productivity, (2) bringing additional land into production, (3) replacing current land use by bioenergy crops, or (4) a mixture of all these options. In the Sauwald region, most land is already under either agricultural or forestry production apart from limited land used for recreation or infrastructure (compare to Fig. 2). Deforestation is prohibited by law and conversion from permanent grassland to cropland is limited by cross compliance under the CAP. Land productivity can be increased by changing factor inputs such as labor or mineral fertilizers. This can incur additional costs to producers which likely will be passed on to regional biomass consumers. Replacing existing crops also incurs opportunity costs for farmers as they have to decrease production of food and feed crops that could have been sold otherwise or may have been eligible for agricultural subsidies.

In order to take these complexities into account, we apply a regional land use modeling system. It consists of the crop rotation model CropRota (Schönhart et al., 2011), the bio-physical process model EPIC (Izaurralde et al., 2006) and a spatially explicit version of the price exogenous linear land use optimization model PASMA (Schmid and Sinabell, 2007). Typical crop rotations – modeled at the municipality level with the crop rotation model CropRota – are input to EPIC in order to estimate spatially explicit crop yields based on homogeneous response units (HRU) and observed regional climate data. Each HRU is homogeneous with respect to soil type, slope, and altitude at a spatial resolution of one to several km^2. In PASMA, supply curves for agricultural bioenergy crops are derived from these crop yields as well as further detailed regional economic data such as production costs, and land and capital endowments. Increasing bioenergy production in the PASMA scenarios is driven by increasing prices for energy crops. Consequently, we can determine relations of quantities and prices to construct a supply curve, as well as cross price and quantity effects. The biomass supply curves are integrated into the energy system model BeWhere to calculate costs of increasing biomass supply from agriculture. With respect to biomass supply from forestry, land cover information is combined with data on historical wood production and supply elasticities for fuel wood, estimated from historical time series. These are combined to derive fuel wood supply curves under increasing harvesting costs and opportunity costs of forest owners when selling certain wood assortments to bioenergy producers. At high prices of forest biomass, even timber may be used as energy wood. Fig. 5 shows all supply curves.

2.6. Scenarios

In the research project, we have followed a relative autarky concept focusing only on the sectors heat and power generation while the transportation sector as well as gray energy is not included in the analysis. The transportation sector was excluded because processing of liquid biofuels within the region is economically not feasible at all due to the limited supply of feedstock and limited demand of fuel. However, we have calculated the amount of power necessary to supply a share of the regional mobility demand with electric cars in one scenario.

We have designed four different scenarios for the year 2020 (see Table 2): (S1) a baseline policy scenario with no energy autarky target, (S2) a scenario of heat and power autarky, (S3) a scenario of heat and power autarky including electricity demand to fuel a share of 10% electric cars in the region, and (S4) a scenario of heat autarky only. In all scenarios, we assume a fossil oil price of 80 \$ bbl^{-1}. The oil price was chosen to be low to show the transition between a heating sector supplied partly with heating oil and a scenario of heat autarky. The effect of the oil price on results is additionally analyzed in the sensitivity analysis. Current tax levels on fossil fuels and power are included in the analysis in detail.

Two demand scenarios are additionally developed and combined with each of the policy scenarios: (E1) a baseline demand

Table 2
Annual energy demand (in GWh) in the 2020 scenarios. S_i indicate different autarky scenarios and are combined with E_i, the efficiency scenarios. Bold numbers indicate that the demand has to be satisfied by local renewables in the respective scenario.

	E1			E2		
	Heat demand	Power demand	Power electric mobility	Heat demand	Power demand	Power electric mobility
S1	159	82	0	120	79	0
S2	**159**	**82**	0	**120**	**79**	0
S3	**159**	**82**	**7**	**120**	**79**	**6**
S4	**159**	82	0	**120**	**79**	0

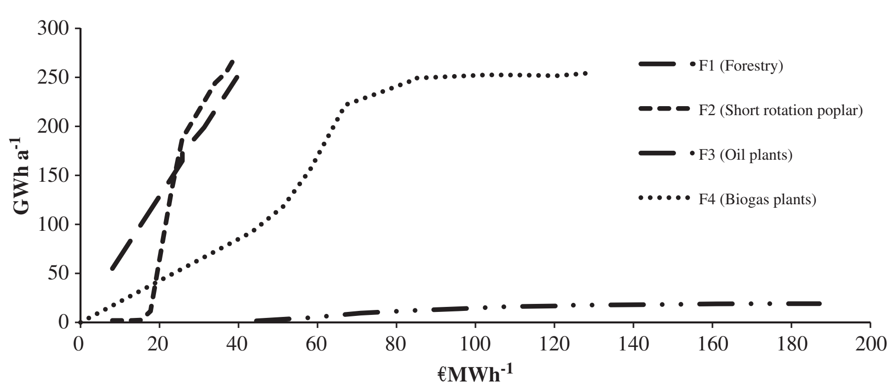

Fig. 5. Annual biomass supply curves for different types of feedstock in the Sauwald region.

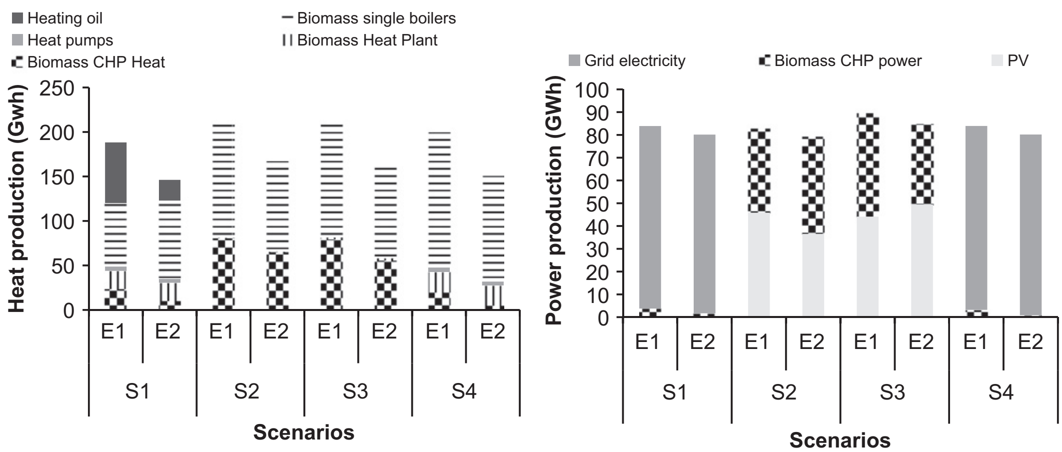

Fig. 6. Annual production of heat (left) and power (right) by technology in the eight scenarios in GWh.

scenario that assumes no change in heating demand, an increase of 18% in power demand and an increase of 21% in transportation fuel demand as well as (E2) an energy efficiency scenario, which assumes that heating demand decreases 25%, power demand increases by only 13%, and transportation fuel demand increases by 1%. All assumptions with respect to the development of demand are taken from the national action plan for renewable energies (Karner et al., 2010), with exemption of the assumption of a 25% decrease of heating demand. This assumption is taken from the regions own energy plan and can be considered a very ambitious target as around 50% of all existing buildings would have to be retrofitted until 2020 to reach such a significant decline.

3. Results

3.1. Technological mix

Fig. 6 shows the mix of energy conversion technologies chosen in the four scenarios. In S1–E1, grid power and fossil oil dominate the power and heat sectors, respectively. Renewables contribute mainly to heat generation: single dwelling boilers, heating and CHP plants generate heat in the region. Some renewable power is produced in CHP plants, while heat pumps are used to a minor extent. The energy efficiency scenario produces similar results, however, fossil oil use declines substantially, while biomass heating in single boilers increases slightly.

In the autarky scenario S2–E1, a massive boost of CHP production is modeled. District heating is almost exclusively supplied by CHPs. PV is a very strong contributor to electricity production. The share of district heating is higher than in S1–E1. The remaining heat is provided by biomass single boilers. The efficiency scenario S2–E2 is similar: No heating plants are built at all in S2–E2, because CHP production supplies the district heating demand. A further increase in power demand (through the introduction of electric vehicles in S3–E1) increases biomass CHP production further. District heating is expanded to accommodate surplus heat produced in biomass CHP plants. This causes that regions of low heating density are included in the district heating network, increasing costs and losses of district heating. Although areas of rather low heating density are included, the surplus heat of CHP plants cannot be fully utilized, causing an increasing amount of waste heat. The energy efficiency scenario S3–E2 produces similar results. In S4–E1, only heat has to be supplied by local resources, implying that CHP production is similar to S1–E1. Heat from biomass is mainly supplied by biomass single boilers and some heat from heating plants. District heating is only significantly expanded in S2 and S3 due to additional CHP production necessary to satisfy regional power demand.

In none of the scenarios, biogas plants or vegetable oil-based plants are chosen because of the high feedstock costs (compare to biomass supply curves in Fig. 5). The main heating technologies chosen in the scenarios for single dwelling boilers are pellets and wood chips boilers, while for power production, Stirling engines are applied in S1. In the scenarios with higher renewable power demand, i.e. S2 and S3, mainly CHP concepts based on gasification are installed due to their high electrical efficiencies compared to Stirling engines and ORC plants.

3.2. Costs and distribution of benefits

Fig. 7 shows the differences in costs between the baseline scenarios S1 (E1 and E2) and the autarky scenarios S2–S4 per person and year. All autarky scenarios lead to net-costs between 17 € $person^{-1}$ a^{-1} and 295 € $person^{-1}$ a^{-1}. Costs for energy supply are lower in the energy efficiency scenarios. However, costs of energy efficiency measures are not considered in the model, total system costs may be higher therefore. Costs for biomass feedstock are a small proportion of the whole additional system costs. This implies a low local added value because machinery and knowledge would have to be imported into the region. Only a small proportion of investment costs may create local added value from construction and engineering services. The effects on local added-value may therefore not be as positive as put forward by proponents of regional energy supply. As total expenditure for energy would increase by as much as 217 (295) € $person^{-1}$ a^{-1} in S2–E1 (S3–E1), the overall regional income effect may be even negative.

Fig. 7 also indicates that local heat supply may be achievable at very low costs – cost differences between S1 and S4 are only between 17 € $person^{-1}$ a^{-1} (efficient case) and 39 € $person^{-1}$ a^{-1} (non-efficient case). In the sensitivity analysis, we show that an increase of the oil price above 80 $ bbl^{-1}, which is the price level assumed in the scenarios, may trigger a transition to biomass heating without further intervention.

3.3. Changes in agricultural and forestry resource consumption

Fig. 8 shows the difference in forestry resource consumption between the baseline scenarios S1 and the autarky scenarios S2 through S4. The increase in forestry consumption is significant for S2–E1 (S3–E1) at levels of 21 GWh (28 GWh) which

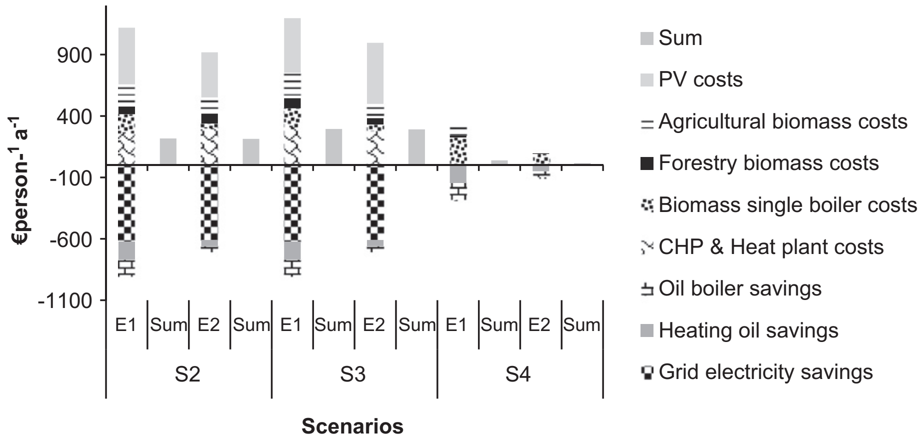

Fig. 7. Annual differences in costs between the baseline scenarios S1 and the autarky scenarios. Sum adds up savings and costs.

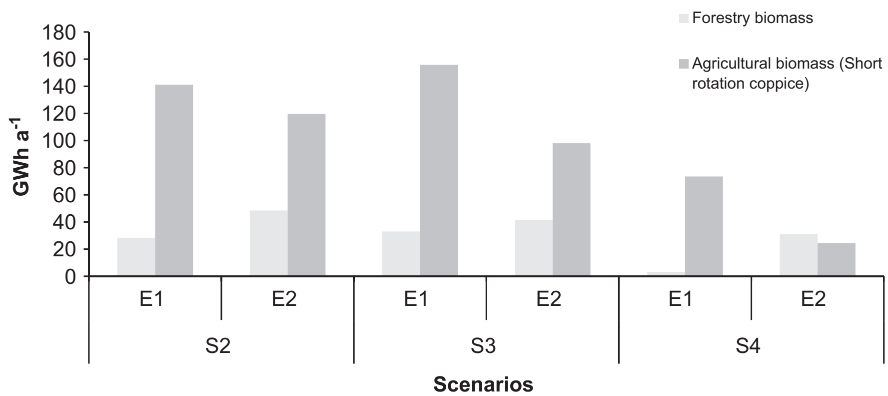

Fig. 8. Absolute differences in resource consumption of forestry and short rotation coppice between S1 and the autarky scenarios in GWh a^{-1}.

corresponds to an increase of 24% (30%) to the levels of S1–E1. The additional consumption of forestry resources in S4–E1 is low. Changes in the consumption of resources from agriculture are much more significant in relative and absolute terms. All scenarios show a significant increase of production of short rotation coppice (no other energy crops are chosen) in S2–E1 (S3–E1) of around 142 GWh (156 GWh). In relative terms, this yields an increase of 490% (530%) as a consequence of little consumption of agricultural resources of 36 GWh in S1–E1. The heat autarky scenarios (S4) require less agricultural resources. However, without energy efficiency measures agricultural production of short rotation coppice still has to increase by 300% in comparison to S1–E1. Increase of resource consumption in forestry in the autarky scenarios is significant and the biomass price levels necessary to trigger the increase in energy wood production may seriously affect the production of forestry resources for other purposes, i.e. sawn wood and industrial wood.

However, the competition among products in the forestry sector is modeled in less detail than in the agricultural sector, because only general supply elasticities are used for supply modeling. A detailed analysis of consequences is therefore not possible.

3.4. Effects on the agricultural sector

The significant increase in the production of short rotation coppice in comparison to S1–E1 affects the production levels of food and feed crops as shown in Fig. 9. The left plot shows the difference in the area planted between the baseline scenarios (S1) and the autarky scenarios while the right plot shows the difference in the production of marketable crops. Livestock production is not affected by the autarky scenarios, because the decrease in feed production, mainly concentrates, is substituted by imports. This creates a leakage effect with respect to autarky, i.e. increased energy self-sufficiency decreases self-sufficiency rates and regional exports of agricultural products. When comparing planted area and production quantities, one can observe more pronounced effects on yields than on area for short rotation coppice due to its above average dry-matter yield among all field crops. Nevertheless, losses in the production of food and feed crops in S2 and S3 reach more than 50%.

Effects on producer rents of farmers are minor in the autarky scenarios (see Fig. 10). The increased prices paid by biomass consumers have to cover increasing production costs, e.g. through feed imports, and forgone agricultural subsidies, i.e. premiums from agri-environmental programs and less-favored area payments. Regional biomass production therefore reduces the amount of national and EU subsidies and has to be compensated by biomass consumers therefore.

3.5. Sensitivity analysis

We have performed a simple sensitivity analysis to check the influence of model parameter changes on results. We assess the influence of the oil price, the electricity price (from the national grid), and the heat demand on the consumption of heating oil and grid electricity. Fig. 11 shows the results of this analysis. While the power price has no and the level of heat demand only minor effects, the oil price significantly affects biomass consumption. The price in the baseline scenario S1–E1 (i.e. 80 \$ bbl^{-1}) resides in a

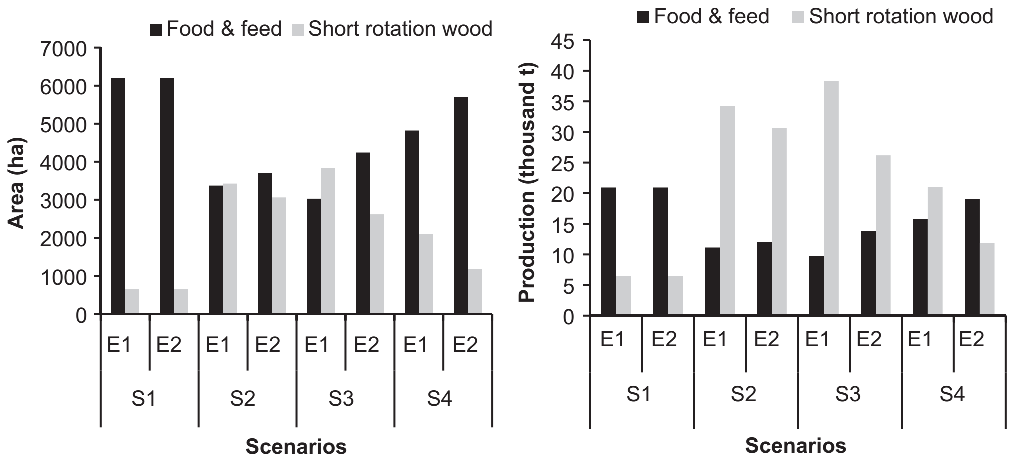

Fig. 9. Land use (left) and annual crop production (right) in the 8 scenarios.

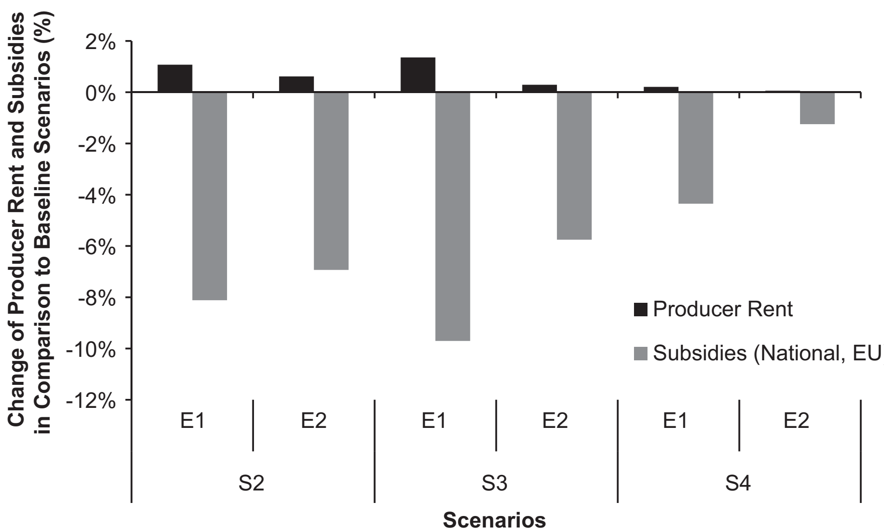

Fig. 10. Relative changes in producer rents and subsidies between the baseline scenarios S1–E1 and S1–E2 and the autarky scenarios.

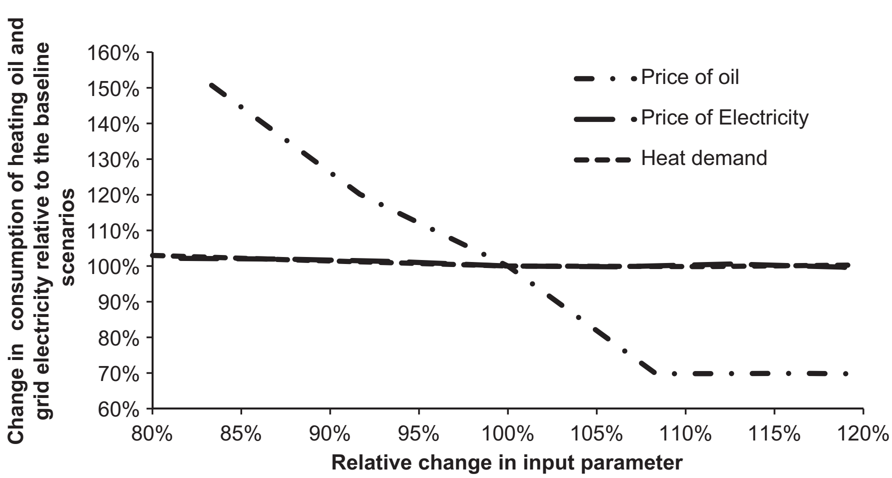

Fig. 11. Sensitivity of biomass consumption to changes in model input parameters.

sensitive region: small increases in the oil price trigger significant increases in the utilization of biomass for heating while small decreases reduce the amount of biomass heating disproportionally. These results imply that future energy prices will most likely influence the competition between fossil and biomass heating while significant amounts of electricity production from local renewables will not be triggered by electricity price changes only. This finding is confirmed by the current situation in the region: renewable energy production can be mainly found in the heating sector (with increasing levels in the last years) while power production from local renewable resources is negligible.

4. Discussion and conclusions

We have presented an integrated modeling approach that is able to show the trade-offs between regional energy autarky and supply of energy with imported fuels. The approach considers heterogeneous biophysical productivity of the land, economic competition for crops and forest wood, and the costs of energy generation technologies and delivery networks. The modeling approach can be applied to any regional, national or super-national analysis of renewable energy options. However, at higher levels of aggregation spatial resolution of input data as well as of model results will have to be decreased due to exponentially increasing computation time with an increasing number of grid cells considered in the energy system.

We assume that the regional economy is closed with respect to energy production, i.e. that no imports of biomass for energy purposes are possible. This is a strong assumption but is at the core of the energy autarky concept. Due to assumed decoupling from the rest of the economy, prices for bioenergy resources increase regionally. If regional decoupling is impossible, which likely is the case for most circumstances, a hectare- or quantity-based bioenergy premium could be introduced instead. It would increase revenues from biomass production for farmers and foresters similar to high price levels. We did not consider currently available subsidies for renewable energies such as feed-in tariffs for PV or subsidies to biomass boilers. All of these subsidies are limited in amount and time and it is not probable that the region is able to acquire subsidies for all of the necessary investments. However, costs may be slightly lower than depicted in our scenarios due to national or EU subsidies to the energy system.

The results indicate that attaining relative energy autarky in a relatively short period of about one decade is a tremendous task under current circumstance of energy markets and technologies even in remotely populated regions with fertile lands. We have excluded transportation fuels from the analysis to allow for feasible solutions and did not consider gray energy embedded in imported products. Furthermore, we apply a relative autarky concept throughout the analysis, implying that underproduction of a resource in one period may be balanced by overproduction in another period. This is mainly relevant for the power sector which is modeled very coarsely in this analysis. We assume that demand as well as supply of the national power grid is able to accommodate any under- or overproduction of electricity. For a small region like the Sauwald this assumption is valid, however, if regional autarky is adopted by more regions, limitations in the electricity system will most certainly arise. Biomass is the most important contributor in attaining energy autarky, particularly in the heating sector, where costs are lower than solar thermal heat generation. Local biomass production is therefore diverted from food, feed and material use to energy production and leads to decreasing exports of agricultural and forestry products to other regions. Bioenergy production is an additional factor in the competition for land and as all productive land is already used for agricultural and forestry production in the Sauwald region, new supplies of biomass can only come from substituting current products or increasing intensity. Increasing intensity is, however, a very limited option, because it is already high in the region. Furthermore, productivity gains by increasing land use intensity can lead to adverse environmental effects, which also may be true for considerable shares of short rotation coppice in a cultural landscape. PV or solar thermal on rooftops does not imply any land use competition. However, costs are still high and may be prohibitive for large scale deployment. Another technology with little land demand is wind power. The local potentials for renewable electricity production would be increased significantly if wind turbines would be included in the analysis. Nevertheless, energy autarky in any case increases energy supply costs significantly above current levels.

Considering energy autarky as the prime objective may also imply a suboptimal use of biomass resources: the high demand for power, that (in addition to PV) has to be met by CHP plants, causes some of the co-generated heat to be wasted due to limited potentials for district heating in the region, although we already have considered CHP plants of very small sizes with high specific investment costs. In general, biomass utilization for CHP production is more efficient in large supra-regional centralized plants, located close to large heat demand centers such as large cities or industrial facilities, than utilization in small regional plants where heat demand densities are low and significant seasonal fluctuations of the heat demand have to be expected resulting in low full load hours per year.

Some of the expected benefits of regional autarky such as the maintenance of cultural landscapes, decreased transportation distances, increased local added-value, creation of local green jobs, and increasing tourism are at least partly questioned by our results. For instance, a main threat for cultural landscapes in the region is reforestation of pastures. However, resources from pastures for bioenergy production are very expensive according to the model results. Without further discrimination of prices or biomass premiums, biomass for energy purposes would more likely be produced on cropland with short rotation coppice plantations implying landscape changes similar to reforestation. Decreased transportation distances for energy resources may be possible through local production. However, the total energy consumption in the system may not be decreased because the feedstock is used less efficiently in small CHP plants with some of the co-generated heat lost due to the lack of district heating demand. Positive effects on local jobs and added-value can be questioned as most of the generated expenditures are imported technologies according to the results. Tourism may be fostered due to interest in the concept of energy autarky. However, this may only be the case if the region is one of a few to follow this strategy and it is therefore not a benefit that could be extrapolated to other regions.

Fostering discussions on energy supply in a region is an important measure to change awareness and outline the options of a region: model results show that a renewable heating sector is achievable at relatively low costs in the case study region Sauwald, particularly if additional heat demand reductions can be achieved. As the energy system model is not dynamic and does not consider restrictions in the deployment of new technologies due to past investments, a renewable heating sector may not be achievable by 2020. However, the model indicates that by mobilizing additional forestry and agricultural resources, there are sufficient local resources available to achieve this goal in the long term.

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Schmidt, J., Leduc, S., Dotzauer, E., Schmid, E., 2011. Cost-effective policy instruments for greenhouse gas emission reduction and fossil fuel substitution through bioenergy production in Austria. Energy Policy 39, 3261–3280.

Schönhart, M., Penker, M., Schmid, E., 2009. Sustainable local food production and consumption: challenges for implementation and research. Outlook on Agriculture 38, 175–182.

Schönhart, M., Schmid, E., Schneider, U.A., 2011. CropRota—A crop rotation model to support integrated land use assessments. European Journal of Agronomy 34, 263–277.

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Streicher, W., Schnitzer, H., Titz, M., Tatzber, F., Heimrath, R., Wetz, I., Hausberger, S., Haas, R., Kalt, G., Damm, A., Steininger, K., Oblasser, S., 2010. Energy autarky for Austria 2050-Feasibility Study (Energieautarkie für Österreich 2050). Climate and Energy Funds. Climate and Energy Funds.

Wieduwilt, J., 2012. Conference about the future energy supply (Fachkonferenz zur Energieversorgung der Zukunft). 2012-03-30. Lausitzer Rundschau.

Part C: CV, scientific activities, publications & teaching portfolio

1. CV – Johannes Schmidt

Date of Birth: 15th of May, 1981
Austrian Nationality

Senior Researcher
Institute for Sustainable Economic Development
University of Natural Resources and Life Sciences, Vienna
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Academic Education and Professional Development

January 2014 – April 2015	**Scholarship "Talents from Abroad" at the Energy Planning Program** Federal University of Rio de Janeiro, Brazil
Since February 2010	**Post-Doc at the Institute for Sustainable Economic Development** University of Natural Resources and Life Sciences, Vienna
March 2007-January 2010	**Doctoral Student in the inter- and transdisciplinary Doctoral School „Sustainable Development"** University of Natural Resources and Life Sciences, Vienna Thesis: "Cost-effective CO2 emission reduction and fossil fuel substitution through bioenergy production in Austria: a spatially explicit modeling approach" Supervisor: Erwin Schmid
May – December 2006	**Research Assistant** Institute of Computer Technology, University of Technology, Vienna
2001-2007	**Bachelor and Master in Computer Science** University of Technology, Vienna

Fellowships

June 2013	**Complex Systems Summer School** Santa Fe Institute, Santa Fe, USA
January - May 2012	**Visiting Scientist** Institute of Energy and Transportation, Joint Research Center of the European Commission, Petten, Netherlands
June – August 2008	**Young Scientists Summer Program** International Institute for Applied Systems Analysis, Laxenburg, Austria

2. Overview of scientific activities relevant for the habilitation

Publications in journals and books[41]

Number	Publication Category	Points / Publication	Total	Requirement
12	Category I / FA, CA, LA*	1.25	15	7
1	Category III	0.75	0.75	
11	Category I	1.25	13.75	
1	Category III	0.75	0.75	
1	Book Chapters	0.75	0.75	
Total			31.00	10

*First Author, Corresponding Author, Last Author

Other publications

Number	Publication type
1	Non peer-reviewed journal
19	Publications in conference proceedings with review
10	Publications in conference proceedings without review
3	Posters
8	Presence in media

Funding

Number	Research project type
9	Research projects (3 project lead, 4 sub-project lead, 2 research associate)
1	International scholarship
2	Research consultancies

Lecturing

Title	Level	Language	Nmb of Semesters	ECTS
University of Natural Resources and Life Sciences				
Energy Economics and Policy	Master	German	6	3
Computer Simulation in Energy and Resource Economics	Master	English	5	3
Operations Research and System Analysis (with Viktoria Gass)	Master	English	3	3
Interdisciplinary Seminar Environmental Information Management (with Gregor Laaha, Helmut Fuchs)	Master	German	4	4
Advanced Economics of Natural Resources (with Mathias Kirchner)	Master	German	1	3
Data in Sciences (with Andreas Muhar, Friedrich Leisch, Michael Ornetzeder)	PhD	English	1	3
Federal University of Rio de Janeiro				
Introduction to R	Master	Portuguese	1	-

[41] Categories for publications relate to the official journal list of the Department of Economics and Social Sciences, while points relate to the official guidelines for habiliations at the University of Natural Resources and Life Sciences, Vienna.

Co-advisor of Master theses and dissertations

Number	Type
16	Completed master theses
4	Completed dissertations

Citation metrics

	Google Scholar	Scopus
Total number of citations	460	252
H-Index	13	10

Scientific Community Services

Reviewer

Since	Journal
2010	Bioresource Technology
2010	Applied Energy
2011	Remote Sensing
2011	Energy Policy (Outstanding contribution to reviewing, 2015)
2012	Biomass & Bioenergy
2012	Global Change Biology - Bioenergy
2012	Biomass Conversion and Biorefinery
2012	Journal of Cleaner Production
2012	International Journal of Energy Research
2013	Energy
2013	Energy Journal (IAEE)
2014	Environmental Science & Technology
2015	Solar Energy
2016	Energy Economics

Conference session chair & convener

Position	Year and Location	Conference
Invited Session Chair	July, 1st-7th 2012, Ohrid, Macedonia	7th Conference on Sustainable Development of Energy, Water, and Environment Systems
Invited Session Convener	April, 17th-22nd 2016, Vienna	European Geosciences Union General Assembly 2016
Invited Member of Scientific Committee	January, 18th-20th 2017, Graz	Central European Biomass Conference

3. Publications & Presentations

Publications Category I – First Author, Corresponding Author or Last Author

Schmidt, J., Cancella, R., Pereira Jr., A.O. (2016). The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal electricity system. *Energy (in press).*

Höltinger, S., Salak, B., Schauppenlehner, T., Scherhaufer, P., Schmidt, J. (2016). Assessing scenarios of socially acceptable wind energy potentials for Austria - a participatory modelling approach. *Energy Policy (in press).*

Schmidt, J., Cancella, R., Pereira Jr., A.O. (2016). The effect of windpower on long-term variability of combined hydro-wind resources: the case of Brazil. *Renewable & Sustainable Energy Reviews 55, 131-141.*

Schmidt, J., Cancella, R., Pereira Jr., A.O., (2016). An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil. *Renewable Energy 85, 137–147.*

Mayr, D., Schmid, E., Trollip, H., Zeyringer, M., Schmidt, J., (2015). The impact of residential photovoltaic power on electricity sales revenues in Cape Town, South Africa. *Utilities Policy 36, 10–23.*

Kirchner, M., Schmidt, J., Kindermann, G., Kulmer, V., Mitter, H., Prettenthaler, F., Rüdisser, J., Schauppenlehner, T., Schönhart, M., Strauss, F., Tappeiner, U., Tasser, E., Schmid, E. (2015). Ecosystem services and economic development in Austrian agricultural landscapes - The impact of policy and climate change scenarios on trade-offs and synergies. *Ecological Economics 109, 161-174.*

Schmidt, J., Lehecka, G., Gass, V. and Schmid, E. (2013). Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines. *Energy Economics 40, 269–276.*

Schmidt, J., Schönhart, M., Biberacher, M., Guggenberger, T., Hausl, S., Kalt, G., Leduc, S., Schardinger, I., Schmid, E. (2012). Regional energy autarky: potentials, costs and consequences for an Austrian region. *Energy* Policy. 47, 201-221.

Schmidt, J., Gass, V., and Schmid, E. (2011). Land use changes, greenhouse gas emissions and fossil fuel substitution of biofuels compared to bioelectricity production for electric cars in Austria. *Biomass and* Bioenergy 35, 4060-4074.

Schmidt, J., Leduc, S., Dotzauer, E., Schmid, E. (2011). Cost-effective policy instruments for greenhouse gas emission reduction and fossil fuel substitution through bioenergy production in Austria. *Energy* Policy 39, 3261-3280.

Schmidt, J., Leduc, S., Dotzauer, E., Kindermann, G. and Schmid, E. (2009). Cost-effective CO_2 emission reduction through heat, power and biofuel production from woody biomass: a spatially explicit comparison of conversion technologies. *Applied* Energy 87, 2128-2141.

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Publications Category III – First Author, Corresponding Author or Last Author

Schmidt, J., Leduc. S., Dotzauer, E., Kindermann, G. and Schmid, E. (2009). Biofuel production in Austria considering the use of waste heat: a study on costs and potentials of greenhouse gas reduction. *In: Yearbook of the Austrian Society of Agricultural Economics (18).*

Publications Category I – Co-Author

Thiel, C., Nijs, W., Simoes, S., Schmidt, J., van Zyl, A., Schmid, E., 2016. The impact of the EU car CO2 regulation on the energy system and the role of electro-mobility to achieve transport decarbonisation. *Energy* Policy 96, 153–166.

Zeyringer, M., Andrews, D., Schmid, E., Schmidt, J., Worrell, E. (2015). Simulation of disaggregated load profiles and development of a proxy microgrid for modelling purposes. *International Journal of Energy* Research 39, 244-255.

Zeyringer, M., Pachauri, S., Schmid, E., Schmidt, J., Worrell, E., Morawetz, U. B. (2015). Analyzing grid extension and stand-alone photovoltaic systems for the cost-effective electrification of Kenya. *Energy Sustainable Development 25, 75-86.*

Thiel, C., Schmidt, J., Van Zyl, A., Schmid, E. (2014). Cost and well-to-wheel implications of the vehicle fleet CO2 emission regulation in the European Union. *Transportation Research. Part A, Policy and* Practice 63, 25-42.

Mayr, D., Schmidt, J., Schmid, E. (2014). The potentials of a reverse auction in allocating subsidies for cost-effective roof-top photovoltaic system deployment. *Energy* Policy 1000, 555-565.

Kristöfel, C., Strasser, C., Morawetz, U., Schmidt, J., Schmid, E. (2014). Analysis of woody biomass commodity price volatility in Austria. *Biomass & Bioenergy 1000,* 112-124.

Höltinger, S., Schmidt, J., Schönhart, M. and Schmid, E. (2014). A spatially explicit techno-economic assessment of green biorefinery concepts. *Biofuels, Bioproducts and Biorefining 8, 325-341.*

Gass, V., Schmidt, J. and Schmid, E. (2014). Analysis of alternative policy instruments to promote electric vehicles in Austria. *Renewable* Energy 61, 96-101.

Gass, V., Schmidt, J., Strauss, F. and Schmid, E. (2013). Assessing the economic wind power potential in Austria. *Energy* Policy 53, 323–330.

Stürmer, B., Schmidt, J., Schmid, E., Sinabell, F. (2013). Implications of agricultural bioenergy crop production in a land constrained economy – The example of Austria. *Land Use Policy 30, 570–581.*

Gass, V., Strauss, F., Schmidt, J., and Schmid, E. (2011). Assessing the effect of wind power uncertainty on profitability. *Renewable and Sustainable Energy Reviews, 15, 2677-2683.*

Publications Category III – Co-Author

Höltinger, S., Schmidt, J., Schmid, E.(2012). The Green Biorefinery Concept: Optimal plant locations and sizes for Austria. *In: Yearbook of the Austrian Society of Agricultural Economics 21/1.*

Publications Book chapter – Co-Author

Leduc, S., Wetterlund, E., Dotzauer, E., Schmidt, J., Natarajan, K., Khatiwada, D. (2015). Policies and modeling of energy systems for reaching European bioenergy targets. *In: Handbook of Clean Energy Systems, Wiley.*

Non-peer reviewed journal publications

Schmidt, J., Reischütz, A., Reischütz, P. L. (2013): Beiträge zur Molluskenfauna von Wien und Niederösterreich XXIX. Die Molluskenfauna des südlichen Teiles der Donauinsel. *Nachr.bl. erste Vorarlb. malak. Ges. 20, 47-49.*

Peer reviewed conference publications

Wehrle, S., Schmidt, J. (2016). Optimal emission prices for a district heating system owner with combined heat and power generation capacities. *In: Proceedings of Swedish Association of Energy Economists Conference 2016, Luleå, Sweden.*

Schmidt, J., Wehrle, S., Rezania, R., (2016). A reduction of fixed distribution grid fees by combined PV and battery systems. *In: Proceedings of 2016 13th International Conference on the European Energy Market (EEM).*

Schmidt, J., Cancella, R., Amaro Jr., O.P. (2015). An optimal mix of solar PV, wind and hydro power for a low-carbon electricity supply in Brazil. In: *Proceedings of 10th Conference on Sustainable Development of Energy, Water and Environment Systems, Dubrovnik.*

Arnold, H., Masad, D., Pagani, G.A., Schmidt, J., Stepanova, E., (2014). Network Disruption and Recovery: Co-Evolution of Defender and Attacker in a Dynamic Game*, in: Complex Networks V, Studies in Computational Intelligence, 141–155.*

Kristöfel, C., Strasser, C., Morawetz, U.B., Schmidt, J., Schmid, E.(2013). Biomass price volatility: Analysis of the historic biomass and energy price volatility in the Austrian market. *In: Proceedings of 21st European Biomass Conference and Exhibition.*

Simoes, S.; Zeyringer, M.; Huld, T.; Schmidt, J.; Mayr, D.(2013). The impact of location on competitiveness of wind and PV electricity generation – a case study for Austria. *In: Proceedings of 2013 10th International Conference on the European Energy Market (EEM).*

Zeyringer, M., Simoes, S., Mayr, D., Schmid, E., Schmidt, J., Lind, J., Worrell, E.,(2013). Solar buildings in Austria: Methodology to assess the potential for optimal PV deployment. *In: Proceedings of 2013 10th International Conference on the European Energy Market (EEM).*

Schmidt, J.; Lehecka, G. V.; Schmid, E.; Gass, V.,(2013): Wind - quo vadis? A spatially explicit assessment of the impact of fixed vs. premium based feed-in tariffs on the deployment of wind turbines. *In: Proceedings of 2013 10th International Conference on the European Energy Market (EEM).*

Mayr, D., Schmidt, J., Schmid, E.(2013). Economic assessment of roof-top photovoltaic potentials: potential efficiency increases due to an auction based allocation policy. *In: Proceedings of IEWT 2013 - 8. Internationale Energiewirtschaftstagung.*

Schmidt, J., Lehecka, G., Gass, V., Schmid, E.(2013): Fixed feed-in tariff versus premium based feed-in tariff schemes: impacts on the spatial diversification of wind turbines. *In: Proceedings of IEWT 2013 - 8. Internationale Energiewirtschaftstagung.*

Schmidt, J., Gass, V., Schmid, E., Strauss, F., Zeyringer, M.(2012): A spatially and temporally highly resolved analysis of wind power potentials in Austria. *In: Proceedings of 2012 9th International Conference on the European Electricity Market.*

Gass, V. , Schmidt, J., Strauss, F., Schmid, E.(2012): Assessing the economic wind power potential in Austria. *In: Proceedings of 2012 9th International Conference on the European Electricity Market.*

Zeyringer, M., Andrews, D., Schmid, E., Schmidt, J., Worrell, E. (2012). Simulation of disaggregated load profiles and construction of a proxy-microgrid for modeling purposes. *In: Proceedings of 2012 9th International Conference on the European Electricity Market.*

Mayr, D., Schmidt, J., Schmid, E.(2012): Assessing rooftop photovoltaic potential increases by optimizing location choices. *In: Book of Abstracts of 7th Conference on Sustainable Development of Energy, Environment Systems.*

Schmidt, J., Schönhart, M., Biberacher, M., Guggenberger, T., Hausl, S., Kalt, G., Schardinger, I., Schmid, E. (2012): Regional energy autarky: potentials, costs and consequences for the Austrian Sauwald region. *In: Book of Abstracts of 7th Conference on Sustainable Development of Energy, Environment Systems.*

Zeyringer, M., Morawetz, U., Pachauri, S., Schmid, E. and Schmidt, J. (2011). Stand alone vs. grid extension for electrification in Kenya - development of a spatially-explicit energy system model. *In: Proceedings of 34th IAEE International Conference.*

Gass, V., Schmidt, J., Schmid, E. (2011). Analysis of alternative policy instruments to promote electric vehicles in Austria. *In: Proceedings of World Renewable Energy Congress 2011.*

Gass, V., Strauss, F., Schmidt, J., Schmid, E. (2011). Economic assessment of wind power uncertainty. *In: Proceedings of World Renewable Energy Congress 2011.*

Schmidt, J., Gass, V., Schmid, E. (2011). Land use, greenhouse gas emissions and fossil fuel substitution of biofuels compared to bioelectricity production for electric cars in Austria. *In: Proceedings of World Renewable Energy Congress 2011.*

Non-Peer reviewed conference publications

Salak, B., Schauppenlehner, T., Brandenburg, C., Jiricka, A., Czachs, C., Höltinger, S., Scherhaufer, P., Schmidt, J. (2015). Bewertung des Landschaftsbildes im Zuge der Errichtung von Windkraftanlagen auf Waldstandorten. *In: Tagungsband der Konferenz Naturschutzfachliche Aspekte von Windenergieanlagen auf Waldstandorten in Deutschland, Österreich und der Schweiz*

Schauppenlehner, T., Salak, B., Höltinger, S., Schmidt, J., Scherhaufer, P.(2015). Low-cost immersive 3D visualizations for evaluating visual impacts of wind parks using smartphones and free software. *In: Book of Abstracts of Conference Energy Landscapes: Perception, Planning, Participation and Power.*

Schauppenlehner, T., Salak, B., Höltinger, S., Schmidt, J., Scherhaufer, P. (2015). Application, opportunities and constraints of different landscape oriented 3D visualization techniques for communication and participation processes of wind energy projects. *In: Book of Abstracts of ECCA 2015.*

Scherhaufer, P., Höltinger, S., Salak, B., Schauppenlehner, T., Schmidt, J. (2015). Zur sozialen Akzeptanz der Windkraft in Österreich. Inter- und transdisziplinäres Arbeiten in Theorie und Praxis. *In: Tagungsband 16.Klimatag – Aktuelle Klimaforschung in Österreich.*

Höltinger, S., Salak, B., Schauppenlehner, T., Scherhaufer, P., Schmidt, J. (2015). Das ökonomische Windkraftpotential Österreichs - ein partizipativer Modellierungsansatz. *In: Tagungsband 16.Klimatag – Aktuelle Klimaforschung in Österreich.*

Kirchner, M., Leclère, D., Schipfer, F., Streicher, G., Deppermann, A., Frank, S., Havlík, P., Kranzl, L., Schmidt, J., Schmid, E. (2015). CC2BBE–Vulnerability of a bio-based economy to global climate change impacts. *In: Tagungsband 16.Klimatag – Aktuelle Klimaforschung in Österreich.*

Hoeltinger, S., Schmidt, J., Schmid, E. (2012). Sustainable Supply Chain Design of Green Biorefineries in Austria. *In: Book of Abstracts of Eigth International Conference on Renewable Resources and Biorefineries.*

Hoeltinger, S., Schmidt, J., Schoenhart, M., Schmid, E. (2012). Optimal Supply Chain Design of Green Biorefineries in Austria: Assessment of Current and Potential Support Schemes. I*n: Book of Abstracts of Conference The Political Economy of the Bioeconomy: Biotechnology and Biofuels.*

Schmidt, J., Leduc, S., Dotzauer, E. and Schmid, E. (2009). Regional bioenergy supply and demand and some implications for rural development. *In: Tagunsband der 19. Jahrestagung der Österreichischen Gesellschaft für Agrarökonomie.*

Rausch, T., Schmidt, J. (2006). Routing Algorithms for Voice Communication Systems in Air Traffic Services Networks. *In: Proceedings of the Huntsville Simulation Conference 20016.*

Poster

Schauppenlehner, T., Scherhaufer, P., Höltinger, S., Salak, B., Schmidt, J. (2014). Den Ausbau der Windenergie sozial verträglich gestalten? Eine inter- und transdisziplinäre Annäherung. *In: Tagungsband des 15. Klimatags.*

Schauppenlehner, T., Salak, B., Scherhaufer, P., Höltinger, S., Schmidt, J. (2015). Gewichtete Sichtbarkeitskarten zur Bewertung der visuellen Präsenz und Landschaftsdominanz potentieller Windenergieanlagen in Österreich. *In: Tagungsband des 16.Klimatags - Aktuelle Klimaforschung in Österreich.*

Schmid, E., Kindermann, G., Rüdisser, J., Schauppenlehner, T., Schmidt, J., Schönhart, M., Strauss, F., Streicher, G., Tappeiner, U., Tasser, E.(2011). Climate change in agriculture and forestry: an integrated assessment of mitigation and adaptation measures in Austria. *In: Tagungsband des 12. Österreichischer Klimatag*

Presentations

Schmidt, J. (2011). Ökonomische Potentiale der energetischen Verwertung von Biomasse. *Kommentare zur thermischen Nutzung von Biomasse. Kommission zur Reinhaltung der Luft, österreichische Akademie der Wissenschaften, 24th of November, Vienna.*

Schmidt, J. (2010). Nahrung vs. Treibstoff: globale Effekte verstärkter Bioenergieproduktion. *Energiegespräche, 21st of September, Vienna.*

Schmidt, J., Leduc, S., Dotzauer, E., Kindermann, G., Greigeritsch, T., Schmid, E. (2008). Potentials of Bioenergy Production in the Austrian Forest Market*, International Scientific Conference: The European Forest-based Sector: Bio-responses to Address New Climate and Energy Challenges? , 6th-8th of November, Nancy.*

Media appearance

„Größer, höher, grüner?“, Wiener Zeitung (Aline Schröder), 03.10.2014 (Online-Ausgabe).
„Windparks: Ein gigantischer Nachbar“, Die Presse (Sophie Hanak), 16.02.2014.
„Ökostrom: Auktion statt Lotterie?“, Die Presse (Matthias Auer), 5.4.2013.
„Wie die Fördervergabe bei Photovoltaik besser funktionieren könnte“, derstandard.at, 2.4.2013.
„Sinn und Unsinn der Treibstoffbeimischung“, Seed (3-4), 2012.
„E10 Biosprit in Österreich“, ORF2 - Hohes Haus., 20.11.2011.
„Biosprit erzürnt die Gemüter.“, Ö1 – Mittagsjournal, 5.11.2011.
„In Österreich keine neuen Flächen für Biosprit“, Die Presse (Matthias Auer)., 5.4.2011.

4. Funding

Name	Grant	Duration	Funding agency
Research projects			
Greenhouse Gas Reduction through Second Generation Biofuels in Austria (Sub-project leader)	44.737€ (Institute) 106.285 € (Total)	01.01.2010 - 31.10.2010	Climate and Energy Funds Austria(CEF)
Regional Integrative Assessment of Bioenergy and Food Utilization Paths in Context of Climate and Global Change (Sub-project leader)	57.360€ (Institute) 262.817€ (Total)	01.03.2010 - 28.02.2012	CEF
Climate change in agriculture and forestry: an integrated assessment of mitigation and adaptation measures in Austria (Executive project leader)	199.745€ (Institute) 297.373€ (Total)	01.05.2011 - 31.12.2013	CEF
Towards the 2020 climate and energy goals: cost-effective policy instruments for CO2 emission reduction and renewable energy support in Austria (Project leader)	84.504€ (Institute & Total)	01.01.2011 - 31.12.2012	Austrian National Bank
Integration of intermittent electricity generation into the dispatch-model ELEA (Project leader)	35.000€ (Institute & Total)	01.05.2014 - 28.02.2015	Wiener Stadtwerke (WS)
Vulnerability of a bio-based economy to global climate change impacts (Research associate)	177.495€ (Institute) 299.001€ (Total)	01.07.2013 - 31.12.2015	CEF
The transition of the Austrian energy system to a high penetration of wind energy - A participatory integrated assessment of the social acceptance (Sub project leader)	70.101€ (Institute) 217.959 € (Total)	01.09.2013 - 30.11.2015	CEF
Potentials for Renewable Energies in the Federal State of Acre (Research associate)	150.000R$ (~40.000€) (Institute & Total)	01.07.2014 – 01.03.2015	WWF (Brazil)
Integrating renewable electricity systems with the biomass conversion sector: a focus on extreme meteorological events (Subproject leader)	130,000€ (Institute) 200,000€ (Total)	1.9.2016 - 31.8.2018	Formas (Sweden)
International scholarship			
A renewable electricity system with high shares of intermittent production: the case of Brazil	191.400R$ (~62.000€)	1.1.2014 - 30.4.2015	CNPq (Brazil)
Consultancies			
Implementing a dispatch model in GAMS	2.500€	April 2013	European Commission – Joint Research Center Petten
Implementing a dispatch model in GAMS	7.000€	July 2013	WS

5. Teaching Portfolio

I developed this teaching portfolio based on my experience of teaching several master level classes at BOKU University in Vienna and one master level class at the Federal University of Rio de Janeiro in the years 2010-2016. It consists of two sections: in the first section, I briefly introduce my general teaching approach, while the second section contains a list of the classes that I taught, and a detailed description of the teaching methods including feedback by students.

5.1. Teaching Approach

Learning, in my opinion, is an active task. A good teacher therefore guides the students to a rich set of resources, and motivates them using those resources to actively engage with the field of study. As the groups that I teach are diverse – i.e. they bring different levels of skills, interests, and a different personal history into class – teaching should also rely on a diverse set of methods to address the needs of as many students as possible.

Therefore, I aim at applying a mix of methods to make the content of my classes as vivid as possible. Lectures are a particularly difficult field of teaching: keeping up attention of students, motivating them to participate, and assessing learning progress is complex in settings where large groups gather in a room to listen to one person. Even under those conditions, lectures should allow for interaction between teacher and students – and they should aim at triggering reflection processes. I use PowerPoint slides, deductions on the blackboard, interactive questions, and brief interactive group activities (such as simulated auctions to determine market prices) for that purpose. A presentation of (new) concepts, in combination with questions that force students to directly apply those concepts to a particular problem, will trigger learning processes – and will keep attention high. Additionally, I design final tests and exams in a way that students have to be able to apply the concepts taught in class to new contexts. In this way, I aim to support understanding of concepts instead of simple memorizing of lecture contents.

Besides lectures, which are mainly related to teaching theoretical concepts, I am also teaching practical skills, mainly in my programming classes. In those classes, students solve programming tasks during class and at home. Thus, they actively engage with the subject – and have to present and discuss the assignments in front of their peers. I see very high success in learning when a problem that was previously handled by students is discussed in class together. Gaining feedback from fellow students and from me and learning about different solutions to the very same problem is highly enlightening.

I consider mutual learning in groups to be a very effective way of acquiring new skills and I support it by asking students to form groups when solving home assignments or writing seminar papers. Also, in one class students have to review the paper of a fellow student group and give constructive feedback. As highlighted by the students, this makes them reflect more on their own paper and gives them the opportunity to increase their competence in assessing the work of others. Competition between students, if applied in a limited way, can also strengthen the engagement of students in my opinion. Therefore, I enforce competition in one class, where groups of students compete in a playful programming tournament.

A very important part of teaching at a university is the supervision of students who write their master or doctoral thesis. Here, the most intensive collaboration between teacher and student occurs and here, guiding the student through the research process most significantly depends on understanding the personal needs and skills of the students. A careful assessment of the student's idea and how it fits to my research profile at the start of the thesis, a rigorous planning of research projects, and quick and substantial feedback during the research process facilitate the process for the students and thus support them in increasing the quality of their work. At the same time, a thesis is mainly the work of the student, so giving freedom to students in developing and executing the research idea is of outmost importance. The balance between guidance by the teacher and freedom is delicate and has to be found individually together with each student.

5.2. Teaching Experience

Advanced Economics of Natural Resources

In German. University of Natural Resources and Life Sciences, Vienna, Austria. With Mathias Kirchner. 3 ECTS.

Content & Methodology

In the first part of this lecture, the students are introduced to the concept of economic growth and the role of capital, population, technological progress, and trade in fostering growth. In the second part of the lecture, we critically reflect how economic growth and sustainable development can be linked, in particular in the fields of resources and climate, institutions, and inequality. The course is a lecture with a final written examination.

Evaluation by students

Semester	Average grade given by students (1 best – 5 worst)	Number of respondents
2015/2016WS	1.31	29

Some selected qualitative comments by the students

- Commitment of teachers very high, they both always attend. Draw figures on blackboard and explain, how they are generated.
- We also get a different view on the situation (e.g. two papers on happiness and treadmill effects)
- Great presentations, try to support understanding and participation of students. Excellent, I really like to attend.
- Great team of teachers, exciting contents, at the cutting edge. Teachers really know about the topic.
- Sometimes more time is necessary to understand complex content, e.g. when treating different theoretical concepts, mathematical derivations, etc. in one class.

Energy Economics and Policy

In German. University of Natural Resources and Life Sciences, Vienna, Austria. 3 ECTS.

Content

A growing world population and increasing living standards cause higher global demand for energy, while external effects of high levels of energy consumption become visible globally at the same time. On the supply side, producers are challenged to satisfy demand and, at the same moment, to reduce social and ecological damage. On the demand side, energy efficiency measures and changes of behavior should reduce consumption. Participants acquire a basic understanding how the particularities of energy demand and supply influence energy markets and how policy measures can be used to steer them. The lecture analyses energy demand and energy efficiency measures, fossil resources, strong and weak sustainability, external effects and policy instruments, electricity markets and renewable energies, and international trade of energy commodities.

Methods

Half of the class is a lecture, which introduces the students to basic concepts of energy economics as described above. At the end of the lecture part, the students take a test – and have to choose a topic for their seminar paper, which is elaborated in a group of three people. Additionally, each group is assigned a paper of a fellow group to review. The papers have to be finished before they are presented in class to give time for the feedback by the other groups and by me. Grading of the seminar paper only occurs at the end of the semester, when students had time to incorporate the feedback from the reviews into their work.

Evaluation by students

Semester	Average grade given by students (1 best – 5 worst)	Number of respondents
2016SS	1.67	12
2015SS	1.73	15
2013/2014WS	1.78	23
2013SS	1.33	6
2012SS	(too few respondents)	2
2011SS	1.44	9

Some qualitative comments by students

- Seminar paper was very instructive. Was able to explain complex content in a simple way.
- Very well organized. Due to the review, one gets some insights into other topic than own.
- Very good organization and structure, clear communication of assignments and grading.
- Useful feedback on the paper before grading.
- Great support, organization of class very helpful (theory, practical exercise, review) -> high level of achieved learning objectives. Should be mandatory class in UBRM energy module.
- I liked the content, has increased my interest in electricity. Reviews are great (although they are hard to take), but one really learns.
- High requirements, high level. Productive and interesting discussions.
- The final examination was too difficult.

Computer Simulation in Energy and Resource Economics

In English. University of Natural Resources and Life Sciences, Vienna, Austria. 3 ECTS. *Nominated for the BOKU Teaching Award in 2016 (Among the five finalists).*

Content

Economic agents that show bounded rationality or strategic behavior and markets that are out of equilibrium pose serious problems to traditional economic modeling techniques. This course introduces the students to the concept of agent based modelling (ABM), a computational tool that allows addressing these challenges. After presenting general ABMs in economics, we focus mainly on modelling electricity markets. The students learn to understand the concept of ABM, get to know important ABMs and learn how to apply them appropriately. Students also learn to implement, verify and validate models in the programming language NetLogo.

Methods

The class is split in two parts: in the lecture part, students learn about the theory behind complex systems and the application in energy economics. They also study the basics of agent based modelling and get to know important agent based models from scientific literature. In the practical part of the class, programming examples are solved in class and at home. Part of the assignment is the "zombie deathmatch", which is a programming competition between groups of students that involves developing strategies for complex group formation and movement.

Evaluation by students

Semester	Average grade given by students (1 best – 5 worst)	Number of respondents
2015/2016WS	1.27	11
2015SS	1.70	10
2013/2014WS	1.46	13
2012/2013WS&2011/2012WS	(too few respondents)	2

Some qualitative comments by the students

- Outstanding teacher. Very interesting topic. Teacher manages to inspire students.
- The playful introduction to the software is well done and animates the students to work with the program. […[] Most theoretical content is a precondition for the practical programming, while one gets to know the general process of ABM. To "tinker" with market models helps to understand energy-economic connections better (merit order -> Price Diff Random/ Simple Trader). Very valuable class, […]. In general, one of the best classes in the master UBRM, despite of (or because of) the high requirements.
- I really like the regular take home assignments. It keeps you involved, you get to know NetLogo better and they are fun and also a bit challenging. I also like the set-up, so that first you always have a theoretical input, followed by the seminar part. The lecturer is really motivated and tries to convey the content as good as possible while still trying to motivate us for thinking ourselves and coming up with own ideas/solutions. I also think that the examination type is very well chosen and fits the lecture perfectly.
- It would be helpful to have sometimes some additional information about the codes/variables used before the assignment. In the course due to the limited time it's sometimes hard to follow.

Operations Research and System Analysis

In English. University of Natural Resources and Life Sciences, Vienna, Austria. With Viktoria Gass. 3 ECTS.

Content

The class introduces operations research (OR) and system analysis using the software package GAMS - General Algebraic Modeling System. OR and its modelling approaches are first defined and an introduction to the theory of linear programming (Proportionality, Additivity, Divisibility, Certainty, Graphical Solution, Simplex-Algorithm, Big M Method, Primal-Dual Relationships, Complementary Slackness, Degeneracy, Reduced Costs and Shadow Prices, Interpretation of results, post-optimality analysis) is given. Afterwards, students are introduced to the optimization software GAMS. Practical problems in the field of water management and energy systems are solved in class and at home, applying multi-objective, and mixed integer programming.

Methodology

The first, theoretical part of the class, which is taught by Viktoria Gass, introduces to theoretical concepts of OR. In the second part of the class, which is taught by me, practical problems are solved in GAMS. We focus on problems from the water and energy sector, i.e. water supply and hydropower. Students have to solve assignments in class and at home.

Evaluation by students

Semester	Average grade given by students (1 best – 5 worst)	Number of respondents
2016SS	(too few respondents)	1
2015SS	(too few respondents)	2
2013SS	1.67	15

Some qualitative comments by the students

- The 2nd part was really well explained.
- Problem-centered studying. Solving problems in the group.

Interdisciplinary Seminar: Environmental Information Management

In German. University of Natural Resources and Life Sciences, Vienna, Austria. With Gregor Laaha and Helmut Fuchs. 3 ECTS.

Content & Methodology

Within class, student groups elaborate a project either in the field of environmental statistics (G. Laaha), geoinformatics (H. Fuchs), or techno-economic modelling (me). The projects address wind power generation and involve modelling of resource potentials, of distributions of wind speeds, of costs of wind power generation, or of suitability zones for wind energy.

Evaluation by students: No data – too few students (all in all, about 4 students take the class each year).

Data in Sciences

(In English). University of Natural Resources and Life Sciences, Vienna, Austria. With Andreas Muhar, Friedrich Leisch, Michael Ornetzeder. 3 ECTS.

Content & Methodology

This is an interdisciplinary course at doctoral level on the most essential constituent of empirical research: data. Teachers and students from a wide range of disciplinary and methodological backgrounds discuss issues such as: models and their data, data selection, selection bias, data resolution, variability of data, reproducibility of results, integration of different data types. After a short introduction by the lecturers, students form groups, and present their own papers on one of the subjects from the above lists of issues, related to their own doctoral thesis.

Evaluation by students: No respondents.

Introduction to R

In Portuguese. Federal University of Rio de Janeiro. April – May 2014. No ECTS (unofficial class)

Content & Methodology

The open source software R is a useful tool for automatizing any type of data analysis, including statistical analysis of large data sets. It comprises of a huge library of statistical functions, complex plotting functions, a large user community, and a huge amount of supporting information available on the internet. It is reasonably fast in data handling if used appropriately. Anything from simple spreadsheet analysis to complex simulations can be programmed within R. The drawback of R – in comparison to spreadsheet software such as Excel - is that the user has to learn the built-in programming language. This course introduces the students to the basic usage of R, the basics of the programming language and aims at making the students able to start their own research projects with the help of the software. Practical exercises during class and assignments to solve at home complement each other.

Evaluation by students: the Federal University of Rio de Janeiro does not offer an evaluation system.

5.3. Co-Supervision of Thesis

Dissertations

Ongoing

Stefan Höltinger. Spatially explicit modelling of the bio-economy: applications in bio-refineries and wind energy. University of Natural Resources and Life Sciences, Vienna.

Marianne Zeyringer. Spatially explicit modelling of electricity demand and supply. Joint Doctorate University of Natural Resources and Life Sciences, Vienna and University of Utrecht.

Completed

Christa Kristöfel (2016). Econometric analyses of the wood fuel market in Austria. University of Natural Resources and Life Sciences, Vienna.

Dieter Mayr (2015). Integrated policy analysis of residential photovoltaics: Bottom-up modelling approaches for Austria and South Africa. University of Natural Resources and Life Sciences, Vienna.

Mathias Kirchner (2015). Integrated Impact Modelling of Climate Change and Policy Scenarios on Agriculture, Land Use Change, and Environment in Austria. University of Natural Resources and Life Sciences, Vienna.

Viktoria Gass (2013). Analyzing Cost-Effective Wind Energy Deployment and Electric Vehicle Adoption in Austria. University of Natural Resources and Life Sciences, Vienna.

Master thesis

Ongoing

Natalie Spittler. The implications of renewable energy integration for strategic price setting in the Austrian-German electricity market. University of Natural Resources and Life Sciences, Vienna.

Karin Egger. Die Simulation und Analyse der Produktion von Photovoltaikanlagen mit MERRA-Daten und ihr Abgleich mit Echtzeitdaten am Beispiel Deutschlands. (Simulation and analysis of PV production with MERRA-data and comparison with real production data for the example of Germany). University of Natural Resources and Life Sciences, Vienna.

Johann Baumgartner. Modelling the aggregated wind power generation of wind parks in comparison to measured output: two case studies. University of Natural Resources and Life Sciences, Vienna.

Sebastian Mooshammer. Validation of MERRA-data with a wind power simulation model in comparison to real production quantities. University of Natural Resources and Life Sciences, Vienna.

Completed

Philip Brandenstein (2016). Simulationsanalysen von dezentralen Stromnetzen mit hohem Anteil erneuerbarer Stromproduktion. (Simulation study of decentralized electricity grids with high shares of renewable power production). University of Natural Resources and Life Sciences, Vienna.

Fabian Wacht (2016). Szenarien der Gasförderung und des Gasverbrauchs in Europa bis 2020. (Scenarios of gas extraction and gas consumption in Europe until 2020). University of Natural Resources and Life Sciences, Vienna.

Florian Ludwig (2015). Optimizing the Electricity Generation Mix in Germany by using a Linear Programming Approach. University of Natural Resources and Life Sciences, Vienna.

Rafael Cancella Morais (2015). Aplicação do fator de valor na avaliação do benefício associado às novas fontes renováveis. (Application of the value factor for evaluating the benefit of new renewable electricity sources). Universidade Federal de Rio de Janeiro.

Robert Buchner (2014). Wind power expansion in Austria: effects on the balancing of regional electricity supply and demand. University of Natural Resources and Life Sciences, Vienna.

Philip Rodemeyer (2014). Der Einfluss von Windenergieanlagen auf den österreichischen Regelenergiemarkt. (The influence of wind power on Austrian balancing markets). University of Natural Resources and Life Sciences, Vienna.

Christoph Zinganell (2014). Ökonomische Analyse von unterschiedlichen solarthermischen Systemen für eine Einbindung in das bestehende Fernwärmenetz der Fernwärme Wien. (Economic analysis of different solar-thermal systems for integration in the existing district heating network of Vienna). University of Natural Resources and Life Sciences, Vienna.

Ulrike Ladin (2014). Biomass fired cogeneration in Austria: current state and analysis of the influence of plant size on the investment costs. University of Natural Resources and Life Sciences, Vienna.

Christof Horvath (2014). Eine Wirtschaftlichkeitsanalyse von Speichermedien in Kombination mit Photovoltaikanlagen auf Haushaltsebene - Eine empirische Fallstudie für Oberösterreich. (An analysis of profitability of storage media in combination with PV panels for households – an empirical case study for Upper Austria). University of Natural Resources and Life Sciences, Vienna.

Korbinian Eierstock (2013). Renewable energy in Small Island Developing States (SIDS): Modeling PV/Diesel hybrid systems in the Maldives. University of Natural Resources and Life Sciences, Vienna.

Alexander Schmidt (2013). Die Wirtschaftlichkeit von Photovoltaik zur Stromversorgung von Elektroautos am Beispiel der Park & Ride Anlage Erdberg in Wien. (Profitability of PV power to supply electricity to electric cars using the example of the park&ride facility in Erdberg, Vienna). University of Natural Resources and Life Sciences, Vienna.

Christoph Zehetner (2012). Transmission System Expansion Planning using a Mixed-Integer Programming Approach: A case study analysis of the Austrian power grid. University of Natural Resources and Life Sciences, Vienna.

Luis Eduardo Ramirez Camargo (2012). A GIS-Based Method for Predicting Hourly Domestic Energy Need for Space Conditioning and Water Heating of Districts and Municipalities. University of Natural Resources and Life Sciences, Vienna.

Florian Havranek (2012). Pumpspeicherkraftwerke als zentraler Baustein der Energiewende: Eine Wirtschaftlichkeitsanalyse für das deutsche und österreichische Marktgebiet. (Pumped-hydro power plants as core technology for the "Energiewende": an economic analysis for the German-Austrian market zone). University of Natural Resources and Life Sciences, Vienna.

Stefan Höltinger (2011). Finding the Optimal Plant Locations and Sizes for Green Biorefineries in Upper Austria using a Spatially Explicit Mixed Integer Programming Model. University of Natural Resources and Life Sciences, Vienna.

Zeyringer, Marianne (2011). Grid Extension versus Photovoltaic Stand-Alone Solutions for Rural Electrification in Kenya - Development of a Spatially Explicit Energy System Model. Technical University of Vienna.