

THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Mapping the historical deployment of onshore wind power

Implications for energy system modeling

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Abstract

Onshore wind power features prominently in modeled low-carbon energy futures. In practice, however, wind power installations are constrained by factors such as local opposition and lengthy permitting procedures. These factors are not well represented by bottom-up energy models, which tend to apply constraints that lack empirical justification. This risks misrepresenting the role onshore wind power can play in a low-carbon energy transition.

To address these limitations, we adapt the *outside* view from the technology diffusion and project management literature, benchmarking wind power assumptions in large-scale energy system models against historical deployment patterns in countries and regions with substantial wind power installations. Such patterns represent what deployment densities and siting outcomes have proved achievable given the range of drivers and constraints present across diverse settings, and can therefore be indicative of how wind power will be deployed in the future.

Paper A investigates the siting of turbines in relation to the regional wind speed distribution over time across 25 countries and regions, and compares it to the allocation of wind power by energy system models. The findings reveal that historical siting patterns in relation to wind speed are heterogeneous across regions but stable over time: year by year, turbines are sited at windier-than-average, though not necessarily the windiest, locations. Endogenous cost minimization in models allocates wind power to sites with higher wind speeds than observed in history, implying that such models may overstate wind power's cost-competitiveness.

Paper B examines how model results change when applying historical deployment patterns in the model instead of typical literature assumptions, drawing on the siting patterns from Paper A and on deployment densities observed at the municipal and county levels. Both parameters substantially increase system costs across diverse regions, and the empirical densities also reduce onshore wind generation considerably. These results indicate that prevailing modeling assumptions may overstate the contribution of onshore wind power and consequently understate the corresponding system cost.

Keywords: Onshore wind power, historical deployment patterns, energy system models, wind potential, turbine siting, deployment density, wind speed

List of Publications

This thesis is based on the following appended papers:

Paper A

Jakobsson, N., **Lundqvist, C.**, Hedenus, F., Rahmad, Y. and Kan, X. (2025). *Turbine siting in relation to wind speed: Insights from historical deployment patterns for energy system modeling*. *Energy Strategy Reviews*, 62, 101990, doi: <https://doi.org/10.1016/j.esr.2025.101990>.

Paper B

Lundqvist, C., Kan, X. and Hedenus, F. (2026). *Empirically based assumptions for wind power: Impacts on low-carbon energy system modeling*. Under review in *Applied Energy*.

Supplementary information is available on request for papers under review.

Author's Contributions

Paper A: Conceptualization: J.N., H.F.; Data curation: J.N., **L.C.**; Formal analysis: J.N., **L.C.**, R.Y.; Funding acquisition: H.F.; Methodology: J.N., H.F., R.Y.; Software: J.N., **L.C.**; Project administration: H.F.; Supervision: H.F., K.X.; Visualization: **L.C.**; Writing - original draft: J.N., **L.C.**; Writing - review and editing: H.F., K.X., R.Y..

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Carin Lundqvist
Göteborg, 2026

Use of generative AI in this thesis

Generative AI tools were used during the writing of this thesis to structure and proof-read text. The questions, analysis, results and reflections are my own, and I take full responsibility for the contents of the thesis. I see learning as the primary purpose of writing a licentiate thesis, and have tried to use AI in a way that facilitated that process, not replaced it.

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Abbreviations

CF	Capacity Factor
CSP	Concentrated Solar Power
ESM	Energy System Model
IAM	Integrated Assessment Model
LCOE	Levelized Cost of Electricity
MCDA	Multi-Criteria Decision Analysis
PV	Photovoltaics

Chapter 1

Introduction

Over two decades, wind power's share of global electricity generation has risen from 1% in 2005 to 9% in 2025 [1], and with a technical potential far exceeding global electricity demand [2], wind power is expected to play a crucial role in decarbonizing electricity systems [3]. As a case in point, wind power is typically the largest generation technology in cost-optimal low-carbon European scenarios, supplying 40–80% of generation [4, 5]. Past expansion has had multiple drivers. Learning effects, improvements in turbine performance, and economies of scale [6–8] have pushed costs of wind energy in many parts of the world to be on par with or below those of fossil electricity generation [8]. In parallel, feed-in tariffs and other policies have facilitated growth [8–10]. However, the pace of installations has slowed down in the United States and parts of Europe [1, 11], and observed global growth rates fall short of the Paris Agreement's 2 °C pathways [12]. There are multiple explanations for the observed growth patterns.

A frequently cited obstacle in Europe and North America is local opposition [11, 13–17]. Opposition stems from several concerns: impacts on human health and wildlife from noise and flickering shadows [18, 19], the visual intrusion of turbines in the landscape [20, 21], and perceived distributional and procedural injustice [22, 23]. While protests from local interest groups have halted multiple wind power projects [17, 24], the effectiveness of opposition depends on the institutional setting and the parties involved. Greater stakeholder involvement can increase acceptance while opening more avenues for resistance [23, 25], and groups with more social capital, for instance more political connections, can be more successful in stopping applications [26, 27].

Besides opposition, other cited obstacles include grid bottlenecks [28], long planning and permitting procedures [11, 17], the lack of supporting infrastructure in developing countries [29], and the suppression of electricity prices at times of high wind energy output [30, 31]. WindEurope reports that at least 500 GW of wind capacity awaits grid connection approval in Europe [32], compared to the 115 GW installed globally in 2024 [3]. At the same time, many social and institutional factors have driven expansion rather than blocking it. Priority areas for wind power in spatial planning have increased deployment locally [33, 34], and local innovators and small-scale producers have contributed to the

development of new wind power technologies [21, 35]. Understanding how such diverse technical and non-technical factors impact deployment, and how they can be represented in models of the energy system, is essential to accurately assess the role of wind power in future low-carbon electricity systems [35–38]. Santos Da Silva et al. [39] showed that uncertainties in renewable potential assumptions, particularly for land suitability, have a larger impact on modeling results than uncertainties in model pathways and climate scenarios.

Energy System Models (ESMs) and Integrated Assessment Models (IAMs) are two model types that have been applied at the global and continental scale to answer questions about the design and cost of future decarbonization scenarios [4, 40–43]. Both create mathematical representations of the components in the energy system to investigate its operations and possible developments. In the past decade, the technical representation of renewables in these models has improved, with a higher spatial and temporal resolution better capturing the intermittency of wind and solar production [44, 45]. However, models often fail to consider how social and institutional factors shape the deployment of renewables [46, 47]. This gap is revealed in how models represent turbine siting. Energy system optimization models tend to assume wind power is sited at the windiest sites to minimize costs [48, 49]. However, for some regions, empirical studies have found that factors other than wind resources can dominate siting decisions [50–52]. For instance, Rahmad et al. [52] showed that previous installations and voter turnout in Swedish municipalities had a greater impact on the distribution of installed wind capacity than wind speed and electricity price.

When energy system models incorporate non-technical factors, they usually enter as input parameters or through ex-post analysis of outputs [35]. Inputs include legally mandated setback distances [53–55], negative externalities such as noise and shadow flicker represented as disamenity costs [56], local acceptability from choice experiments [57], and the effect of scenicness on project rejection [58]. Most inputs are intended to capture local acceptance or negative externalities, and are incorporated in a way that constrains wind power installations [38]. There are exceptions, such as Fisch-Romito et al. [59], who included both driving and impeding factors for renewables directly in the modeling process, or studies that explicitly investigate trade-offs between factors [60], but these remain rare.

These studies share several limitations. Many include only one factor intended to represent social preference, and do so without justifying the threshold selected, or without regard for the responsiveness of planning procedures and political systems to that social preference. For example, Fisch-Romito et al. [59] assumed

that wind capacity cannot be built if more than 60% of the local population has a negative perception of the technology. The threshold of 60% lacks empirical justification and runs counter to the hypothesis in the social acceptance literature that protests against wind power are largely driven by a small “vocal minority” whose opinions do not necessarily reflect the stance of the majority of residents [61, 62]. Without coherent methods for quantifying social factors in models, there is a risk that adding more factors contributes to complexity, and the appearance of realism, without actually improving the performance of the model against reality [36]. Furthermore, approaches that involve surveys or consulting local stakeholders [57] can be vulnerable to bias [63] and are not viable on the continental or global scale.

This thesis aims to address these limitations by drawing on historical deployment patterns for onshore wind power. Extrapolating from empirical data is a recognized method for quantifying where, how much, and how fast wind power can expand [36, 38], yet is barely used in potential analysis and energy system modeling. How models site wind power in relation to wind speed has never been systematically evaluated against empirical data, and only one wind potential assessment, Nitsch et al. [64], has compared potential estimates using historical patterns and conventional literature assumptions [65]. Whether energy system modeling results would be much different if historical deployment patterns were considered remains unexplored. The advantage of historical patterns is that they reflect the combined effect of all technical and non-technical factors shaping deployment, and so reveal what deployment patterns are feasible under real-life constraints and drivers. However, the use of historical data in modeling also comes with challenges: patterns may shift over time and might not be transferable between regions. The core challenge of this thesis is how historical data can be used to improve the realism of model representations of onshore wind power, and to tackle this challenge, this thesis addresses the following research questions:

- RQ1:** How has onshore wind power been sited in relation to wind speed, and how has this evolved over time?
- RQ2:** How does the representation of onshore wind power in energy system models align with historical patterns?
- RQ3:** How are the results of energy system models affected by considering historical deployment patterns for onshore wind power?

In answering these questions, this thesis considers the broader question of how historical deployment patterns can inform the modeling of large-scale future electricity systems and develops new methodological approaches for incorporating historical data – drawing on the *outside* view of Kahneman and Lovallo [66].

1.1 Outline

This thesis includes two papers, Papers A and B. Paper A compares the historical siting of wind power in relation to wind speed against model siting. The results from Paper A feed into Paper B, which investigates how the results of energy system models are affected by considering historical deployment patterns for onshore wind power. Consequently, RQ1 is tackled by Paper A, RQ2 is tackled by Papers A and B, and RQ3 is tackled by Paper B. The content of the papers is distributed and expanded upon throughout the thesis. Hence, references to these papers will appear at multiple points in the text.

The structure of this thesis is as follows. The next two chapters explain the foundations for modeling renewables, with Chapter 2 introducing renewable potentials for wind power, solar photovoltaics (PV) and biomass, and Chapter 3 describing the representation of wind power in ESMs and IAMs. Chapter 4 motivates the use of historical data in modeling and sets out the theoretical framework behind it. Then, Chapter 5 compares current modeling assumptions with empirical findings, and Chapter 6 investigates how the results of energy system models are affected by considering historical deployment patterns as inputs for onshore wind power. Finally, Chapter 7 presents a discussion on the method and future work, and Chapter 8 contains the conclusion.

Chapter 2

Renewable potentials

All renewable energy sources are contingent on local resource conditions; hydropower requires sufficient water flows, wind power output is dependent on wind speed, and geothermal relies on accessible subsurface heat. Wind energy, solar energy, and bioenergy face an additional constraint in that they are limited by the available surface area because they directly, or indirectly, rely on the constant flow of energy from the sun [67]. Hence, their theoretical potential, i.e. the theoretical upper boundary of how much energy can be extracted, is decided by both the resource quality and the total surface area of the Earth. The difference in the productivity and area requirements between energy technologies can be illustrated by the power density, which is annual average power divided by the area occupied by the generation technology: solar PV can directly absorb solar radiation at maximum power densities on the order of magnitude of 10^1 W/m^2 , whereas only a small portion of radiation is translated into atmospheric circulation and photosynthesis, resulting in 10^0 W/m^2 for wind power and 1 to 10^{-1} W/m^2 for biomass [68].

The purpose of a potential in a large-scale energy system model is to set the ceiling for the expansion of renewable energy technologies. There are also other uses for potentials, such as informing policy targets for renewables [69], evaluating land use conflicts [70], and identifying suitable sites for installations at the local level, where multi-criteria decision analysis (MCDA) is often employed to assess the aggregated effect of many factors [71, 72]. However, these other uses are not considered in this thesis.

While the theoretical potential could be used for setting the ceiling of renewable expansion, in practice, various technical, economic, social and institutional factors place additional restrictions on energy extraction that are not captured by the theoretical potential. In response, models tend to incorporate types of potentials that consider additional constraints, such as the technical potential or economic potential, which are further defined below. This makes a general definition of the potential difficult because it depends on its type and application. Yet for the purposes of this thesis the potential is defined as *a quantification of the limits of energy extraction for a specific energy technology and a defined geographic area given a set of physical characteristics (e.g. wind speed, solar irradiation,*

biomass yields) and constraints (e.g. *land availability*).

The concepts corresponding to potentials, for fossil and mineral resources, are reserves and resources [73]. Resources are all available fuel or material on Earth, discovered or undiscovered, and are approximately equivalent to the theoretical potential for renewables. Whereas the theoretical potential is decided by land area and resource quality, resources are dependent on the size of the stock (measured as volume, mass or energy content). Reserves, by contrast, are the fraction of resources that are known and economically feasible to extract with the currently available technology. The economic potential is the closest equivalent to reserves for renewables because it quantifies the amount of energy that is both technically feasible and profitable to extract.

Resources and the theoretical potential are largely static, only changing over the long term, for instance, as wind speeds change due to climate change [72, 74] or new fossil fuels are formed. In comparison, reserves and the other potentials are dynamic concepts. The size of the potential can be affected by such things as changes in technology, legislation and cost. For instance, forests were long considered unsuitable for wind power as the turbines were too short to clear the turbulence close to the forest canopy. This has shifted as turbines have grown taller, facilitating installations in forested regions like Sweden [52]. Failing to consider the dynamic nature of potentials and reserves can lead to inaccurate conclusions: many researchers during the 20th century predicted the peak and decline of oil production by the end of the century, referring to the limited size of known oil reserves [75]. What they failed to recognize was that improvements in drilling technologies and increases in the oil price would expand reserves, and keep oil consumption steadily ticking upwards to this day.

Section 2.1 elaborates on the different types of potentials, and Section 2.2 explains how they are estimated.

2.1 Types of potentials

2.1.1 Definitions

At present “there is not one single terminology used in regards to potential analysis” [72]. A short survey of the potential assessment literature reveals *theoretical, physical, geographical, technical, technological, environmental, economic, social, achievable, usable, feasible, exploitable, developable, implementation and market potentials* [36, 72, 76]. Recent reviews by McKenna et al. [36] and Heinrichs et al. [77] have attempted to consolidate them into *Theoretical, Geographical, Technical,*

Economic and Feasible. This thesis modifies this terminology somewhat, inspired by Hoogwijk et al. [67] and Dupré La Tour [76], and defines the following types for use in energy system models:

The theoretical potential is the total energy content of the primary resource within the defined region; for wind power it is the kinetic energy of the wind.

The extractable potential is the maximum amount of energy that can be extracted across the total area of the defined region for a specific technology, considering the losses in the transformation from primary energy to secondary energy. This potential considers the physical limits of energy conversion, such as maximum theoretical efficiencies, as well as technology design and layout, such as the height and rated capacity of wind turbines. It can be given either as generated energy [MWh] or as the total installable capacity required to produce it [MW].

The technical potential is a subset of the extractable potential that excludes areas based on certain constraints. For example, steep slopes or settled areas may be excluded because they are technically infeasible, too expensive, or illegal to build on.

The economic potential is also a subset of the extractable potential that satisfies some criteria of economic profitability. Usually an economic constraint is added, such as only including sites with a sufficiently low levelized cost of electricity.

The feasible potential is the potential that is actually realistic to achieve after accounting for social, political and institutional barriers and drivers. It has also been called the social, market, achievable, and usable potential.

The presented definitions are valid for wind energy, solar energy, and bioenergy. Note that assessments of bioenergy are slightly more complicated than assessments of solar and wind because they must also consider long-term sustainable extraction rates from biomass stocks and competing uses of biomass [78].

The geographical potential from the terminology of McKenna et al. [36] and Heinrichs et al. [77] is excluded because it quantifies the total area or share of land available for an energy technology (see for example Ryberg et al. [79]), not the upper limits to energy extraction, and only the latter is relevant for energy system models. Calculating the amount of available land is seen as a

step in estimating the technical, economic and feasible potentials, not as its own potential type.

2.1.2 Inconsistency between potential estimates

Estimates of renewable potentials span a wide range: global technical potentials differ by two orders of magnitude for wind power and three for solar PV and bioenergy [72, 80]. The difference between estimates stems from what restrictions are applied, with assessments of the technical potential adopting differing assumptions for land availability, spatial and temporal resolution, technology spacing, and technical specifications, among other factors.

This inconsistency extends to the potential types. The hierarchy of potentials is often characterized as a series of nested subsets, running from the largest theoretical potential to the most restricted feasible potential [72, 81]. However, the borders between these categories are often indistinct, and the feasible potential is especially contested: studies disagree on whether the feasible potential is a subset of the economic potential [81], or can surpass it, for instance by states deploying subsidies and making previously unprofitable sites financially viable for firms to develop [82]. Dupré La Tour [76] found that the type of potential does not explain the variation in estimates, demonstrating that the nested-subset model does not reflect current practice. Moreover, it is unclear which assumptions belong to which potential: for instance, the exclusion of settlements and protected areas has been attributed to both the technical and feasible potentials [83, 84].

2.1.3 Suggested hierarchy of potentials

We present an alternative way of viewing the relationships between potential types, shown in Figure 2.1: the extractable potential forms a subset of the theoretical potential, and the technical, economic, and feasible potentials are in turn subsets of the extractable potential, though not of one another. We believe this better describes how potentials are defined in practice, and highlights that economic, social and institutional factors are not restrictive layers to be placed on top of a fixed technical potential. The technical potential is not fixed and evolves with technological developments. Examples from history include wind turbines moving into forests as they became high enough to clear the turbulence of the forest canopy, or floating offshore wind unlocking access to deeper waters. Moreover, social factors can act as drivers in the system, not only barriers (subsidies being an evident example).

Instead, we view the technical, economic and feasible potentials as all including a variety of constraints on land, yet with each placing greater emphasis on a particular type of criterion. The figure includes economic, social and environmental constraints, though one can also imagine constraints being technical, institutional, or legal. The economic potential does not exclusively consider factors related to site profitability but places greater emphasis on economic criteria such as Levelized Cost of Electricity (LCOE) (see Section 2.2.4), whereas the feasible potential is distinguished by a greater focus on social, legal or political criteria. The technical potential often acts as an umbrella term, including all potential estimates that are not assigned to a more specific category. However, it tends to differ from the feasible potential by focusing on criteria that are considered more permanent – a technical potential often excludes areas that are prohibited by legislation, such as nature conservation areas, but rarely excludes areas due to social opposition.

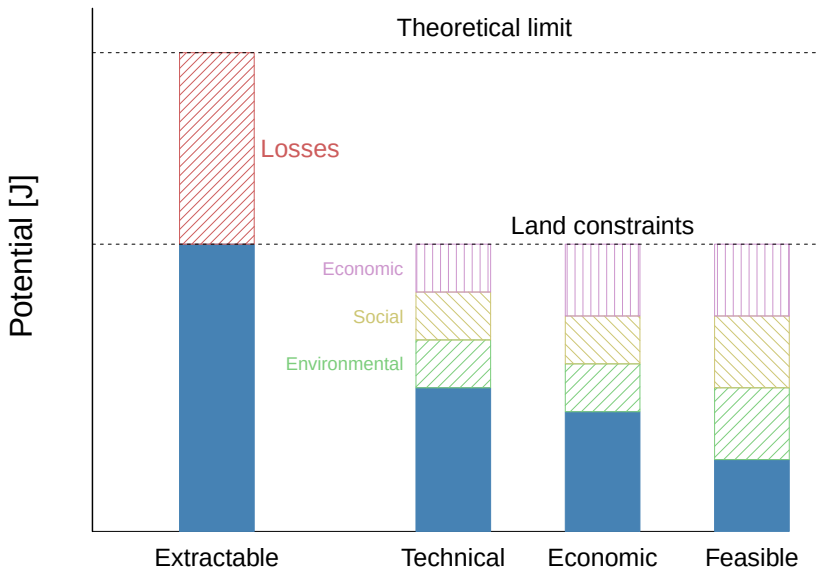


Figure 2.1: The relationship between the potential types defined in this thesis. The technical, economic and feasible potentials are subsets of the extractable potential, which in turn is a subset of the theoretical potential. The technical, economic and feasible potentials tend to apply partially overlapping constraints on land, yet are distinguished by adding or emphasizing criteria of a particular type.

2.2 Calculating potentials

2.2.1 Theoretical potential

The theoretical potential is estimated by calculating the energy contained in the primary resource, i.e. the radiant energy of sunlight, the kinetic energy of wind, and the chemical energy of biomass. A square meter of ground on Earth receives on average 188 W/m^2 from the sun, with the actual irradiance depending on location, seasonal and daily variations, and noontime maxima being just above 1000 W/m^2 [68]. The sun powers atmospheric circulation at a rate of 2.5 MW/km^2 [85]. Furthermore, sunlight is turned into biomass through photosynthesis with an efficiency of around 1% [86].

2.2.2 Extractable potential

The extractable potential considers the losses in the transformation from primary to secondary energy. It corresponds to the energy extracted if the defined region were entirely covered by wind farms or solar PV arrays. For wind power and solar PV, the secondary energy is electricity; for concentrated solar power it is a mix of electricity and heat; for windmills it is mechanical energy; and for bioenergy it can be electricity, heat, or a chemical energy carrier. The losses are set by the efficiency of the technology and by physical limits on the conversion itself, such as the Betz coefficient. The Betz coefficient is the maximum share of the kinetic energy in the wind that a turbine can extract, and is 59%. The limit arises because extracting energy slows the air behind the rotor. Extracting all of it would bring the air to a standstill, so no further air could pass through.

The layout of the technology matters as well. A wind turbine creates a wind shadow that reduces the energy available to turbines downstream, known as the wake effect. Packing turbines more tightly therefore raises the installed capacity per unit of land but lowers the output of each turbine, and the extractable potential depends on the balance between the two. This makes both the placement of turbines within a farm and the placement of farms relative to one another important. For solar PV, the spacing and angle of the panels must likewise avoid mutual shading, and leave room for supporting infrastructure such as substations and roads.

Together, the choice of technology and its layout determine the capacity density d : the capacity installed per unit of land within a farm. For wind power, d is estimated by, for instance, assuming that 5 MW turbines are placed in a grid pattern with a spacing of 10 rotor diameters. The extractable potential

expressed as installable capacity [MW] is then the capacity density d [MW/km²] multiplied by the total area of the defined region A [km²]. Some assessments instead place individual units, siting each turbine so as to minimize wake losses [53, 87]. This is computationally expensive and is therefore usually reserved for areas smaller than countries or continents.

Expressed as energy [MWh/year], the extractable potential is obtained by multiplying the installable capacity by the capacity factor (CF) in each time step, often an hour, and summing over the year. The capacity factor is actual output divided by rated output, and depends on the resource conditions (wind speed, solar irradiation, etc.) as well as on the efficiency of the energy technology.

2.2.3 Technical potential

The technical potential is a subset of the extractable potential that considers the exclusion of certain types of land. Most technical potentials are calculated in a bottom-up manner, where the relevant geographic area is divided into a raster [77]. Then, criteria are used to exclude certain raster cells which are deemed unsuitable for installations.

For wind power, the most common criteria are the exclusion of settled areas, infrastructure such as roads and transmission lines, water bodies, protected areas, steep slopes and high altitudes [36]. For open-field solar PV, the most common exclusion criteria are steep slopes, water bodies, protected areas, and built-up/settled areas [77]. These criteria can be implemented with or without buffer distances, or combined with a suitability factor (see eq. (2.1)). Depending on the datasets deployed, the raster resolution can vary drastically: from cells of 100 km² down to 0.01 km² [36, 77, 88]. The greater the spatial scope, the worse the data availability and resolution usually are.

The equation for calculating the technical potential given as installed capacity can be defined as

$$P_{pot} = \sum_i A_i (1 - \epsilon_i) D_i, \text{ where } D_i = d s_i. \quad (2.1)$$

P_{pot} [MW] is the total potential, and d is the capacity density. For each raster cell i , A_i [km²] is the area, ϵ_i is a binary exclusion (1 if the cell is excluded, and 0 otherwise), and s_i is the suitability factor. The suitability factor is a number between 0 and 1 that accounts for any remaining constraints on land not covered by land exclusion criteria. For example, it has been used to represent the suitability of different land types for renewable installations [89], or social

resistance [90].

Together the capacity density and suitability factor form the deployment density D_i [MW/km²]: the amount of wind power that can be installed per unit of suitable land. The extractable potential is a special case of this equation where $\epsilon_i = 0$ and $s_i = 1$, signifying no exclusion of land. Equation (2.1) can also be used for the economic and feasible potentials by adjusting the land exclusion criteria or suitability factor.

2.2.4 Economic potential

The economic potential identifies areas that are economically feasible to utilize, usually from the perspective of an investor [72]. The most commonly used economic indicator is the LCOE, which is total discounted costs divided by the discounted energy production over the lifetime of the technology T :

$$\text{LCOE} = \frac{\sum_{t=1}^T \frac{C_t + O_t}{(1+r)^t}}{\sum_{t=1}^T \frac{E_t}{(1+r)^t}}. \quad (2.2)$$

r , C_t , O_t and E_t are the discount rate, capital costs, operational and maintenance costs, and electricity production in the year t , respectively. Ryberg et al. [65], for example, present the economic potential at or below defined LCOE thresholds. This carries the implicit assumption that the cheapest sites, which are usually the windiest sites, are utilized first.

It is also possible to sort cells by LCOE, creating cost-supply curves that can be used as inputs in models [91]. This allows the models to endogenously choose which sites to use, rather than capping the potential at a predetermined LCOE. Energy system models consider the cost of the full electricity system, including balancing and network costs, whereas the economic potential only considers the cost of a single energy technology [36].

2.2.5 Feasible potential

McKenna et al. [36] define three approaches for calculating feasible potentials: land-eligibility, welfare analysis and MCDA. The land-eligibility approach applies the same methodology as the technical potential but with additional and more explicitly socio-political constraints, such as considering local acceptance [54], or how people respond to installations in scenic areas [92]. Some assessments consult local stakeholders or use surveys to decide which areas to exclude [87]. Welfare analysis tries to identify a socially optimal distribution of an energy

technology. Lohr et al. [56] investigated which allocation of wind turbines minimizes a total system cost including the cost of reduced housing prices in the vicinity of turbines. Finally, MCDA uses weights to investigate the trade-offs between different criteria. For instance, Weinand et al. [60] explored the trade-off between cost-efficiency, disamenity costs and regional equity.

Some studies state that the purpose of the feasible potential is to represent the actually realizable potential after the consideration of socio-political constraints [81, 93]. However, assessments of socio-political constraints require both normative and subjective assumptions about future developments [36]. Moreover, the feasible potential is a constantly moving target as legislation and public perceptions of the energy technologies change. Hence, it is more useful to view the feasible potential as a tool for weighing different social objectives, rather than as a definite answer to the upper limit of installations.

Chapter 3

Modeling wind power

The previous chapter defined renewable potentials for wind power, solar PV, and biomass. This chapter, and the rest of the thesis, focuses solely on onshore wind power and its representation in large-scale energy system models.

Real energy systems are complex and contain many interacting components. Changes in one part of the system might have unexpected and diverse effects elsewhere. Energy system models represent some of these components and interactions mathematically, and allow us to change one condition at a time to understand how the energy system operates, something that is difficult to experiment with in the actual system.

Not all energy system models include detailed representations of wind power, and the exact representation differs between model types. Consequently, Section 3.1 delineates which models are relevant for the scope of this thesis and explains the basics of how they operate. Section 3.2 describes the spatial and temporal resolution of such models and how the resolution has changed over the past decade to better represent variable renewables. Thereafter, Sections 3.3 and 3.4 present findings from Paper B, which describe current assumptions found within energy system modeling for the wind power potential and siting with respect to wind speed, respectively. These two parameters dictate the “how much” and “where” of wind power expansions in bottom-up energy system models.

3.1 Model scope

As stated previously, Energy System Models (ESMs) and Integrated Assessment Models (IAMs) are two types of models that are commonly used to answer questions about the design and cost of future decarbonization scenarios, as well as about the role that certain energy technologies can play in such scenarios [94]. The primary differences between ESMs and IAMs are their system boundaries and time horizons.

ESMs perform detailed, bottom-up modeling of the energy system that represents the interaction between different energy technologies using technology characteristics and costs [95]. This modeling is performed on a scale from the power sector to a full sector-coupled energy system, which includes heating,

electricity, transport, etc. [44, 96], and the spatial scope varies from the global to the very local [97]. In terms of the time horizon, ESMs can be divided into *capacity expansion models*, which are used for planning the energy system one or a few decades into the future, and *dispatch models*, which evaluate the operation of a predetermined system over shorter time periods such as a year [44]. Many models are combined capacity expansion and dispatch models (e.g. PyPSA-Eur).

By comparison, the purpose of IAMs is to understand long-term societal changes by representing the interaction between different man-made and natural systems. They often simulate changes at the global level decades, or centuries, into the future. To do so they usually model the energy system at varying levels of detail, and link it to the climate system, the economy and/or different land-use sectors [98].

The relevant ESMs and IAMs for this thesis are those that include detailed bottom-up representations of the supply side of the energy sector at the global or continental scale, and model the system at least a few years or decades into the future (hereafter referred to as bottom-up energy system models, or simply energy system models). It is these models that have explicit representations of wind power operations and incorporate potentials to define the upper limits of installations. This excludes, for instance, pure dispatch ESMs and top-down IAMs, where the latter use marginal abatement cost curves or production functions instead of detailed techno-economic representations [94]. Many of the commonly used models, such as TIMES/MARKAL, MESSAGEix, PyPSA, ReEDS, OSeMOSYS, Calliope and PLEXOS, have detailed supply-side representations of the energy system and are included within the scope of this thesis.

Bottom-up energy system models can be categorized into optimization and simulation models [44]. Optimization models try to find the best solution according to a specified objective, often to minimize total system cost. They do this given a set of starting parameters (such as technology costs and weather data), constraints (representing physical limits or regulations, for instance a carbon cap), and decision variables which are optimized endogenously by the model (such as installed capacity and transmission). Simulation models instead define a set of rules and heuristics by which the system operates. The boundaries between these categories are fluid, yet where a model falls on this spectrum can have implications for how wind power is allocated in relation to wind speed (see Section 3.4).

3.2 Temporal and spatial resolution

In the past decade, research on bottom-up energy system models has focused on improving their temporal and spatial resolution to better represent variable renewables [44]. The temporal resolution refers to how frequently the wind speeds and solar irradiation are sampled over time. Due to computational limits, some models used yearly averaged weather data or seasonal/daily time slices [99]. For instance, the TIMES model was used with 12 time slices to represent day, night and peak hours [100]. This underestimated the intermittency of variable renewables and, consequently, could cause an overestimation of their cost-effectiveness and installed capacity [45]. Today, hourly time resolution is generally considered sufficient to represent wind and solar power [101] and models often use high-resolution reanalysis wind speeds and solar irradiance based on historical weather years [102]. Examples include PyPSA [96], Calliope [103], and ReEDS [104], as well as the energy system model employed in Paper B [105]. Nevertheless, models with a long time horizon, wide system boundaries, or high spatial resolution may still have a coarser temporal resolution due to computational constraints [106]. This includes global IAMs such as REMIND and POLES, and ESMs such as MESSAGEix and OSeMOSYS [107, 108].

The spatial resolution of a model is dependent on two things: the spatial scope and the aggregation of supply- and demand-side resources [109]. To reduce complexity and computation time, models assign energy sources, energy conversion units, energy storage and demand sources within a defined geographical area to a node, ignoring their spatial distribution within the area [96]. This is called a “copper-plate” assumption. Node areas are often defined based on national or regional administrative units [109], and nodes are connected by links that represent energy flows (e.g. high-voltage transmission lines). Running a capacity expansion model usually entails that the model makes decisions about which energy technologies to invest in for a selected node and how to dimension links between nodes. It does so within the assumed constraints, one such being the renewable potential assigned to each node. There is a trade-off between computational time and spatial resolution [110]. Hence, models with a greater spatial scope tend to have a coarser spatial resolution, with nodes that cover larger areas such as whole nations.

For the representation of wind power, it was and still is rather common for models to merge all wind turbines within a node into a single generator with an average output (e.g. [41, 43]). This has two distinct effects. First, it obscures heterogeneous resource endowments across the node. Wind speeds are highly

dependent on local topography, and aggregating both low- and high-quality sites within a region removes the option for the model to invest in locations with better capacity factors [48]. The effect is less pronounced for solar because solar irradiation primarily varies with latitude, not local topographical conditions. Second, merging all generators can overstate the smoothness of generator output, also known as “geographical smoothing” [111]. Because wind speed varies locally, turbines even within one park have slightly different generation profiles, and aggregating them yields a smoother profile than that of any single turbine; the larger the area, the smoother the result, as variation between parks averages out. The copper-plate assumption can exaggerate geographical smoothing compared to reality due to ignoring the grid constraints within the node. The consequence is less need for storage and lower system costs in the model. In a cost-minimization model, the two effects – aggregation of heterogeneous resources and geographical smoothing – work in opposite directions: obscuring high-quality sites makes wind power less lucrative for investments, whereas geographical smoothing makes it more lucrative.

Over the past decade, models have added the option to introduce a number of wind resource classes per node [112, 113]. Each resource class corresponds to a bracket of wind speeds, with each containing a generator with a unique production profile (e.g., an average generator for all sites with average wind speeds of 5–6 m/s, 6–7 m/s, and so on). As an example, the default in PyPSA-Eur is one resource class per node, equivalent to one average generator per node, but since 2025 the model allows the user to increase the number of resource classes [112]. Having more classes increases the spatial resolution of the supply side of the model, thereby reducing smoothing and revealing wind power sites with heterogeneous resource qualities.

If the node is already small, or wind resources are very homogeneous, the effect on system cost and capacity mix of adding further resource classes is likely small. However, for studies treating large countries as single nodes (see e.g. [41]), classes are essential for capturing the heterogeneity and smoothing of wind power generation. There is no single recommendation for spatial resolution, but studies need to choose a resolution suitable for their research question and spatial scope while considering the computational burden [101, 109].

3.3 Wind power potential in energy system models

Previous sections have described how bottom-up energy system models operate and represent onshore wind power more generally. This section investigates the

assumptions that such models use to estimate the wind power potential. No studies have mapped wind potential assumptions specifically in energy system models, with previous reviews only focusing on assumptions in wind resource assessments [36, 38, 72, 76, 81]. Advances in wind resource assessment tend to make their way into energy system model assumptions. However, because the wind power potential is one input among many in energy system models, the assumptions that underlie it tend to receive less attention.

Table 3.1 is taken from Paper B and shows the prevalence and range of wind power assumptions found within widely used energy system models. The chosen studies cover large geographical areas, from single large countries such as the United States and China to the whole world. Importantly, while only one study is listed in the table per model, identical assumptions are often applied in other studies using the same modeling framework.

Table 3.1: Assumptions for onshore wind power potential and siting assumptions in bottom-up energy system models. The suitability factor is the share of land that is deemed suitable for wind farms after land exclusions, the capacity density measures the wind power capacity installed per unit of land within the wind farm, and the deployment density is the capacity that can be installed per unit of suitable land.

ESM	Land exclusion	Capacity density [MW/km ²]	Suitability factor	Deployment density [MW/km ²]	Siting method
Reichenberg et al. [42]: Supergrid	Excludes urban areas, wetlands, protected areas, population density >150/km ² .	5	8%	0.4	Endogenous optimization.
MacDonald et al. [40]: NEWS	Excludes national forests, slope >10%, state/national parks, recreation areas, military bases, airports, urban areas. Reduces exploitable area by 5,000 m ² /capita.	2.0–3.2	100%	2.0–3.2	Endogenous optimization.
Brown and Botterud [114]	Excludes water bodies, national parks, urban areas, mountains, Native American territories.	1.6 ^a	100%	1.6	Endogenous optimization.

Continued on next page...

Table 3.1 – Continued from previous page

ESM	Land exclusion	Capacity density [MW/km ²]	Suitability factor	Deployment density [MW/km ²]	Siting method
Pickering et al. [115]: Euro-Calliope	Includes farmland, forest, open vegetation, bare land, slope <20°. Excludes protected areas.	8	10%	0.8	Endogenous optimization.
Gils et al. [116]: REMix	Includes shrubland, grassland, sparse/bare areas, wind speed > 4 m/s. Excludes glaciers, sand dunes, salt pans, water bodies, wetlands, protected areas, settled areas, slope >15°, elevation > 2.5 km.	10.4	3–33%	0.3–3.4	Endogenous optimization.
Burandt et al. [89]: GENeSYS-MOD	Excludes forests, cropland, wetland, urban built-up land, water bodies, snow, glaciers, protected land, wind speed < 6 m/s, elevation > 3 km, slope > 20°.	2–8	30–90%	0.6–7.2	Endogenous optimization.
Millinger et al. [117]: PyPSA-Eur	Includes farmland, pastures, grasslands, forests, shrubland, barren land. Excludes Natura, urban areas, infrastructure, wetlands, water bodies, permanent snow/ice.	10	30%	3	Endogenous optimization.
Barnes et al. [43]: OSeMOSYS Global	Excludes irrigated croplands, flooded areas, urban areas, water bodies, snow/ice, protected areas, elevation > 2.5 km, slope > 20%.	5	10–90%	0.5–4.5	Endogenous optimization.

Continued on next page...

3.3. Wind power potential in energy system models

Table 3.1 – Continued from previous page

ESM	Land exclusion	Capacity density [MW/km ²]	Suitability factor	Deployment density [MW/km ²]	Siting method
Sepulveda et al. [118]: GenX	Excludes federal lands, National Park Service and U.S. Fish and Wildlife Service-managed lands, water bodies, slope >20%. Buffer around developed land and airports.	0.5–4	100%	0.5–4	Endogenous optimization.
Mai et al. [119]: ReEDS	Excludes setback 1.1x turbine tip height, urban areas, airports, radar, setback and height ordinances, protected public lands, water bodies, wetlands, slope > 25%, elevation > 9000 ft.	3	100%	3	Endogenous optimization.
Eberle et al. [120]: ReEDS	Same as [119] with a wind speed threshold for each turbine design.	Endogenous optimization for each site given capital costs and wake losses.	-	Median: 1.9–4.4	Endogenous optimization.
Bogdanov and Breyer [113]: LUT Energy System Transition Model	No areas excluded.	8.4	4%	0.34	60% in 80-100th percentiles of windiest areas, 20% in 70-80th and 50-70th.
Schlachtberger et al. [4]	Excludes urban areas, sand dunes, ice/snow, burnt areas, water bodies, wetlands, protected areas, Natura 2000.	10	20%	2	Proportional to capacity factor.
Jacobson et al. [41]: LOAD-MATCH model	No areas excluded.	7.1	0.5–15%	0.04–1.1	Uniformly

^a Brown and Botterud [114] used multiple turbine designs but stated only a single capacity density.

All potentials in Table 3.1 can be categorized as technical potentials. The exclusion criteria cover a mix of constraints with no explicit focus on social factors and with economic aspects being handled endogenously by the model. The most common criteria are the exclusion of protected areas, water bodies, and developed/urban/settled areas. Besides those, there is a fair bit of variation. Some of this variation likely stems from consideration of local context, for instance the exclusion of Native American territories by Brown and Botterud [114], or from data constraints; global studies lack sufficient resolution to exclude infrastructure such as roads or airports [121] and tend to apply uniform assumptions over large areas. Other variation lacks clear motivation, for instance, why only some of the European studies exclude wetlands and steep slopes [4, 42, 115–117]. The studies that exclude no areas either assume that a relatively small fraction of land can be used for installations by assigning a low suitability factor uniformly [113], or adapt the suitability factors based on land type rather than excluding certain types of land completely [41]. How much these inconsistencies matter depends on the criteria. Adding or dropping a criterion barely affects the resulting potential if it excludes very little land, as with airports, or if it largely overlaps with a criterion already applied, as with population density and urban areas. Other criteria are decisive, however: slope is the second most influential constraint on European land availability [79].

Capacity densities in the table describe how densely wind turbines are placed within a farm and range from 0.5 MW/km^2 to 10.4 MW/km^2 . They are typically estimated by assuming that a specific turbine design is placed in a grid pattern with certain spacing requirements where the spacing is dependent on turbine rotor diameter. Then, the capacity density is the total capacity of the wind farm divided by its area. Consequently, a capacity density is dependent on a) the capacity and rotor diameter of the assumed turbine, b) the selected spacing requirements, and c) the area calculation method. All of these suffer from uncertainties: turbine designs evolve over time [65], spacing requirements can range “from 4 – 16 rotor diameters (median 10) in the prevailing wind direction and 3 – 16 rotor diameters (median 5) in the crosswind direction” [81, p. 13], and there is no standardized methodology for defining the area associated with a wind farm [76, 122]. These uncertainties explain the variation in capacity density between studies.

Similarly, suitability factors are highly variable, with studies assuming wind farms are placed on between 0.5 and 100% of non-excluded land. Most of the studies in the table provide no justification for the chosen suitability factor, and

while a few studies state that the suitability factor represents social resistance or the suitability of different land types for wind power [89, 90], they do not motivate the specific threshold set. The same issue is prevalent in the wind potential assessment literature, with studies justifying a chosen threshold by citing previous literature, which in turn provide no empirical justification for their values [76].

Deployment densities are the product of the capacity density and the suitability factor and are defined as the average installed capacity per unit of land available for installations. Because of the substantial variation in assumed capacity densities and suitability factors, deployment densities are also inconsistent, spanning a range from 0.04 MW/km^2 [41] to 7.2 MW/km^2 [89]. This implies more than a 100-fold difference in assumed capacity per km^2 .

In summary, the parameters used to calculate wind power potentials in bottom-up energy system models suffer from inconsistencies similar to those in potential estimates outside of models. Some of these inconsistencies cancel each other out. For example, a similar potential can be produced by applying either extensive land exclusion criteria or a low suitability factor. Importantly, the inconsistencies in assumed parameters are not necessarily a problem in themselves. Depending on the scenario and research question, variations in potential assumptions can be warranted, for instance when investigating a what-if scenario of how the energy system would look with low public acceptance and stringent environmental protection [123]. Issues emerge when studies do not motivate their assumptions in relation to their research aims, which is commonly the case. Even exploratory scenarios lose their explanatory power if the underlying assumptions and their thresholds lack reasonable justification, let alone a basis in empirical reality. Consequently, Section 5.1 compares current potential assumptions in modeling to historical deployment patterns to assess whether there is a systematic discrepancy between common modeling assumptions and historical deployment patterns. Then, Chapter 6 explores the implications of such a discrepancy for modeling results.

3.4 Wind power siting in energy system models

The potential dictates the ceiling of wind power installations. Within that potential, wind power can be allocated to sites with different wind speeds. The

power of a wind turbine scales with the cube of the wind speed:

$$P = \frac{\rho A c_b v^3}{2}. \quad (3.1)$$

P is the maximum power output without considering losses, ρ is the air density, A is the swept rotor area, c_b is the Betz coefficient, and v is the wind speed [68]. Consequently, the wind speeds at wind power locations have a major influence on generation, and hence on the cost-competitiveness, of wind power, both in real life and in ESMs. Paper B identifies the siting in relation to wind speed in models as primarily dependent on two factors: the spatial resolution and the siting method.

As described in Section 3.2, the spatial resolution of a model determines to what extent sites with heterogeneous wind conditions are aggregated. A region modeled with a single node and a single resource class has one generator to invest in, representing the average wind conditions of that region. By contrast, a region with many nodes and classes has multiple distinct generators, each representing sites within a narrower range of wind speeds. A higher spatial resolution therefore reveals sites with higher wind speeds and allows the model to build there. Figure 3.1 shows the estimated spatial resolution of all studies in Table 3.1, measured as the mean area per unique wind speed temporal profile, i.e., the total area of the region divided by the number of unique aggregated generators.

The models with very high spatial resolutions to the left in the figure all focus on the United States. They either keep the sites unaggregated [40] or use many classes and nodes [119, 120]. In contrast, the lowest spatial resolutions are found among global models with one or very few nodes per country and one class per node [41, 43]. The other models have a few nodes per country with 1–5 resource classes per node.

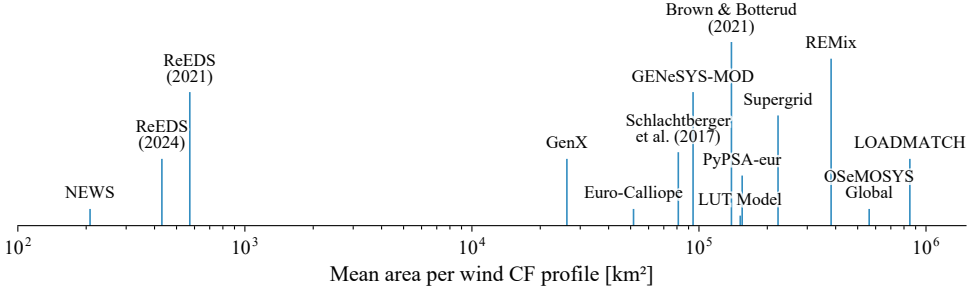


Figure 3.1: The spatial resolution of wind power for all studies in Table 3.1, represented by the mean area per wind CF profile for the modeled regions. The metric is calculated by dividing the total area of the modeled regions by the number of distinct aggregated wind CF profiles (time series or yearly averages), where a model has one profile for each combination of node and wind resource class. Note that the spatial resolution can differ between studies using the same model.

For a given spatial resolution, most optimization models in Table 3.1 allocate wind power to minimize costs. If the spatial resolution is high, this usually results in wind power being allocated to the windiest sites. However, grid limitations between nodes and lower spatial resolution can result in siting at lower wind speeds and closer to demand [48, 124]. This siting method reflects the logic that the best locations are utilized first, and that installations shift to areas with lower wind speeds when encountering area constraints.

A few studies use heuristics to model a more spread-out siting of turbines with respect to wind speed: Schlachtberger et al. [4] sited wind power proportionally to the capacity factor, and Bogdanov and Breyer [113] allocated a fixed share of wind power capacity to each wind resource class. The only simulation model in the table, Jacobson et al. [41], modeled a single generator per node, which is equivalent to distributing wind power uniformly across all available land within the node. How these approaches compare to historical installations is evaluated in Section 5.2 and Chapter 6.

Chapter 4

Historical data in energy system modeling

The core challenge of this thesis is how historical deployment data can be used to improve the realism of model representations of onshore wind power. Previous chapters have described current representations of wind power in bottom-up energy system models. Section 4.1 presents the rationale for using historical patterns to inform these representations. Sections 4.2 and 4.3 outline a theoretical framework for considering historical data – the *outside* and *inside* views of doing forecasts by Kahneman and Lovallo [66] – and apply this framework to onshore wind power.

4.1 Why historical patterns?

Previous chapters have highlighted that assumptions for wind power in bottom-up energy system models and wind resource assessments are very inconsistent. Santos Da Silva et al. [39] showed that uncertainty in renewable potentials resulting from differences in land exclusion criteria affects global wind and solar electricity projections more than the uncertainty from climate models or scenarios does. When assumptions for renewables are inconsistent and lack a clear benchmark, it is difficult to assess whether model results provide meaningful insights into the energy system or are merely an artifact of the assumptions imposed on the model. This uncertainty should be especially concerning for energy system modelers who investigate the cost and composition of future systems to advise policy-makers on investment decisions.

One approach for anchoring assumptions is to benchmark them against historical data and trends. Neij [125] provides an example, using experience curves to analyze the diffusion of wind power and solar PV. She gathered Danish data on wind turbine costs per kW in the 1990s to estimate how costs declined as cumulative installed capacity grew, and extrapolated this relationship to predict future costs. Another, more recent example comes from Jewell and colleagues [12, 126, 127]. Vinichenko et al. [126] measured the fastest observed growth rates for nuclear, wind and solar power. With these numbers, they evaluated renewable targets in the EU, concluding that the targets are feasible if the growth rates for solar PV and wind power match the growth of European nuclear power

in the 1970s and 1980s – the highest observed growth rate in the sample. Their assessment was complemented by an analysis of the agency of the involved actors and the underlying preconditions, showing that the high nuclear growth rate was achieved during a period of substantial demand growth and reasoning that future renewable and nuclear expansion might benefit from similar preconditions.

A common objection to the use of historical data is that it makes estimates too conservative. This can be a valid critique. For example, early predictions by the International Energy Agency (IEA) consistently underestimated the growth of solar PV given previous performance [128]. Vinichenko et al. [126] argue against the notion that the use of historical trends must be conservative by stating that growth in the future will likely be driven and constrained by mechanisms similar to those that drove growth in the past: technological development, cost declines, policies, et cetera [6–8]. Consequently, the frontier of observed growth rates can be indicative of what is achievable in the future, and achieving higher growth rates than seen in the historical record would require “unprecedented efforts or new causal mechanisms” [126]. Importantly, modelers using higher growth rates would need to motivate why the future would be different from the past.

We make a similar argument for using observed deployment densities and siting patterns. These too are the result of all the drivers and constraints that affect wind power deployment, and can thereby act as benchmarks for future modeling. However, the extrapolation from historical data to future scenarios is not trivial, and our theoretical approach for doing so is discussed below.

4.2 The inside and outside views

Jewell and Cherp [63] describe the *inside* and *outside* views of doing forecasts, originally introduced by Kahneman and Lovallo [66]. An *inside* view generates a forecast by looking at the case at hand, and by

“considering the plan and obstacles to its completion, by constructing scenarios of future progress, and by extrapolating current trends [66, p. 25].”

By contrast, an *outside* view

“ignores the details of the case at hand, and involves no attempt at detailed forecasting of the future history of the project. Instead it focuses on the statistics of a class of cases chosen to be similar in relevant aspects to the present one [66, p. 25].”

In other words, the *inside* view evaluates a forecast according to its own internal logic and assumptions, while an *outside* view instead asks whether comparable cases have occurred before and how they turned out.

Estimates of the wind potential tend to adopt an *inside* view. Assessments try to understand all factors that can impact wind power installations and then try to represent them by restricting available land. The challenge with this approach is that we do not yet have a clear understanding of how various local phenomena, such as local acceptance, translate into potential at the national level or beyond. McKenna et al. [92] have shown that wind projects have a greater chance of being rejected in areas considered more scenic by the public. However, this does not automatically entail that all areas with a high scenicness value should be excluded. Projects are at times built in scenic areas, and while a rejection slows down the deployment process, it does not permanently make a site unavailable. McKenna et al. [92] make this point themselves, noting that scenic areas may require more applications per approval, and that some projects have been built in areas with the maximum scenicness rating. The influence of scenicness on the permit procedure also likely varies from case to case, and may change over time as alternative locations become scarce or procedures are reformed.

This makes it difficult to assume a fixed threshold for local acceptance or scenicness above which land is excluded, and more difficult to apply such a threshold across multiple cases. Doing so takes an *inside* view of a process we do not yet fully understand: it identifies an obstacle and constructs a scenario from unknown mechanisms. Better insight into those mechanisms could help, but it is no guarantee of a better forecast. An illustrative example is found among researchers. We tend to consistently underestimate the time it takes to write a research paper, despite having done it many times before, because we base our assessments on current writing progress and anticipated obstacles, forgetting all the things that can go wrong and have gone wrong in previous projects.

The *outside* view presents an alternative approach which does not rely on identifying and understanding all the drivers and barriers of a project. Instead, a target case (such as a climate scenario or a potential) can be estimated or evaluated by examining historical analogies (reference cases) and quantifying their outcomes [63]. Here, the specifics of the target case are ignored and the focus is on the statistics of a class of cases similar to the target case. This is the approach taken by Flyvbjerg and Gardner [129] to assess the cost and time of large infrastructure projects. They first ask if there are historical reference cases within the same class on which to base predictions. For a new metro line, this could be previous metro lines, tunnel projects or overground railroads.

One course of action would be to look among the reference cases to find the case most similar to the target case. However, Flyvbjerg warns against this instinct, which stems from what he calls *uniqueness bias* [130]: the tendency to view a project as singular with little to learn from other projects. He argues that it is very difficult to know in advance all the ways in which projects are similar or dissimilar, and surprises may arise along the way. Instead, he argues it is better to consider the full range of outcomes and issues observed in the reference cases, and take an average as the forecast. This approach will not yield a perfect forecast and will fail to predict extreme or exceptional events. However, researchers on average would likely be much better at estimating the completion time of papers if they based their forecasts on a large set of previous papers.

4.3 The outside view of wind deployment patterns

While the *outside* view was originally applied to projects, we believe it can also be extended to historical deployment patterns for onshore wind power, albeit with some modifications. The first question is what our historical reference cases should be. The one potential assessment we found that can be interpreted as using the *outside* view is by Nitsch et al. [64]. Their target case, Czechia, had virtually no wind power installations. Therefore, for reference cases, they turned to Austria and Denmark, countries with long wind power histories. From the historical reference cases they extrapolated average capacity densities as well as ranges for land exclusion criteria, which were constructed into land use scenarios. For this thesis, we also turn to countries with substantial wind power installations for our reference cases. Similarly to Jewell and Cherp [63], we argue that historical deployment patterns in such countries are indicative of what can be achieved in other regions with fewer installations.

The second question is which metrics we should quantify in the reference cases. To capture wind power expansion in bottom-up energy system models, three questions must be answered: where, how much, and how fast [36]. The work centered on growth rates already deals with how fast. That leaves where and how much, and these two aspects are represented by the land exclusion criteria, deployment density, and siting choice in relation to wind speed. All these can be informed by historical deployment patterns, yet their inclusion in modeling also presents challenges. The first concerns the spatial level at which the metrics should be measured. The second concerns how they should be extrapolated from the reference cases to the target case. These challenges are explored in Chapters 5, 6, and 7.

Chapter 5

Historical deployment patterns

Previous chapters have described current practices and assumptions for representing onshore wind power in bottom-up energy system models, and motivated the use of historical data. This chapter describes findings from empirical studies on wind power deployment densities and siting, and compares those deployment patterns to current modeling practice. Section 5.1 reviews the findings of the previous empirical literature. Then, Section 5.2 presents the method and findings of Paper A, which investigates the siting in relation to wind speed in 25 countries and regions, and compares it to the siting methods in four different energy system models. Additionally, Paper A develops a new heuristic method for representing historical siting patterns in energy system optimization models – *the bracket method* – which is later incorporated into Paper B in Chapter 6.

5.1 Previous empirical work

5.1.1 Deployment density and capacity density

A handful of studies [131–135] have investigated empirical capacity densities inside wind farms. Their reported mean capacity densities were 1.5 MW/km² [131], 3 MW/km² [132], 4.0–6.2 MW/km² [133], 4.3 MW/km² [134] and 19.8 MW/km² [135], with substantial variation between farms within a country, more so than between countries [133]. The large range of mean capacity densities is primarily a result of inconsistent definitions of wind farm area [122], as less than 5% of a wind farm’s area is occupied by actual infrastructure [134] and wind farm layouts vary drastically [132].

Instead of measuring the capacity density inside wind farms, Hedenus et al. [49] calculated deployment densities over whole municipalities and counties in the United States, Canada, Australia and Europe, by dividing total installed capacity by total regional area. They only included states, provinces and countries with significant wind power installations. Unlike the capacity densities, which only depend on spacing, area definition for wind farms and turbine design, their deployment densities implicitly account for all technical and non-technical factors affecting wind power deployment within the municipalities or counties.

The mean deployment density was 0.126 MW/km^2 and the highest observed value was an outlier reaching 1.5 MW/km^2 . Very few municipalities and counties surpassed 1.0 MW/km^2 and even in the famously wind-power-dense countries Denmark and Germany, almost all municipalities remained below 0.5 MW/km^2 . These results can be compared to the observed country-level deployment densities in Europe, which range from 0.03 MW/km^2 in France to almost 0.2 MW/km^2 in Germany [76].

Comparison with model assumptions

If only comparing capacity densities, all studies in Table 3.1 seem to fall within the observed empirical range. However, this ignores the suitability factors. There is empirical precedent for assuming a capacity density of 3 MW/km^2 for an individual farm. Yet there is, to our knowledge, no empirical precedent for the assumption that farms could cover more than 20% of all area outside of urban, mountainous and protected areas across whole continents, as assumed by multiple studies in Table 3.1. The obvious solution, to measure the suitability factor, would be difficult: it is dependent on the wind farm area definition as well as the land exclusion criteria, which both have uncertainties.

An alternative is to measure and compare deployment densities. These are defined over areas larger than a single wind farm but smaller than a country, and they implicitly include the suitability factor. The choice of spatial unit is important. Unlike large infrastructure projects, which have a defined endpoint, wind power installations are ongoing, and deployment densities defined over whole countries do not reflect the upper boundaries of installations. We hypothesize that smaller units behave differently: after decades of development, municipalities or counties can become “saturated” with wind power, whether by grid constraints, social opposition, or competing land uses. If so, the highest deployment densities observed in these units approximate an upper limit on how much capacity can be installed per unit of land under current technical, institutional and social conditions.

We argue that these values also serve as an upper bound for larger areas. Presumably, few municipalities in the future will achieve much higher deployment densities than those observed in the most wind-power-dense municipalities today, especially considering that the capacity density of new annual additions has been decreasing [131, 134]. Furthermore, every large country contains areas where little wind power is likely to be developed, due to extremely low electricity demand or limited grid availability, so a national average is unlikely to surpass

the upper range observed in small, densely deployed units. We therefore adopt the upper range of municipal and county deployment densities as the empirical benchmark for larger areas.

Some values in Table 3.1 fall within the range of the municipal deployment densities from Hedenus et al. [49], yet many far exceed what has been observed in countries such as Denmark and Germany, and very few are low enough to be close to the mean observed deployment density. Furthermore, such values are applied over large areas such as continents. Few studies assume deployment densities within the empirical range. This implies that many energy system models run scenarios with unprecedented deployment densities for wind power, which in reality would likely require substantial shifts in institutional and social settings.

One difference between the deployment densities of Hedenus et al. [49] and those assumed in Table 3.1 is the treatment of land. The former are measured over the entire area of each municipality or county, whereas the latter apply only to the land that remains after exclusions. For studies with little exclusion of land (e.g. [4, 113]), the two are directly comparable. Where exclusions are more extensive, the average deployment density across total land falls below the value listed in the table, so the comparison is not exact. Even so, deployment densities in such studies risk exceeding historical precedent in subregions where little land is excluded.

5.1.2 Siting

Land types and built environments

Next we consider siting in relation to infrastructure, land types and other common exclusion criteria. Studies seem to agree that wind power is usually placed in areas with lower population densities, though not in very remote areas without access to infrastructure such as roads and the electricity grid [49, 64, 134, 136, 137]. Surprisingly, some wind turbines are sited close to infrastructure and in areas with urban population densities (>1000 people/km²) [49, 134]. Similarly, wind farms tend to be located relatively close to the grid and roads [136, 137]. Most wind turbines globally are located on grassland or cropland [49, 134, 136, 138], though forest installations dominate in certain countries [139]. Wind turbines are generally placed away from protected areas [27, 33, 137], but there are exceptions [49].

When the empirical findings are compared with the studies in Table 3.1, most land exclusion criteria are consistent with historical deployment patterns.

However, the exclusion of forests and urban land is more restrictive than observed for actual installations.

Wind speed

Wind speed is broadly considered the most influential factor when choosing turbine sites [140]. Previous studies have shown that countries and regions with comparatively high wind speeds have more installed wind capacity [141–143] and that turbines are rarely placed at sites with wind speeds below 6 m/s [49]. However, deployment patterns across continents or individual countries are often very heterogeneous, and the correlation between wind power installations and higher wind speeds differs between studies and areas.

Studies with high resolution ($<1 \text{ km}^2$) identified wind speed as the most important predictor of siting in Europe and the United States, though the absolute importance varied between states [144, 145]. Studies of larger areas, such as census tracts or municipalities, found significant correlations between wind speed and installations in the United States, Sweden and Germany [33, 137, 146]. In contrast, another study of Sweden [52] and studies across districts in Germany and Czechia as well as the NUTS2 regions in the EU [50, 51, 147] yielded no significant results for wind speed or the size of the wind potential. Furthermore, descriptive results from Hedenus et al. [49] and Weinand et al. [148] indicated that there are substantial differences between countries in how much wind power installations are pushed towards the windiest sites.

This calls into question how well bottom-up energy system models, and particularly optimization models with their assumption that the windiest sites are used first, represent siting with respect to wind speed for diverse regions. This is investigated in Paper A below.

5.2 Siting with respect to wind speed

This section presents the findings of Paper A, which asks the questions: how has wind power been sited in relation to wind speed, how has this evolved over time, and how does the siting of wind power in energy system models align with historical patterns?

5.2.1 Findings

Siting in relation to wind speed over time

Our analysis shows that new turbines within each region are sited at similar average wind speeds each year. Wind farm and wind turbine location data are compiled from regions with substantial wind power generation, including Germany [53, 149], Sweden [150], Denmark [151], France, Ireland, Estonia, Portugal [149], as well as states and provinces from the United States [152], Canada, and Australia [149], and compared against average wind speeds from the Global Wind Atlas (GWA) at a 1 km² resolution [153]. For each region and year, we compute the mean wind speed across all sites commissioned that year and fit a linear trend over time.

In 20 of the 25 regions, the trend is smaller than 0.05 m/s per year. In the remaining five, the trend is only marginally steeper or too uncertain to interpret, given the large year-to-year variation. The siting patterns are consistent both for regions with decades of installations, such as Germany and Denmark, and regions with shorter development histories. This stability contradicts a widely held expectation in the modeling community and among wind power developers that turbines are progressively relegated to sites of poorer resource quality as deployment increases [154, 155]. The windiest sites may eventually become saturated, forcing installation at progressively lower wind speeds; the empirical results of Weinand et al. [156] point in this direction, as several countries have exhausted a larger share of their potential at the highest wind speed sites than at lower wind speed sites. However, our results provide no support for this hypothesis.

Siting in relation to wind speed within regions

While wind speeds at new turbine locations are consistent over time within each region, turbines are not placed at the same wind speeds in all regions. Naturally, regions differ in how windy they are, how heterogeneous the wind speeds are

within their territory, and how accessible the windiest sites are. For example, the mean site in Ireland has an average wind speed of 9 m/s, compared to 7 m/s in Germany, resulting in siting at different wind speeds across regions. Yet this raises the question of how turbines are sited relative to each region's underlying wind speed distribution.

We find that wind turbines tend to be placed at relatively windy sites, with wind speeds that are on average higher than the mean wind speed across sites within each region. This is shown in Figure 5.1 by the distribution of wind speeds at turbine sites being shifted to the right of the regional wind speed distribution for the four sample regions. Notably, the extent of the right-shift varies between regions: Colorado sites wind power at the windiest sites within the state whereas Denmark sites wind turbines almost uniformly across all land. Fitting the mean wind speeds at turbine sites y as a function of the mean regional wind speeds x for each region yields the expression $y = 0.8x + 1.9$ with $R^2 = 0.66$. This means that 66% of the variation in wind speeds at turbine sites between regions is explained by the underlying wind speed distribution of each region.

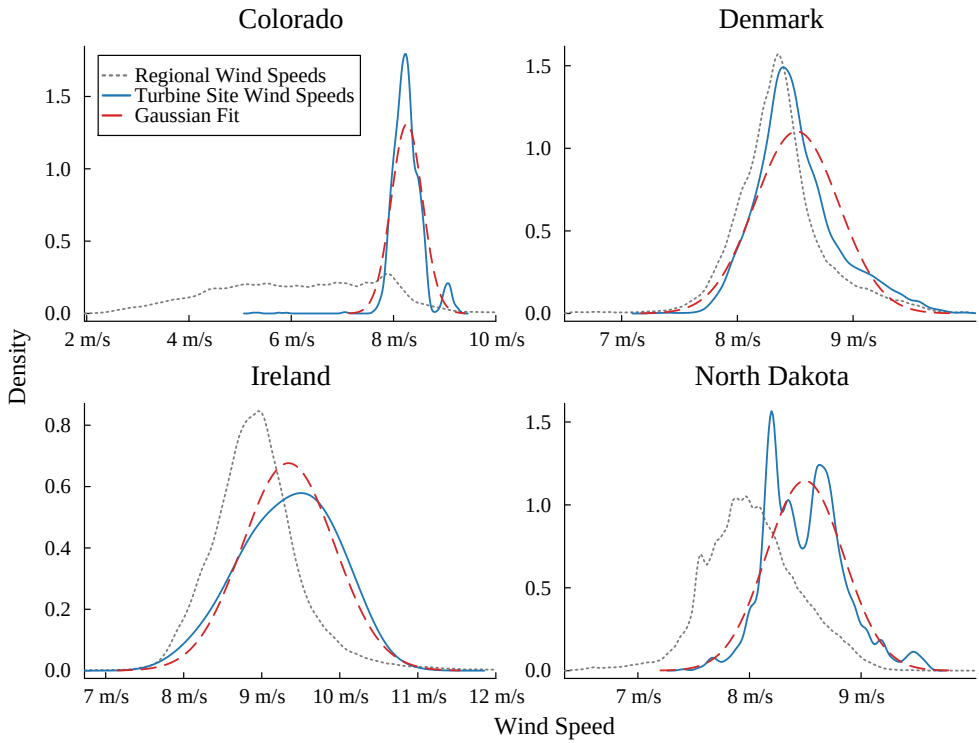


Figure 5.1: The distribution of average wind speeds at turbine locations compared to the distribution of wind speeds across the whole region, visualized as Kernel Density Estimates. The wind speeds at turbine sites are shifted to the right of the mean regional wind speed and resemble a Normal distribution.

Region	Population Distribution										
	Coefficient	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Germany	0.65	0	0	1	1	1	1	1	2	1	2
Austria	0.66	0	0	0	1	1	2	2	4	0	0
Denmark	0.70	0	0	1	1	1	1	1	1	2	2
Ireland	0.71	1	0	0	1	1	1	0	1	2	3
Portugal	0.76	0	0	1	0	0	1	1	2	3	2
Estonia	0.81	0	0	0	0	0	0	3	0	3	4
France	0.81	0	0	0	1	1	1	2	1	2	2
Iowa	0.82	0	0	0	0	0	1	1	2	2	4
Sweden	0.83	0	0	0	1	1	1	2	2	2	1
South Dakota	0.86	0	0	0	0	0	0	1	1	2	6
Oklahoma	0.87	0	0	0	0	1	1	1	1	2	4
North Dakota	0.87	0	0	0	0	0	0	2	2	2	4
Minnesota	0.88	0	0	0	0	0	0	0	0	1	9
Illinois	0.90	0	0	0	0	0	0	1	2	3	4
Kansas	0.91	0	0	0	1	0	0	1	1	3	4
Texas	0.93	0	0	0	1	1	0	1	1	2	4
Alberta	0.94	0	0	0	0	0	0	0	1	3	6
Victoria	0.94	0	0	0	0	0	0	0	2	2	6
California	0.95	0	0	0	0	0	0	0	0	2	8
Oregon	0.95	0	0	0	0	0	1	1	1	3	4
Colorado	0.95	0	0	0	0	0	0	0	2	6	2
New South Wales	0.96	0	1	0	1	0	0	0	1	0	7
Ontario	0.98	0	0	0	0	0	0	0	0	1	9
Québec	0.99	1	0	1	0	1	3	2	1	1	0
South Australia	0.99	1	0	0	0	0	0	0	1	1	7

Figure 5.2: The allocation heuristics for each region calibrated with the *bracket method*. The allocation heuristics are expressed as the number of 10%-multiples of installed capacity allocated to each wind speed class. Classes are ranked, containing wind speeds just above 6 m/s in the 1st, to the highest wind speeds in the 10th.

Table 5.1: Summary of variables used in the statistical analysis.

Dependent variable	Independent variable	
Share of installed capacity allocated to windiest brackets	Wind resource	Land-use competition
	↓ Mean regional wind speed	↓ Demand density ↑ Population distribution

↑ indicates a positive correlation hypothesis; ↓ indicates a negative correlation hypothesis.

To explore to what extent each region concentrates installed wind capacity at the windiest sites, we introduce a new method called the *bracket method*. The *bracket method* divides all possible wind power sites in each region – those with wind speeds from just above 6 m/s up to the highest in the region – into ten wind resource classes of equal area. We then calculate the share of installed capacity in each wind resource class. This produces a *regional allocation heuristic* that shows how each region has allocated wind capacity relative to its underlying wind speed distribution (see Figure 5.2). The allocation heuristics reveal that regions differ markedly in how they have installed their wind capacity. Two regions, Minnesota and Ontario, site 90% of their wind power capacity in the windiest 10th class, whereas Germany and Denmark site only 20%, with most falling between these extremes. The regions that site no capacity in the windiest class have their highest wind speeds in remote or mountainous areas, far from demand centers and the grid.

An exploratory multivariate linear regression is conducted to investigate possible explanations for this variation. It tests whether regions with lower wind speeds or less pressure from competing land uses are more prone to installing a greater share of wind capacity in the windiest classes (see dependent and independent variables in Table 5.1).

Table 5.2: The results from the linear regression models show the relationship between the independent variables and the share of installed capacity allocated to the windiest brackets using the bracket method. A significant correlation was found for the population distribution coefficient.

Model	Dependent variable	Independent variables			Adjusted R ²
		Wind Resource	Land-use competition		
	Share of installed capacity in	Mean regional wind speed	Demand density	Population distribution	
1	10th class	NS	NS		0.128
2	10th class	NS		1.408*	0.229
3	10th & 9th classes	NS	NS		0.147
4	10th & 9th classes	NS		1.383*	0.312

Dependent variable: Share of installed capacity in the 10th and 9th wind speed brackets. Reported values are standardized estimated coefficients. ** $p < 0.001$, * $p < 0.01$, NS $p > 0.01$. Empty cells show that the corresponding independent variable is excluded from the model due to testing the same hypothesis.

The results in Table 5.2 reveal a statistically significant correlation between the population distribution coefficient and the share of installed capacity in the windiest class, and in the two windiest classes. A value of 0 for the population distribution coefficient indicates a uniform population distribution everywhere within a region and a value of 1 indicates the entire population is concentrated in a single square kilometer. Our results suggest that regions with more concentrated populations (higher coefficient) are more likely to optimize their siting with respect to wind speed. No significant relationships are found for the demand density, where a higher value represents more human and industrial activity in a limited area, or the mean regional wind speed. The robustness of these findings should be validated for a larger sample in an analysis that also considers physical constraints to wind power installations such as mountain ranges before drawing major conclusions. Yet, the findings raise the possibility for modelers to extrapolate allocation heuristics calibrated on historical patterns to new regions based on parameters like the population distribution.

Model comparison

Four methods for allocating wind power capacity are selected for comparison against the historical siting patterns. These four methods are chosen because they are representative of siting methods used in ESMs at large. One study, Reichenberg et al. [42], applied endogenous cost-minimization to allocate wind capacity. The other three applied heuristics: Pleßmann and Blechinger [157] allocated wind capacity uniformly over the 33–100 percentiles of all regional area, Schlachtberger et al. [4] allocated capacity in proportion to the capacity factor, and Bogdanov and Breyer [113] assumed 60% of the installed wind capacity is deployed in the 80–100 percentiles of sites ranked by average wind speed, followed by 20% each in the 70–80 percentiles and 50–70 percentiles. Except for Bogdanov and Breyer [113], who compared their wind power generation with actual Finnish generation data, these have never previously been evaluated against empirical data.

These methods are evaluated together with a novel heuristic allocation based on the historical deployment patterns of all regions. Using the *bracket method*, we calibrate all possible combinations of allocating 10%-multiples of wind power capacity into 10 brackets against actual capacity allocations in all regions. The combination that comes closest to representing the mean wind speed at existing turbine sites for all regions, as measured by the Root Mean Square Deviation (RMSD), assigns 10% of capacity to the 10th class (the windiest class), 50% to the 9th and 40% to the 8th. This is labeled the top-performing bracket heuristic.

The evaluation of the siting methods against actual installations demonstrates that a cost-minimization approach consistently sites wind power capacity at higher wind speeds than in reality. Each vertical set of symbols in Figure 5.3 represents the siting methods for a single region, and a siting method that perfectly represents the actual mean wind speed of a region should be on the identity line. The method of Reichenberg et al. [42] is above the identity line for almost all regions. By contrast, the heuristics of Schlachtberger et al. [4] and Pleßmann and Blechinger [157] are consistently below. The best performance is obtained with the heuristic of Bogdanov and Breyer [113] and the top-performing heuristic from the bracket method. However, no method consistently represents the historical deployment patterns for all regions. Hence, if possible, it would be preferable for modelers to apply historical siting patterns from the modeled region or a similar region.

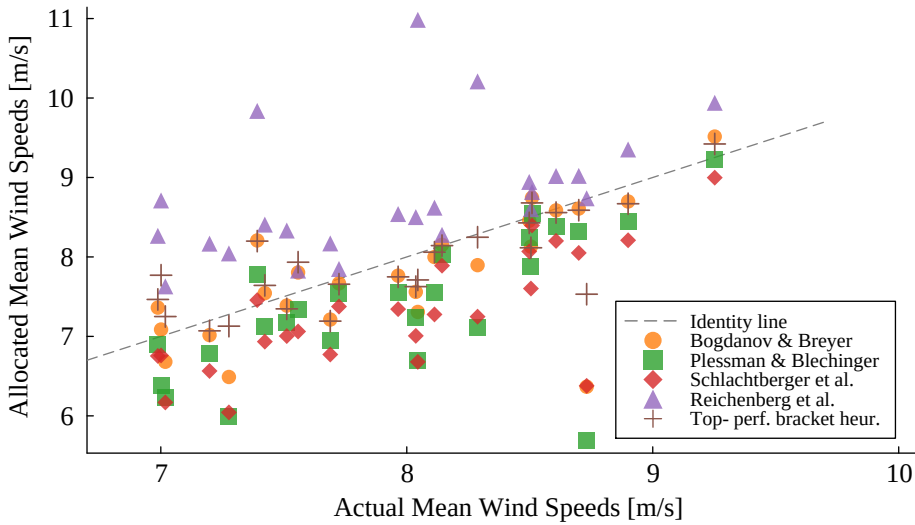


Figure 5.3: Each symbol represents a different siting method, four from previous studies [4, 42, 113, 157], and one top-performing allocation heuristic from the *bracket method*. Each vertical set of symbols represents the siting outcomes, given as the weighted mean of the wind speeds at sites with allocated capacity, of the siting methods for a specific region.

5.2.2 Implications

What the findings of Paper A imply for the modeling practices summarized in Table 3.1 depends on where each falls in Figure 3.1. Models that combine endogenous cost-minimization with a fine spatial resolution (e.g. [40, 119, 120]) are likely to place turbines at higher wind speeds than have been observed historically. At the other extreme, studies that spread wind power uniformly across all available land in a very large area due to coarse spatial resolution [41, 89, 116] may yield a wind power allocation that, on average, matches the dispersed siting of regions such as Denmark, but fail to capture the wind speeds seen elsewhere in the sample. Most studies lie between these extremes, and their siting outcome depends on the land and transmission constraints of the particular region. Such models may reproduce observed historical siting patterns for a target region, but incidentally rather than by design. Therefore, to ensure that the spatial allocation approach applied in the model sufficiently captures real-world wind power siting, historical deployment patterns should be used as a benchmark for validation.

Chapter 6

Implications of historical deployment patterns for modeling

The previous chapter established that there are systematic discrepancies between common modeling assumptions and historical onshore wind installations. However, whether these discrepancies substantially affect the results of modeling future low-carbon systems remains unresolved. This chapter addresses that question by presenting the findings of Paper B, which compares common modeling assumptions with empirically derived assumptions for the deployment density and siting in relation to wind speed in an energy system optimization model. The purpose is to assess whether prevailing assumptions introduce systematic bias in estimates of system cost and wind power cost-competitiveness. The paper offers a methodological contribution by incorporating historical deployment data into future scenarios.

6.1 Methodology

6.1.1 Model

The energy system model is a capacity expansion model that uses linear optimization to model cost-effective future electricity systems. It has previously been used for continental [42, 105] and global [158, 159] energy system analyses. The advantage of the model is that it can be applied to any user-defined region, allowing the impacts of empirically grounded wind power assumptions to be compared systematically across diverse countries. The energy system model and the software used for processing the input data for renewables and demand are openly available [160, 161], and detailed in a separate paper [105].

The scenarios in the main analysis are run for the 166 countries and areas shown in Figure 6.1, hereafter referred to as regions. Regions are excluded from the analysis if they are smaller than 1000 km², lack demand data, produce infeasible/unbounded model solutions, or have system costs exceeding 100 €/MWh. Small regions are excluded because they can exhibit unrealistic system costs of several hundred €/MWh, arising from limited land availability for area-intensive renewable technologies and absent/constrained electricity trade.

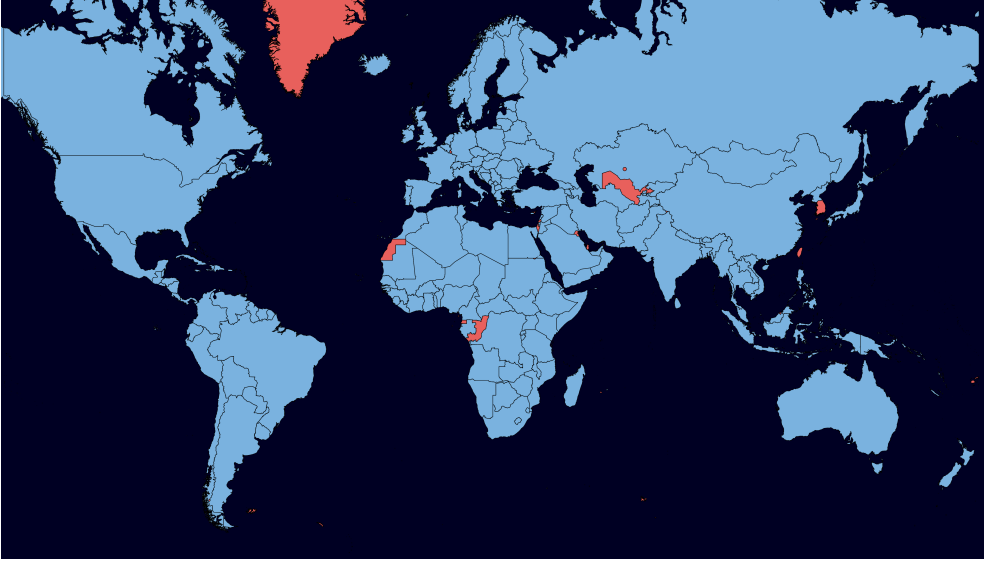


Figure 6.1: The 166 regions marked in blue are included in the main analysis. The regions marked in red are excluded from the analysis because of data unavailability, small size, too high system cost, or infeasible/unbounded solutions.

Since we are interested in evaluating the effect of empirically based assumptions in low-carbon electricity systems with substantial renewable installations, maximum emissions are set to 10 g CO₂ per kWh of electricity. The included energy technologies are solar PV (rooftop and utility-scale), concentrated solar power (CSP), wind power (onshore and offshore), hydropower, natural gas and bio gas turbines (open- and closed-cycle), coal plants and batteries. In the main analysis, each region is modeled in isolation as a “copper plate”, meaning that electricity can be traded freely within a region but not across its borders. Hydropower is capped at the existing installed capacity. Demand for 2050 is estimated from the SSP2 scenario, and a uniform discount rate of 5% is applied to all regions. Load shedding is permitted at a cost of 1000 €/MWh for up to 5% of hourly demand.

For the wind potential, town and city centers, areas far from the electricity grid, areas with average wind speeds below 6 m/s, as well as some protected area categories with practically no historical installations are excluded, in line with the findings from Hedenus et al. [49]. The aim is not to represent individual regions accurately, but to investigate how wind power assumptions affect regions with different resource endowments. Therefore, the land exclusion criteria are

applied uniformly across all regions.

6.1.2 Incorporation of historical data

Drawing on the *outside* view by Kahneman and Lovallo [66], we incorporate empirical deployment densities from Hedenus et al. [49] and empirical siting patterns from Paper A (see Sections 5.1.1 and 5.2).

Deployment density

While Flyvbjerg and Gardner [129] argue that taking the mean of the relevant metric from the reference cases is appropriate for making projections, this argument was made in the context of infrastructure projects. In the context of energy system modeling, where renewables are continuously expanding, and the potential acts as a cap to total deployment, assuming the mean empirical deployment density would be too restrictive. Like Jewell and colleagues (e.g. Vinichenko et al. [126]), we instead consider the distribution of observed deployment densities (growth rates in their case), and particularly the upper range values. For ex-post evaluation it is sufficient to compare model outputs to the empirical range. However, here we use historical data as inputs and apply them globally. Consequently, values for the deployment density cannot be so low that they become overly restrictive, yet must also be realistic to achieve across large areas.

The highest observed municipal deployment density is 1.5 MW/km^2 , from a single, very windy and relatively sparsely populated German municipality [49]. However, extrapolating this value to all land globally is very optimistic since most regions worldwide do not have the very favorable characteristics for wind power of this one municipality. Furthermore, it will be easier and quicker to achieve a high deployment density in a single municipality than across whole nations or continents. Instead, we define our *High empirical* and *Low empirical* deployment densities as 0.35 MW/km^2 and 0.1 MW/km^2 , respectively. The former corresponds to the 95th percentile in the empirical sample, representing an optimistic future estimate, and the latter corresponds to the empirical median, representing typical current levels of deployment. With these inputs there can be no exceptional German municipalities as the deployment density is a hard upper limit in the model. However, deployment densities should on average be more realistic across whole countries worldwide: a deployment density of 0.35 MW/km^2 is around double what is observed in Germany currently [76].

The values chosen are intended to illustrate the impact of applying empirically grounded deployment densities, not to predict the exact upper limit.

Siting patterns

Unlike the deployment density, there is no upper boundary for siting in relation to wind speed that can be inferred from reference cases. Instead, we try to span the range of observed empirical siting patterns. The regional allocation heuristics from Paper A (Figure 5.2) are stylized into three distinct siting approaches. These are the *Concentrated*, *Intermediate*, and *Dispersed* siting approaches, which allocate 90%, 30% and 10% of wind power capacity to the windiest class, respectively (see Figure 6.2).

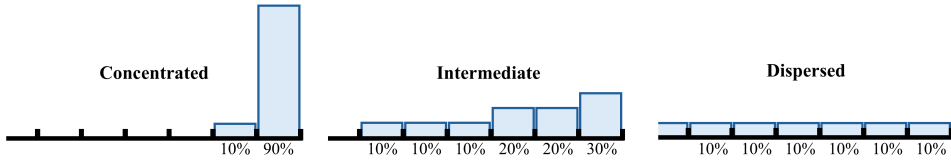


Figure 6.2: Illustration of *Concentrated*, *Intermediate* and *Dispersed* siting approaches. Each bar represents the share of wind capacity allocated to a wind resource class, with the rightmost class corresponding to the top 10% windiest sites in the region after excluding sites with wind speeds below 6 m/s.

The siting approaches are implemented with the following constraint:

$$C_{r,c} \leq s_{r,c} \sum_{c'} C_{r,c'} \quad \forall r, c. \quad (6.1)$$

The sets are r for the regions and $c = 1, 2, \dots, 10$ for the classes. The variable $C_{r,c}$ is the installed onshore wind capacity in region r and class c . The parameter $s_{r,c}$ is the share of the total installed capacity that is allocated to resource class c for region r .

The heuristics can make wind power less cost-efficient, causing the model to favor other energy technologies and reduce total installed wind capacity. Conversely, the model can also increase total installed wind capacity to compensate for the decline in production resulting from siting at lower wind speeds, if wind power remains cost-efficient in relation to other energy technologies.

The empirical analysis shows that turbines have been sited at remarkably similar wind speeds over time within nearly all regions, and hence we deem

it reasonable to extrapolate the historical patterns into the future. Yet, siting patterns might change in the future if the pressure to install more renewables becomes large enough. Because of this and because future electricity systems may have significantly more wind power capacity than the historical samples, we implement an “overflow” mechanism. It allows the model to be more flexible with siting by redirecting capacity to classes with lower wind speeds if the potentials in higher classes are fully utilized, provided that wind power remains sufficiently cost-competitive to meet remaining electricity demand.

6.1.3 Scenarios

To investigate the effect of historical deployment patterns more generally, rather than trying to predict the patterns for specific regions, we construct a set of empirically based scenarios. Making more specific predictions would require more information about the characteristics and causal mechanisms behind the outcomes in the reference cases than is currently available.

The two key parameters – empirical deployment density and empirical siting approach – are combined into empirically based scenarios spanning the range of historical deployment patterns. These are compared against a reference scenario in which turbines are sited cost-optimally and wind power potential is calculated using a deployment density of 1.6 MW/km^2 [114], hereafter the *Reference* density. Given the wide spread of deployment densities reported in the literature, many values could fill this role; we select one that is relatively optimistic yet not too far from the upper range of observed empirical values. All scenarios are illustrated in Figure 6.3. Scenarios with only one empirical parameter are not treated as fully empirical, but are included to isolate the contribution of each parameter.

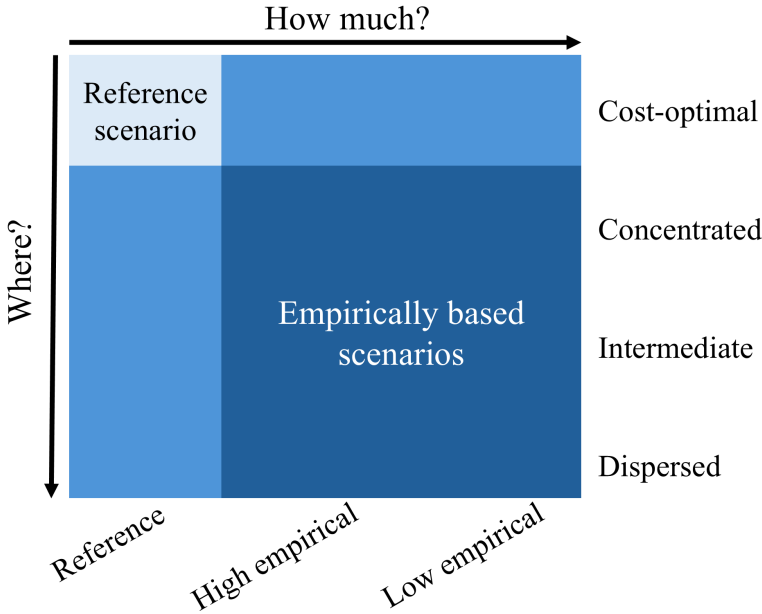


Figure 6.3: The space of scenarios investigated, spanned by our two parameters: deployment density (x-axis) and siting approach (y-axis). Together, they represent how much and where wind capacity can be installed in models. The *High* and *Low Empirical* deployment densities correspond to 0.35 and 0.1 MW/km², respectively, and the siting approaches are shown in Figure 6.2. The empirically based scenarios are compared to the reference scenario with *Cost-optimal* siting and *Reference* deployment density (1.6 MW/km²).

6.2 Findings

In the reference scenario, we model an optimal system configuration for a future low-carbon world without nuclear power. Onshore wind power provides half of annual global demand, followed by solar PV at 37%. System costs across all regions range from 24 €/MWh to 80 €/MWh, the median being 39 €/MWh. The median cost is relatively low because of pre-existing hydropower in some regions and because the copper-plate assumption smooths wind power production over large areas, reducing storage needs.

6.2.1 Isolating the effects of each parameter

Increases in region-level system costs range between 0 and +20%, with a median increase of +2.5%, when introducing the *Intermediate* siting approach

in isolation (see left side of Figure 6.4). Changes in onshore wind generation are quantified as the absolute difference in the share of demand covered by onshore wind, in percentage points (pp), compared to the reference scenario for each region. The horizontal cluster around zero in the figure shows that most regions experience a small absolute change in onshore wind share when forced to adopt the *Intermediate* siting approach. This implies that wind power remains cost-competitive in many regions despite being installed at lower wind speeds compared to *Cost-optimal* siting. However, to compensate for the lower production at low-resource sites, regions must install more wind capacity, increasing their system cost. This may also increase wind power production throughout the year, causing a slight increase in the absolute onshore wind share compared to the reference scenario.

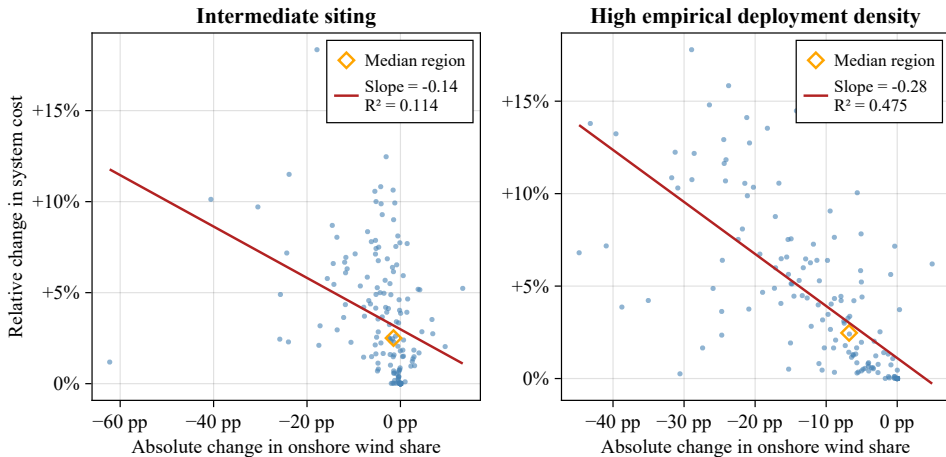


Figure 6.4: The change in system cost and onshore wind share for each region (represented as blue circles) resulting from applying the *Intermediate* siting approach and the *High empirical* (0.35 MW/km^2) deployment density compared to the reference scenario (*Cost-optimal* siting and 1.6 MW/km^2). The onshore wind share is measured as the absolute change in share of demand given in percentage points (pp). The siting approach primarily affects system cost while keeping the generation composition relatively constant, whereas the lower deployment density affects both system cost and onshore wind generation.

The introduction of the *High empirical* deployment density causes very similar increases in system cost to the *Intermediate* siting approach (see right side of Figure 6.4). However, unlike the siting approach, lowering the deployment density compared to the reference scenario causes an evident reduction in the

absolute onshore wind share for many regions. The greatest reduction is by -44 pp, from 50% to 6% for the Netherlands, with the median across all regions being -7 pp. Decreases in absolute wind share are caused either by the wind potential being fully utilized and capping total installed capacity, or by the potential being constrained at high-wind-speed classes, which forces installations at lower wind speeds and can make wind power less cost-efficient than other energy technologies.

Regions sensitive to empirical siting and empirical deployment densities are found on every continent, but the two sensitivities have different causes. Lower deployment densities penalize regions that combine high demand with limited available land. Empirical siting instead penalizes regions with abundant high-quality wind resources: their potential remains sufficient at lower densities, but siting at lower wind speeds forces either additional wind capacity or a shift to other technologies, both of which raise system cost. There are three cases where system costs remain unchanged – where the reference scenario deploys little onshore wind, where alternative technologies are available at costs comparable to onshore wind, or where *Cost-optimal* siting already approaches the capacity ceiling. In the third case the overflow mechanism relaxes the siting constraint so as not to restrict total installed capacity, with the result that *Intermediate* and *Cost-optimal* siting converge.

6.2.2 Impact of empirically based assumptions

Our results demonstrate that empirically grounded representations of onshore wind deployment, based on historical patterns, have a substantial impact on system cost and wind power generation across regions with diverse resource endowments. Across all empirically based scenarios that apply historical patterns for both onshore wind power siting and deployment density, median increases in system cost range from 2.8% to 9.8% compared to the reference scenario based on typical literature assumptions (see left side of Figure 6.5). Additionally, the global onshore wind power generation, summed across all regions, is reduced by 40–70% (see right side of Figure 6.5). A reduction of 70% in onshore wind power generation corresponds to 35% of global electricity demand in the reference scenario, and is mainly covered by solar PV and offshore wind power. For comparison, requiring European countries to be self-sufficient rather than allowing cost-optimal transmission interconnections raised system costs by 12% [162] — the same order of magnitude as the increases found here.

In line with the results in Figure 6.4, Figure 6.5 also shows that deployment

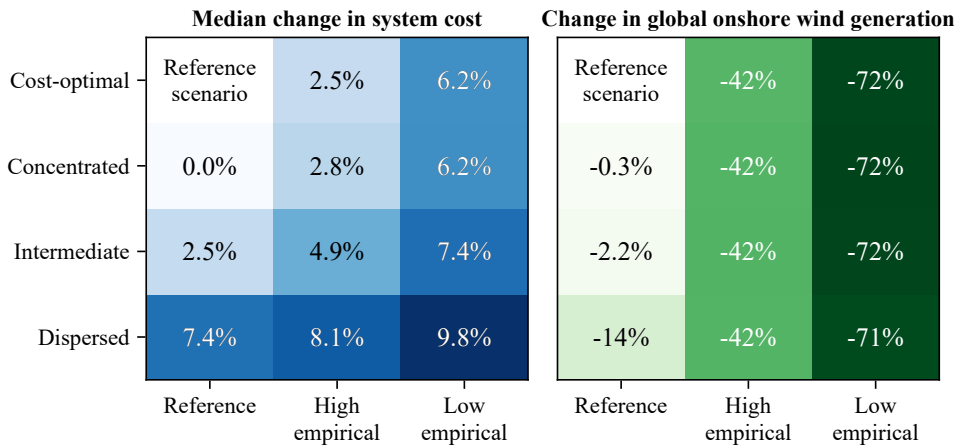


Figure 6.5: Median increase in system cost across all regions and total change in global onshore wind generation compared to the reference scenario. Y-axis shows the siting approach and X-axis shows the deployment density.

density has a greater impact on onshore wind generation than siting approach. Moreover, the effects of the different siting approaches become more similar to each other and to *Cost-optimal* siting as the deployment density decreases. This is due to the overflow mechanism explained above, which particularly affects the *Concentrated* siting approach because it is the most similar to *Cost-optimal* siting to begin with. However, this does not imply that siting with respect to wind speed can be ignored: applying a very dispersed siting with respect to wind speed – typical of densely populated regions like Germany and Denmark – at the *Reference* deployment density causes a median increase in system cost of 7% and decreases global onshore wind power generation by 14%. Such results are relevant when modeling regions where wind power tends to be allocated over a wider range of wind speeds, as has been the case in densely deployed European countries (Figure 6.2).

6.2.3 Implications for modelers

Our findings suggest that many ESMs overstate the contribution of wind power and thereby underestimate system costs by inadequately representing the real-world constraints on deployment. We argue that empirical deployment densities defined over larger regions such as municipalities capture what institutional systems and technical constraints actually permit at the municipal scale. Yet many

models [40, 43, 89, 117–120] apply values that are twice the highest observed municipal density (1.5 MW/km^2) across whole continents – an assumption that requires justification.

Both deployment density and siting can have a substantial effect on system cost, and deployment density in particular impacts the generation mix. Considering historical deployment patterns for onshore wind power is especially relevant for studies that investigate the cost and composition of future low-carbon systems [40, 89, 113] or study the effect of balancing measures such as transmission expansion [4, 42, 114, 116].

Ideally, energy system modelers should derive country-specific, empirically grounded estimates rather than applying generic upper bounds that have no precedent in observed deployment patterns. Yet, we have only scratched the surface of what drives the great spatial heterogeneity both within and between countries. Further research is needed to identify what drives cross-country variation in deployment density and siting patterns, and how it relates to geography, population density, and institutional context. Deployment densities higher than 1.5 MW/km^2 may emerge in regions with favorable physical and institutional conditions for wind power, such as permissive planning regimes. However, modelers carry the burden of proof when applying such values across whole countries or continents.

For now, we argue that an *outside* view of the deployment density and siting patterns is the preferred approach. The extrapolation of currently observed deployment patterns into the future or to new countries is genuinely uncertain, and without knowledge about the causal mechanisms behind a deployment density, it risks becoming too high or too low for specific regions. Yet, the nearest real-world counterpart is a better anchor than an assumption with no empirical grounding at all.

Chapter 7

Discussion and future work

This chapter discusses the methodological approaches and theory adopted in this thesis, reflecting on both limitations and possible future work.

7.1 Input, model structure or output

There are three steps in the modeling process where historical data can be integrated: (i) inputs, storylines and scenarios, (ii) model structure, for instance objective functions or constraints, and (iii) analysis and discussion of model output [35, 163, 164]. For Paper B, we decided to implement empirical results from Paper A and Hedenus et al. [49] as inputs and constraints in a deterministic energy system model. Here, we want to reflect on the limitations of this approach and assess other options for considering historical data.

The issue with integrating historical data as an upper cap or as a constraint is that it can become too restrictive and inflexible in certain contexts. One example is that our chosen empirical deployment densities (e.g. 0.35 MW/km^2) cap installations at the same level in all regions, despite values of 0.5 MW/km^2 being entirely plausible for small countries. The allocation heuristics are a second example. Without an overflow mechanism, our siting approaches would have restricted total installed wind capacity when the potential was binding.

This is contrary to what we would expect to happen in reality. As expansion approaches some perceived upper boundary, there is likely room for agency in the form of policy or technological developments to push back the incoming ceiling. Despite our empirical findings, we expect regions to shift installations to lower wind speeds if the high-quality sites run out and there is sufficient demand. The overflow mechanism mimics this logic by allowing capacity to overflow to lower wind resource classes if the potential is filling up in the higher ones. This solution accounts for the endogeneity of the potential – letting the potential respond to developments within the system – yet also implicitly assumes that it is the distance from the ceiling that determines whether a siting pattern is relaxed. That assumption is untested. Whether proximity to the perceived ceiling changes siting patterns in practice, and how close installations must come before it does, remains an open question.

An interesting alternative to imposing inputs as hard constraints is to incorporate historical data into the model structure. One example is the use of disamenity costs [56, 165] to penalize siting in populated areas without forbidding it. This accounts for the issue of endogeneity by allowing installations in less favorable areas if there is a lack of other cost-effective options.

The third option, which requires neither the use of constraining inputs nor changes to the mechanism of the model, is ex-post evaluation of outputs. Jewell and colleagues do this for growth rates, and the same could be done for siting and deployment density. Ex-post analysis does not constrain installations within the model. Furthermore, it can be a fairer evaluation of existing models. Observed deployment densities are what was actually realized and more closely correspond to the capacity installed by the model rather than to its input potential. Similarly, ex-post analysis could capture how transmission constraints and spatial resolution affect the allocation of wind power in relation to wind speed, and how close that allocation comes to observed siting.

7.2 Empirical data

While this thesis has focused on the use of empirical data, the gathering and validation of such data are just as important questions. The gathering of data currently faces multiple obstacles, the primary one being data availability. For wind turbines globally, the only dataset that is available for free at high spatial resolution is OpenStreetMap, which relies on community contributions and rarely contains information on turbine characteristics, developer or commissioning date. Besides that, the only free options are national datasets of varying quality and accessibility. Even within the EU, many countries do not maintain a publicly available dataset of existing wind power installations (e.g. Spain, Italy and Czechia), and of those that do, many only provide snapshots (e.g. Portugal and Ireland), which risk becoming outdated and hinder analyses of wind power deployment over time. Best practice is seen among nations such as Sweden, the United Kingdom, Denmark, and Germany, which regularly update their wind turbine datasets, and, at least in the case of Sweden and the UK, include rejected applications.

The restricted data availability impacts which reference cases the *outside* view can draw on. Although the samples of Hedenus et al. [49] and Paper A draw on historical data from different parts of the world, they rely most heavily on data from the Global North. While many regions in the Global South have too short histories of wind power deployment to draw from, countries like China and India

have substantial wind power installations and might exhibit different deployment patterns from those observed in the cited studies. Extrapolation from reference cases to a target case is difficult, and densities achieved in Germany or Denmark may not indicate what is achievable in countries with very different institutional settings for technology diffusion. This should be carefully considered when choosing the reference cases, and warrants further empirical analysis.

Issues with data availability are also present for solar PV and offshore wind power. Offshore wind power has fewer data points, and both technologies have shorter time series than onshore wind power, which complicates the extrapolation of historical deployment patterns. However, utility-scale solar PV in particular is approaching a point where measuring empirical deployment densities becomes viable – a potential avenue for future research.

Better datasets will not only benefit bottom-up energy system models. They would also facilitate studies on the impact of wind turbines on economies, people, and specific social groups. So far, such studies have mainly been concentrated to the United States and a few other nations [15, 26, 137, 166–169], leaving a gap for cross-national comparisons.

7.3 Deployment density

Several questions concerning observed deployment densities remain open, both for onshore wind power and for other energy technologies.

The first concerns stability over time. We have assumed that the deployment densities of municipalities and counties indicate the ceiling of wind power expansion on the grounds that small regions approach saturation faster than whole countries do. Whether that ceiling holds is untested. Small regions may experience repeated growth pulses after periods of low installation, as has been observed at the national level [127], and densities may also fall as turbines reach end-of-life and are not replaced. Tracking the highest observed densities over time would establish whether they represent an actual limit or merely a current level.

The second concerns the choice of spatial unit. Hedenus et al. [49] used municipalities and counties because decisions on renewable energy are often made at these levels. However, these units vary substantially in size both within and between countries, and the measured density depends on where their boundaries happen to fall. Investigating how alternative definitions affect the result would show how sensitive the benchmark is to this choice.

The third concerns what distinguishes the densest regions. Identifying the

physical, economic and institutional properties shared by the regions at the top of the distribution would make it possible to select reference cases that match a given target region, rather than applying a single density everywhere. Densities could then be assigned separately to subregions within a model, and the resulting scenarios compared against those built on uniform assumptions.

7.4 Feasible potential

Potential assessments at the continental or global level contain considerable uncertainty and necessarily average over local variation. Under these conditions, we argue that an *outside* view of the deployment density is better suited to estimating the potential than the current dominant practice of adding successive layers of social and institutional restrictions to a technological base, often using thresholds that lack empirical justification. An *outside* view does not resolve the uncertainty, but it anchors wind power assumptions in observed outcomes. Furthermore, as the selection of reference cases improves, so might the quality of the potential estimates.

Where such an estimate belongs in the potential terminology is not obvious. Because it implicitly accounts for all factors affecting deployment, including social and institutional ones, it could reasonably be classified as a feasible potential. However, its methodology differs markedly from that of existing feasible potentials, and we therefore suggest a separate designation: the *empirical potential*.

Research focusing on other spatial scopes or research questions is likely to require different methods. For studies exploring how the energy system might develop in a specific country, it may be more informative to begin with current installations and assess the barriers and drivers that could shift future development, as proposed by Verbruggen et al. [170]. The potential then becomes something created rather than measured – a framing that is arguably conceptually closer to the truth, though it might be difficult to apply across many countries at once. This also takes an *inside* view, but it begins at the other end: starting from existing installations and moving up, rather than starting from the theoretical potential and moving down.

Chapter 8

Conclusion

Returning to the first research question, this thesis has provided a cross-regional account of where wind power has been sited relative to the underlying regional wind speed distributions in 25 countries, states and provinces. Historical siting patterns are heterogeneous across regions and consistent over time. Onshore wind power has been sited at similar wind speeds year by year, both for regions with decades of deployment and for regions with short deployment histories. This contradicts the widely held expectation among modelers and developers that turbines are progressively relegated to poorer sites as the best ones are exhausted. Our results also show that turbines are consistently sited at windier-than-average locations, yet the degree to which capacity is concentrated at the windiest sites varies substantially across regions: from placing 0% to 90% of wind capacity in the windiest decile of land. An exploratory regression indicates that regions with more spatially concentrated populations allocate a larger share of capacity to the windiest areas.

Findings from the second research question reveal that energy system models tend to both assume higher deployment densities and allocate wind capacity to higher wind speeds than observed in the historical record. In almost every region, endogenous cost-minimization selects sites windier than those where turbines are actually built, and the higher the spatial resolution of a model, the more high-quality wind resource sites are revealed, potentially exaggerating the push towards high wind speeds. Assumed deployment densities span two orders of magnitude, with some studies assuming values within the empirical range, while others assume cross-continental values that are more than twice the value observed in the most wind-power-dense municipality to date.

Finally, results related to the third research question show that applying empirically based assumptions for the deployment density and siting with respect to wind speed substantially increases system costs across diverse regions compared to a reference scenario with common modeling assumptions. Lower empirical deployment densities also drive decreases in onshore wind power generation. The siting approach can affect both system cost and onshore wind generation if turbines are dispersed across a large range of wind speeds, as found in densely populated European countries, and if the deployment density is

high. Taken together, these results indicate that prevailing assumptions may lead models to overstate the contribution of onshore wind power and to understate system cost.

The primary contribution of this thesis is methodological, spanning large-scale wind resource assessment and energy system modeling. Drawing on the wind power literature on siting patterns and on theory from technology diffusion and project management, we establish historical deployment patterns as benchmarks for scenario realism. These benchmarks have implications for how we model the future electricity system, and for what futures are seen as possible by decision makers. Our results show that siting patterns are surprisingly heterogeneous across regions yet stable over time, that deployment densities are often lower than assumed, and that these assumptions carry consequences for future energy system costs and the role of wind power within such systems. Such findings admit two parallel interpretations: first, that previous assessments may have overstated the contribution of onshore wind power and that future scenarios should be adjusted accordingly; and second, that decision makers need to work to overcome the forces constraining further development. We do not yet know enough about what produces these patterns to determine the extent to which they can be overcome, or instead need to be treated as persistent constraints in future planning. In the meantime, we argue that an *outside* view of onshore wind power, and of other energy technologies, can offer an empirical grounding for model assumptions.

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