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Turbine siting in relation to wind speed: Insights from historical deployment patterns for energy system modeling

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A R T I C L E I N F O

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A B S T R A C T

Wind turbine output heavily depends on the wind speed at the deployment site. Energy system optimization models (ESOMs) typically allocate turbines in a cost-optimal manner, leading to siting at the windiest locations. However, such allocation methods lack an empirical base and risk overestimating the cost-competitiveness of wind power compared to real-life. This study assesses the historical siting of onshore wind turbines with respect to wind speed across 25 regions and introduces a heuristic method to represent wind power deployment patterns within ESOMs. Additionally, we conduct a comprehensive evaluation of existing wind turbine allocation methods in ESOMs. Our results show that turbines are typically sited at locations with slightly higher wind speeds than the regional mean, and new turbines within each region are consistently placed at sites with similar average wind speeds each year. The heuristics that best match historical deployment patterns tend to allocate 80–100 % of wind capacity to the 70th to 90th percentiles of the windiest areas. The cost-optimal turbine siting approach consistently favors windier locations compared to historical deployment. Overall, the findings present a promising avenue for incorporating historical data to improve the representation of wind power in future energy system modeling.

1. Introduction

Over the last two decades, the deployment of wind power has increased significantly [1] with countries such as Denmark and Ireland now generating over 30 % of their electricity from wind. As wind power continues to expand, it is expected to play an important role in future energy systems. Energy system optimization models (ESOMs) are widely used to investigate the contribution of different energy technologies, including wind power, for future decarbonized energy systems [2]. Such models typically yield optimal configurations of the energy system under different scenarios, considering technology costs and resource quality [3]. It is well established that the power output of wind turbines is heavily dependent on site wind speeds. ESOMs typically deploy wind power capacity in areas with the highest wind speeds to minimize system cost [4–7]. However, the deployment of wind power is a complex process where windiness alone can only partly explain where wind power is deployed [8–11], and it has been shown that installations are not concentrated at the windiest sites [12]. Thus, these models may overestimate the cost-competitiveness of wind power by allocating capacity to sites with higher average wind speeds than those selected for wind power in the real world. This study assesses the siting of onshore wind turbines with respect to wind speed in 25 regions and introduces a heuristic method to represent historical wind power deployment patterns. Additionally, we conduct a comprehensive evaluation of wind turbine allocation methods in ESOMs.

While wind speed is an important factor in selecting turbine sites [13], wind power deployment exhibits substantial spatial heterogeneity both between and within countries. Previous studies have shown that countries and regions with comparatively high wind speeds have more installed wind capacity [14–16] and that turbines are rarely placed at sites with wind speeds below 6 m/s [12]. Studies on individual countries have provided no consensus on whether more wind power is deployed at higher wind speeds [9–11,17–19]. For Swedish municipalities, Lauf et al. [9] and Ek et al. [17] observed that higher average wind speeds increase the probability of wind power investment, whereas Rahmad et al. [18] found no correlation between higher wind speeds and higher

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deployment levels. Wind power installations were correlated with higher wind speeds or higher wind potential across German districts [9], but not across Czech districts [19]. Similar inconsistencies were observed for national studies with a higher spatial resolution of 1 km [10,11]. Examining wind speeds at turbine sites across multiple countries, as well as states and provinces in Australia, Canada, and the U.S., Hedenus et al. [12] observed significant differences in the share of wind power capacity allocated to the areas with the highest wind speeds. In summary, wind speed alone only partly explains where turbines are sited. Turbine siting is also affected by competition with other land uses such as residential areas, agriculture, and nature conservation [9,20, 21]. Additionally, factors such as grid access [10], the prevalence of existing turbines [11,22], economic disenfranchisement [19,23,24], and the education level of residents [25] have been shown to affect turbine siting.

Some studies have claimed that "the siting quality of new wind turbines is decreasing" [26] due to the limited availability of sites with high wind speeds and the best locations being utilized first [27]. If true, wind turbines should increasingly be placed at sites with lower wind speeds as countries continue to deploy wind power. We test this claim in our study. The results can inform wind turbine allocation with respect to wind speed across different time horizons and deployment levels in energy system modeling.

Despite the heterogeneity in wind power deployment, ESOMs often use simplistic approaches to allocate wind power. After excluding land deemed unsuitable for turbines, optimization models usually deploy wind capacity in areas with the highest wind speeds first to minimize cost, while accounting for the interaction between different energy technologies [4–7]. Some ESOMs apply heuristics to allocate wind power instead of assuming that turbines are placed cost-optimally [28, 29]. Wind power in these models is assigned to sites with varying wind speeds based on an exogenous distribution. For instance, Bogdanov and Breyer [30] assumed that 60 % of wind turbines are placed in the top 20 % windiest sites in each region, while Schlachtberger et al. [31] allocated wind power in proportion to the capacity factor, resulting in some wind power also being assigned to less windy sites. While the representation of wind power in ESOMs has become more sophisticated over the past years, through improvements such as explicit turbine siting [32] and increased spatial resolution [33], the methods employed to allocate wind power still vary significantly between studies and, more importantly, have not yet been empirically validated.

In this study, we address the research gaps presented above by investigating the average wind speeds in 25 countries and regions that have already deployed substantial amounts of onshore wind power. These regions provide a basis for observing the patterns of wind turbine deployment with respect to wind speed and how these patterns have evolved over time. Our aim is to identify common patterns in wind power deployment that can inform the allocation of wind power capacity in ESOMs. Based on historical deployment patterns, we develop a new heuristic method to represent wind power siting and evaluate different methods for allocating wind power capacity with respect to wind speed in ESOMs.

2. Method

2.1. Data description

We targeted our analysis at areas that have a substantial proportion of electricity demand supplied by onshore wind power, as their development so far may provide insights into future wind power deployment. We also selected areas with similar energy policies and institutional environments throughout. For small countries, we perform the analysis at the national level, whereas for large federal countries, the analysis is conducted at the provincial or state level. In addition, we were constrained to areas where high-quality data on turbine locations were available. These criteria leave us with Austria, Denmark, Estonia, France, Germany, Ireland, Portugal, and Sweden, as well as eleven U.S. states, and three provinces in each of Australia and Canada, all hereafter referred to as regions.

For the analysis, we used two different kinds of datasets for wind power installations. One with exact individual turbine locations and the other with locations of wind farms, both up to and including the year 2023. The turbine datasets provide the exact turbine location, capacity, and installation year for the U.S. [34], Denmark [35], Sweden [36], and Germany [37]. For all other regions, we used commercial wind farm data from The Wind Power [38]. This dataset provides the location, capacity, and installation year of wind parks. The location data for these regions are not as precise as those for regions with exact turbine locations. All wind farm locations are labeled as either "accurate" or "inaccurate" in the dataset. Accurate locations usually have coordinates verified inside or adjacent to each wind farm, with some wind farms having coordinates centered on the estate where the farm is located. Inaccurate locations at least have coordinates within the correct municipality. The accuracy of the coordinate data for each region was assessed and confirmed to be sufficient for the scope of this analysis. After this assessment, turbines with both "accurate" and "inaccurate" locations were kept for the included regions. In the case of Germany, where we have the exact turbine locations until 2015 and park-level data from 2016 onwards, we merged the two datasets.

We applied several criteria to clean the dataset. Regions were excluded from the analysis if more than 6 % of wind parks had missing capacity (in MW), location (longitude/latitude coordinates), or installation year. Regions were also excluded if they had a substantial share of wind farms with "inaccurate" locations. For the remaining regions, parks with missing data were omitted, whereas decommissioned parks were kept to capture the complete historical deployment pattern over time. For an overview of selected regions as well as their wind

Table 1
Analyzed regions and their wind share of electricity demand, number of turbines/parks included in the analysis, and the share of turbines/parks with accurate locations. Data on demand and electricity generation were taken from Refs. [39–43] for the year 2023.

Region	Wind share[a]	Type of data	Number of turbines/parks	Share with accurate location
California	6 %	Turbines	3857	100 %
Colorado	30 %	Turbines	2816	100 %
Denmark	53 %	Turbines	7174	100 %
Illinois	17 %	Turbines	3552	100 %
Iowa	83 %	Turbines	6287	100 %
Kansas	70 %	Turbines	3927	100 %
Minnesota	22 %	Turbines	2696	100 %
North Dakota	63 %	Turbines	2086	100 %
Oklahoma	55 %	Turbines	5344	100 %
Oregon	15 %	Turbines	2109	100 %
South Dakota	76 %	Turbines	1331	100 %
Sweden	25 %	Turbines	5470	100 %
Texas	25 %	Turbines	18317	100 %
Alberta	13 %	Parks	51	90 %
Austria	12 %	Parks	310	86 %
Estonia	8 %	Parks	24	71 %
France	10 %	Parks	1790	85 %
Ireland	32 %	Parks	307	84 %
New South Wales	9 %	Parks	26	96 %
Ontario	12 %	Parks	111	97 %
Portugal	24 %	Parks	447	92 %
Québec	12 %	Parks	56	98 %
South Australia	58 %	Parks	31	94 %
Victoria	25 %	Parks	38	92 %
Germany[b]	27 %	Turbines/ Parks	24441/2514	100 %/57 %

[a] The wind share includes both onshore and offshore wind power.
[b] The German data is a combination of two datasets [37,38], before and after 2016, whose information is separated by forward slashes.

deployment and data quality, see Table 1. The cumulative capacity for the European data is consistent with WindEurope [44].

Average wind speeds were extracted from Global Wind Atlas [45,46] at 100 m altitude. Global Wind Atlas provides average wind speeds for the period between 2008 and 2017 based on down-scaled climate data from the ERA5 dataset. The wind speeds were processed using the open-source GlobalEnergyGIS package, which rasterizes or rescales datasets to a common resolution of 0.01°, equivalent to roughly 1 km at the equator [47]. As a result, each region was segmented into a grid of cells, each approximately 1 km by 1 km, with a corresponding average wind speed. All regions were defined using the global GADM dataset of administrative areas [48].

2.2. Analyzing wind speeds at turbine sites

We investigated the distribution of wind speeds at turbine sites by analyzing the average wind speeds of sites with installed capacity. The wind speeds at turbine sites were compared to the distribution of wind speeds over land for each of the 25 regions. The distributions were compared by visualizing them as Kernel Density Estimates (KDEs). The bandwidths of the KDEs were set according to the Sheather and Jones method for all cases, which is an appropriate method for visualization when the shape of the distribution is unknown beforehand [49].

To show how the wind speeds at turbine sites have changed over time for each region, we computed the yearly mean wind speed for cells that had new turbines installed on them for each year. The yearly mean was computed from the regional take-off year, which is defined as the year when electricity from wind power reaches 1 % of the regional electricity generation in the region and is used to separate the growth phase from the formative phase [50]. Years belonging to the formative phase were excluded since the phase is characterized by slow and erratic growth due to high costs and uncertainties. The mean wind speed at turbine sites $\bar{v}_t$ for turbines installed in the year t was calculated as a capacity-weighted average:

$$\bar{v}_t = \frac{\sum_i^n v_{it} C_{it}}{\sum_i^n C_{it}}, \tag{1}$$

where v_{it} is the mean wind speed at site i in year t, C_{it} is the installed capacity at site i in year t, and n is the total number of turbines or wind farms installed in year t.

2.3. Developing a new heuristic allocation method

We developed a new heuristic allocation method called the *bracket method* that allocates percentiles of installed capacity into wind speed brackets to create heuristics that represent historical deployment patterns. This method divides land with wind speeds above 6 m/s into brackets ranked based on wind speed and allocates fractions of the actual installed capacity to each bracket, illustrated in Fig. 1. A bracket b^q is an interval defined by a minimum and maximum wind speed, $b^q = (v^q_{min}, v^q_{max}]$. q is the bracket index with brackets sorted in ascending order according to increasing wind speeds such that $v^q_{max} = v^{q+1}_{min}$. Wind speeds below 6 m/s are excluded since it is very uncommon for turbines to be placed at such low wind speeds [12]. This exclusion removed a maximum of 7 % of parks in the case of Portugal, with 20 out of the 25 regions losing less than 1 % of their turbines/parks.

The *bracket method* is a generalization of previously proposed heuristic methods [29–31]. It can be used to represent any allocation of wind power, given sufficiently many brackets and small enough fractions of installed capacity. Consequently, it can be used to evaluate all historical allocations of wind power capacity. However, increasing the number of brackets leads to more empty brackets and makes the allocation of capacity more sensitive to the historical data, since the addition of even a single built turbine in the past is more likely to change the distribution of capacity among the brackets. Consequently, we chose to allocate 10 % percentiles of capacity into 10 brackets, as it provides a good balance between accurately reflecting actual installation patterns, maintaining consistency over time, and remaining interpretable.

We used the *bracket method* to calibrate how wind power capacity is allocated (*allocation heuristics*) based on historical data. The *allocation heuristics* are defined as a rule of thumb by which wind power capacity is allocated. For instance, for a given region, we calculated the share of actual capacity C^q/C^{tot} installed within each bracket b^q and rounded it to the nearest 10 %-multiple. If the capacity did not add up to 100 % due to rounding errors, the Largest Remainder Method was used as a correction. This allowed us to generate a heuristic for a specific region.

To further generate a general heuristic for all regions, we created all possible heuristics of placing 10 %-multiples of wind power capacity in 10 brackets and calibrated them with the data for all 25 regions. This enabled us to capture the common historical deployment patterns suitably well for all regions, making the heuristics potentially useful for energy system modeling on the continental or global scale.

Allocating 10 %-multiples of wind power capacity into 10 brackets is a combinatorial problem identical to the classic stars and bars problem, yielding 92 378 possible allocation heuristics h for each region. The heuristics allocated fractions of actual installed capacity to each bracket b^q, distributing it evenly over all cells in a bracket. To ensure reasonable deployment levels within each bracket, we imposed a limit that maximum 12 % of the area could be occupied by turbines, similar to the method in Bogdanov and Breyer [30]. The heuristics were calibrated using historical deployment patterns for all regions, with the Root Mean Square Deviation (RMSD) employed as a Goodness-of-Fit (GoF) measure to quantify how much a given heuristic deviates from historical deployment. The GoF measure for each heuristic was calculated as

$$\mathrm{RMSD}_h = \sqrt{\frac{\sum_{r=1}^N w_r \left(\bar{v}_r - \bar{v}_{h,r}\right)^2}{\sum_{r=1}^N w_r}}. \tag{3}$$

N is the number of regions r in the sample. $\bar{v}_r$ is the capacity-weighted mean wind speed of existing turbine sites in each region. $\bar{v}_{h,r}$ is the capacity-weighted mean wind speed for each possible heuristic for each region. w_r is an optional weight that can be applied to each region. For the presented results, w_r was set to 1, which means all regions had an equal impact on the GoF measure. Other weights were tested during the

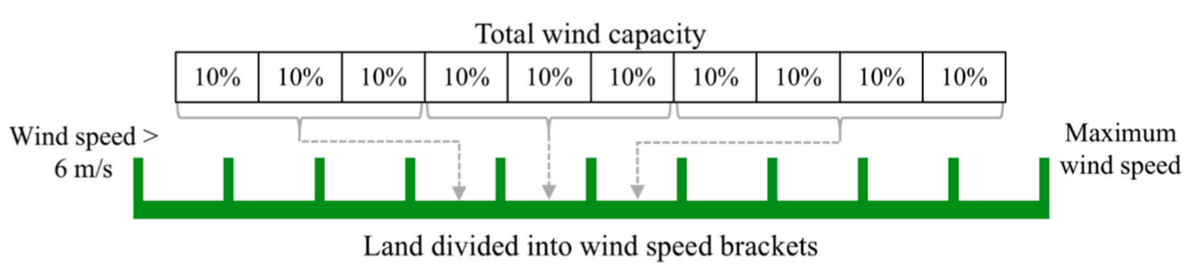

Fig. 1. Illustration of the bracket method. Land is divided into brackets ranked based on wind speed. 10 %-multiples of total installed wind capacity are allocated to the brackets.

analysis, setting w_r to the total installed wind capacity within each region, total installed wind capacity divided by the total area, or wind share of electricity demand. Based on the RMSD, the allocation heuristics could be ranked based on their match with historical deployment patterns.

2.4. Reviewing allocation methods

We empirically evaluated four different methods used for allocating wind power capacity, deemed representative of allocation methods used in ESOMs at large [4,29–31], as well as the top-performing general heuristic provided by the *bracket method*. The allocation methods were evaluated by redistributing the actual installed capacity in each region according to the assumptions underlying each method. Wind speeds at allocated sites were then compared with wind speeds at existing turbine sites. The allocated capacity with respect to wind speed was visualized as KDEs, weighted by the installed capacity at each site, and the means of the distributions were compared. The mean wind speed at allocated sites ($\overline{v}_m$) and at existing sites ($\overline{v}$) for each region across all years were defined as

$$\overline{v}_m = \frac{\sum_k v_{m,k} C_{m,k}}{\sum_k C_{m,k}} \text{ and } \overline{v} = \frac{\sum_i v_i C_i}{\sum_i C_i}. \tag{4}$$

k are sites with wind power capacity allocated by method m, whereas i refers to existing turbine sites. $C_{m,k}$ and C_i are the installed capacities at the allocated and existing turbine sites, respectively.

Three of the allocation methods use different heuristics to assign capacity to sites with varying wind speeds based on an exogenous distribution, prioritizing high wind speeds [30], high capacity factors [31], or excluding the lowest wind speeds in a region [29], respectively. Bogdanov and Breyer [30] assume 60 % of the installed wind capacity is deployed in the 80–100 percentiles of sites ranked by average wind speed, 20 % of capacity in 70–80 percentiles, and the remaining 20 % in 50–70 percentiles. Furthermore, they assume that a maximum of 12 % of each cell area can be used for wind power, with the total land useable for onshore wind power in a region restricted to 4 %. In contrast, Plessmann and Blechinger [29] allocate wind uniformly over the 33–100 percentiles of the area within a region. Schlachtberger et al. [31], on the other hand, allocate wind power in proportion to the capacity factor. Since we base our analysis on wind speeds rather than capacity factors, we made a crude estimate of the relationship between the average wind speeds and the capacity factors using data from Ayodele et al. [51]. We estimated the capacity factor C_j in cell j based on the average wind speed v_j as

$$C_j = 7v_j - 25. \tag{5}$$

We calculated the share of total wind power capacity α_j in each cell as

$$\alpha_j = \frac{C_j A_j}{\sum_j C_j A_j}, \tag{6}$$

where A_j is the total cell area.

In addition to the heuristic methods, we selected one allocation method from Reichenberg et al. [4] that use a cost-optimal approach for siting turbines. They assume 8 % of the regional area is available for wind power. We represented the method by assuming turbines in a region are installed starting at sites with the highest average wind speeds, gradually moving down to lower wind speeds. This reflects the assumption that a higher average wind speed translates to more cost-effective production. In practice, the instantaneous wind speed determines energy production, and the temporal production profile is incorporated into their model. Nevertheless, we consider average wind speed to be a sufficient parameter for siting turbines since the temporal variability of wind speeds has a comparably small impact on wind power electricity production (see Supplementary Section A and Fig. A1–A2).

Since we do not run the models from which the allocation methods originate, we simplified and harmonized the allocation mechanisms slightly. First, we assumed a capacity density of 8.4 MW/km^2 [30], even though some of the studies assumed other values. Second, we assumed that all land types are available for deployment, even though some models exclude certain types of land. We consider this appropriate since the evaluated models exclude relatively few land types, and it has been shown that turbines have been placed on most land types, even in densely populated areas [12]. These simplifications might affect the specific allocation of wind power for a given method, but the overall trend of capacity allocation with respect to wind speed remains the same, as it is determined by the allocation method itself.

2.5. Statistical model

Using statistical analysis, we explored how variables related to wind resource endowment and land-use competition are correlated with the extent to which different regions utilize their best wind resources. To our knowledge, no similar analysis has been conducted before, making this a first explorative attempt to identify factors associated with the utilization of high-wind speed sites.

We used linear regression to model the relationship between a dependent variable (the outcome variable of interest) and a set of independent variables (the predictors that influence the outcome). The dependent variable is the share of installed capacity allocated to the windiest brackets for each region using the *bracket method*. The dependent variable describes the extent to which a region has optimized its turbine siting relative to its wind speed distribution. In other words, it captures how much of a region's capacity is placed at sites with the best wind resources. For an illustration of the share of capacity allocated to the two windiest brackets, see the red, shaded area in Fig. 2. For the analysis, we tested separately the share allocated to the windiest bracket and the share allocated to the two windiest brackets. This dependent variable was chosen over the mean of wind speeds across all turbine sites, as the latter does not capture how turbines are located in relation to the windiest sites.

We tested three independent variables that may influence how wind turbines are placed in relation to the windiest sites, one related to resource endowment and two related to land-use competition. The mean regional wind speed represented wind resource endowment and was calculated as the mean wind speed over all areas with wind speeds above 6 m/s. Our hypothesis was that regions with lower mean regional wind speeds have a stronger incentive to optimize turbine siting with respect to wind speed to maximize electricity generation and profitability, given

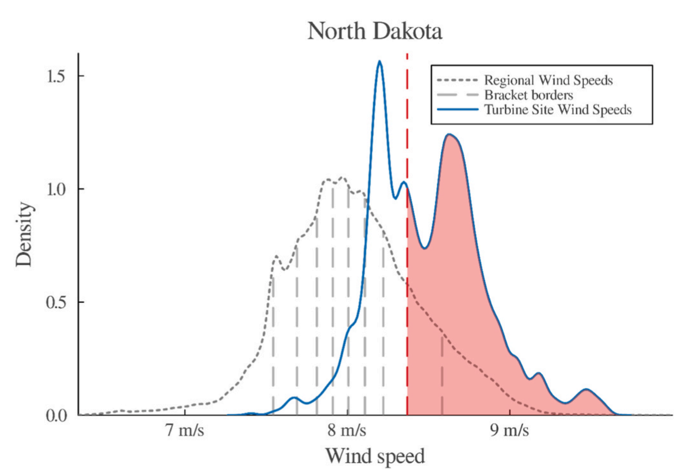

Fig. 2. The distribution of regional wind speeds divided into 10 brackets and the distribution of wind speeds at turbine sites. The shaded red area represents the dependent variable: the fraction of capacity allocated to the windiest brackets with the bracket method.

their available resources. Conversely, regions with higher mean regional wind speeds have less incentive to optimize their turbine siting since profitability is sufficient without selecting the windiest sites.

We tested the hypothesis on land-use competition using two different variables: demand density and population distribution. The demand density is the total electricity demand of the region normalized by total land area. We hypothesized that higher demand density might indicate more competing interests over limited land, such as by residences and industry, which may restrict turbine siting. Conversely, low demand density might suggest abundant land or weaker pressure from other land uses, allowing more flexible turbine siting and increasing the likelihood of utilizing the windiest sites. Our hypothesis, therefore, predicted a negative correlation between demand density and the amount of capacity allocated to the windiest sites.

We use the population distribution coefficient to quantify how a population is distributed across the total land area within each region. It was calculated following the same principle as the Gini coefficient, as illustrated in Supplementary Figure B1, with a value of 0 indicating a uniform population distribution everywhere within the region and a value of 1 indicating the entire population is concentrated in a single square kilometer. We hypothesized a positive correlation between the population distribution coefficient and the dependent variable, as greater population concentration suggests less competition over land, making it more likely for sites with better wind resources to be utilized. The demand density and population distribution coefficient are correlated and were thus not included simultaneously in the statistical model.

Table 2 summarizes the variables used in the statistical analysis. Supplementary Figure B1 provides variable definitions, sources, and descriptive statistics. The results of our multicollinearity tests for these variables are also shown in Supplementary Table B2-B3, and they show acceptably low multicollinearity among the included variables.

Table 2
Summary of variables used in the statistical analysis.

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

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

3. Results

3.1. Wind speeds at turbine sites

As illustrated by the four sample regions in Fig. 3, the distribution of wind speeds at turbine sites is shifted to the right relative to the regional wind speed distribution. This indicates that turbines are typically placed in areas where the wind speeds are higher than the mean regional wind speed. However, the extent of the right shift varies by region: Denmark's turbine distribution closely follows the regional wind speed distribution, whereas Ireland exhibits a more pronounced right shift. Note that the sample regions are chosen to display different outcomes and are not a representative subset of all regions.

When examining the full sample in Supplementary Figure C1, the distribution of wind speeds at turbine sites appears to be close to Normally distributed. Some regions, such as North Dakota in Fig. 3, display multimodal or skewed distributions. However, for most regions, a Normal distribution fits surprisingly well. To ensure that the observed Normality is not a result of over-smoothing from the bandwidth selection, we computed QQ-plots comparing the quantiles of actual wind speeds at turbine sites with those of the best-fitting Normal distribution, through maximum likelihood estimation, for each region. The QQ-plots in Supplementary Figure C2 support the interpretation that wind speeds at turbine sites can be considered Normally distributed. In general, the shape of the wind speed distribution at turbine sites is affected by the underlying regional wind speed distribution yet cannot be explained solely by it (see Fig. 3). Colorado is a clear example where the turbine site wind speed distribution is Normal, but the regional wind speed distribution is not.

To check whether the mean of wind speeds at all turbine sites, referred to as the mean turbine site wind speed, can be predicted based on the underlying wind speed distribution, we perform a simple linear one-parameter fit of the mean turbine site wind speed and the mean regional wind speed for each region, see Fig. 4. The mean turbine site wind speed is higher than the mean regional wind speed in all cases except one, which confirms the observed right shift of the turbine site wind speed distributions in Fig. 3. The function of the fit is $y = 0.8x + 1.9$ and has an R^2 value of 0.66, meaning that a large share of the variance in mean turbine site wind speeds is explained by the mean regional wind speeds. Note that wind speeds below 6 m/s were excluded for both dependent and independent variables since it is very uncommon for turbines to be placed at such low wind speeds, and their inclusion might skew the potential correlation.

3.2. Turbine siting with respect to wind speed over time

To examine whether the windiest sites are utilized first for wind power, we analyzed the siting of wind turbines with respect to wind speed over time. Fig. 5 shows that countries install wind turbines at largely the same mean wind speed each year. If the yearly mean of wind speeds at newly built turbine sites were to follow the linear fit, 20 out of the 25 regions would experience a change in mean wind speed of less than 0.05 m/s per year. In other words, the change in mean wind speed is small enough to be negligible in most cases. Some regions exhibit more distinctive trends, such as Colorado and New South Wales. However, these regions tend to have data with large interannual variations and, therefore, large confidence intervals. As the true underlying trend lies within the interval with a 95 % probability, it is difficult to make a definitive statement about the actual direction and magnitude of the trend for those regions. Across the full sample, no clear trends were observed in the standard deviation over time. In summary, turbines within a region have been deployed at sites with wind speeds that remain surprisingly constant over time, with some regions exhibiting a small decreasing trend.

3.3. Heuristics representing regional deployment patterns

To represent historical wind power deployment patterns, we developed a new heuristic method for allocating wind power capacity called the *bracket method*. The method divides land with wind speeds above 6 m/s into ten ranked brackets based on wind speed and allocates multiples of 10 % of the actual installed capacity to each bracket. Calibrating the *bracket method* based on turbine sitings in each region yields the allocation heuristics in Fig. 6. The brackets are arranged in ascending order based on wind speed, from the first to the tenth. Using Germany as an example, the heuristic should be interpreted as allocating 20 % of installed capacity to the windiest areas, 10 % in the second windiest, and so forth.

Fig. 6 displays a wide variety in how regions allocate their wind capacity across the ten brackets. In European countries, the installed capacity is generally spread out across a broad range of wind speeds, while regions in Australia, Canada, and the U.S. tend to concentrate turbines at higher wind speeds. Some regions in the table stand out by allocating no or very little capacity to the windiest 10th bracket. This is likely due to the lack of supporting infrastructure in areas with high wind speeds, such as remote areas in Québec or mountainous areas in Austria.

Multiple linear regression was conducted to explore the relationship

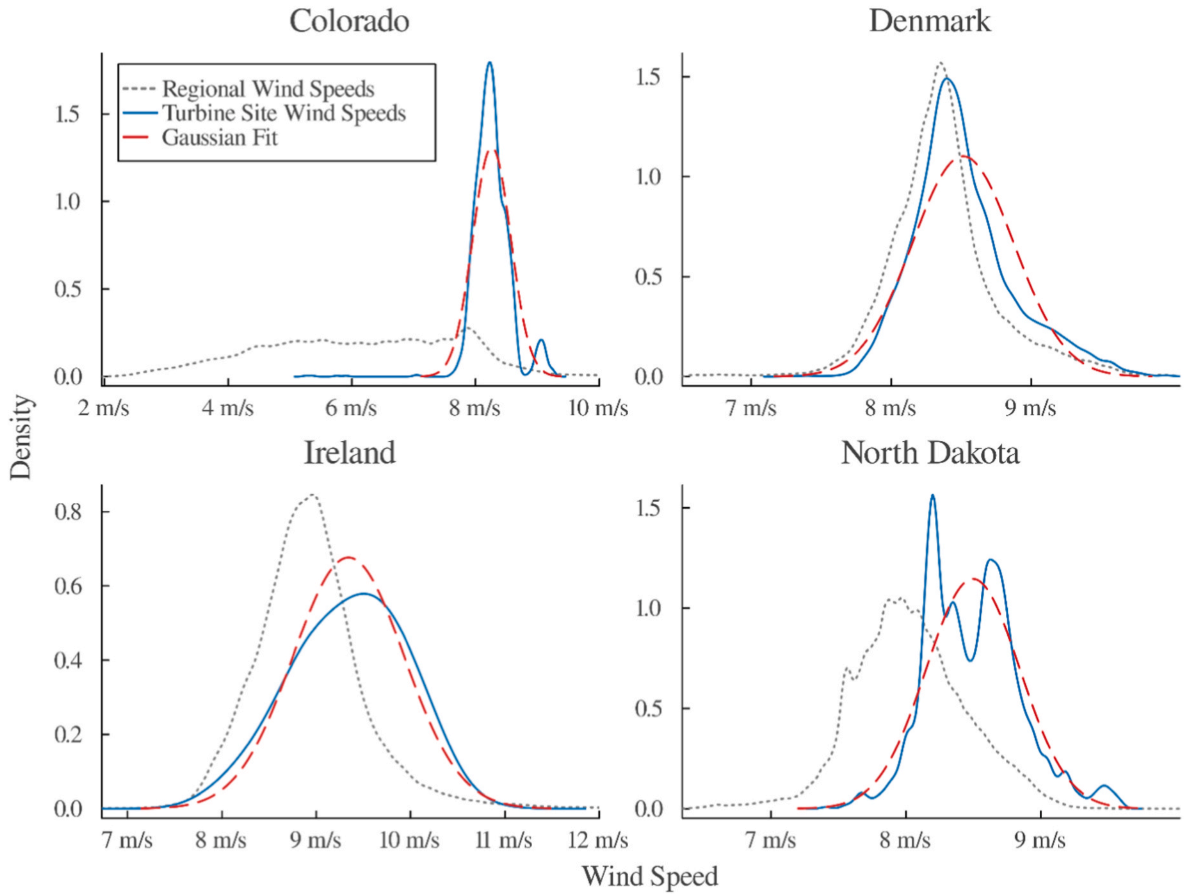

Fig. 3. Regional wind speed distributions versus wind speed distributions at turbine sites in four selected regions. The distribution of wind speeds at turbine sites resembles a Normal distribution shifted to the right of the mean regional wind speed. The sample regions are chosen to show different outcomes and are not a representative subset of all regions.

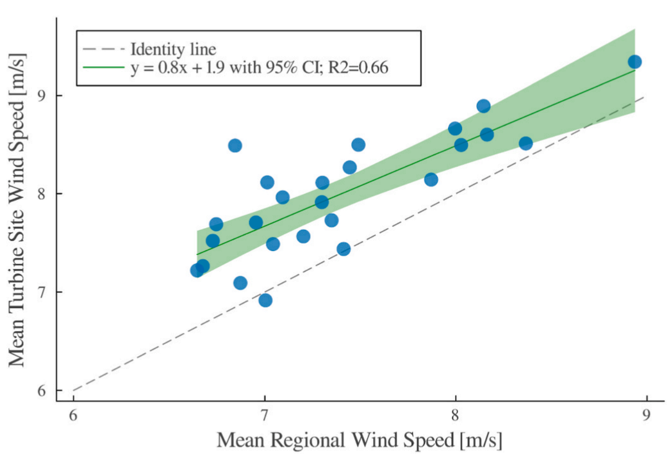

Fig. 4. Regression of mean regional wind speed and mean turbine site wind speed for each region, excluding wind speeds below 6 m/s. The linear fit shows that a large share of the variance in mean turbine site wind speeds is explained by the regional wind speed.

between the share of wind power capacity allocated to the windiest and second windiest brackets and independent variables representing resource endowment (mean regional wind speed) and land-use competition (demand density and population distribution). The results are shown in Table 3 for all regions in the sample. A significance level of less than 0.01 for the p-value was chosen as a conservative measure to account for multiple hypothesis testing and reduce the chance of obtaining false positive results. The analysis reveals statistically significant correlations between the population distribution coefficient and the share of installed capacity in both the windiest bracket and the two windiest brackets. However, the significance of the population distribution coefficient might be a result of the difference in deployment patterns between the European countries and the states and provinces in Australia, Canada, and the U.S. As can be seen in Fig. 6 and Supplementary Figures B2-B3, European countries tend to have a more evenly spread-out population and less concentrated installations with respect to wind speed than the states and provinces. Thus, while there seems to be a relationship between the allocation of wind power with respect to the windiest sites and the population distribution coefficient, a more extensive analysis is needed to determine the robustness of the relationship observed in our study. Additionally, no significant correlation was found for the mean regional wind speed or the demand density in any of the statistical models.

3.4. General heuristics for multiple regions

Using the *bracket method*, we created all possible allocation heuristics for allocating wind power capacity to the brackets and calibrated them based on all sample data. We obtained a ranking of allocation heuristics, shown in Fig. 7. The small variation in GoF values among the top thousand heuristics indicates that the order and performance of these heuristics are highly sensitive to changes in the sample. This suggests that there is no single best heuristic that can accurately represent the deployment patterns for all regions. Yet, the ten best-performing heuristics consistently assign a large share of capacity to the 8th and 9th bracket (corresponding to the 70th–90th percentiles of windiest areas

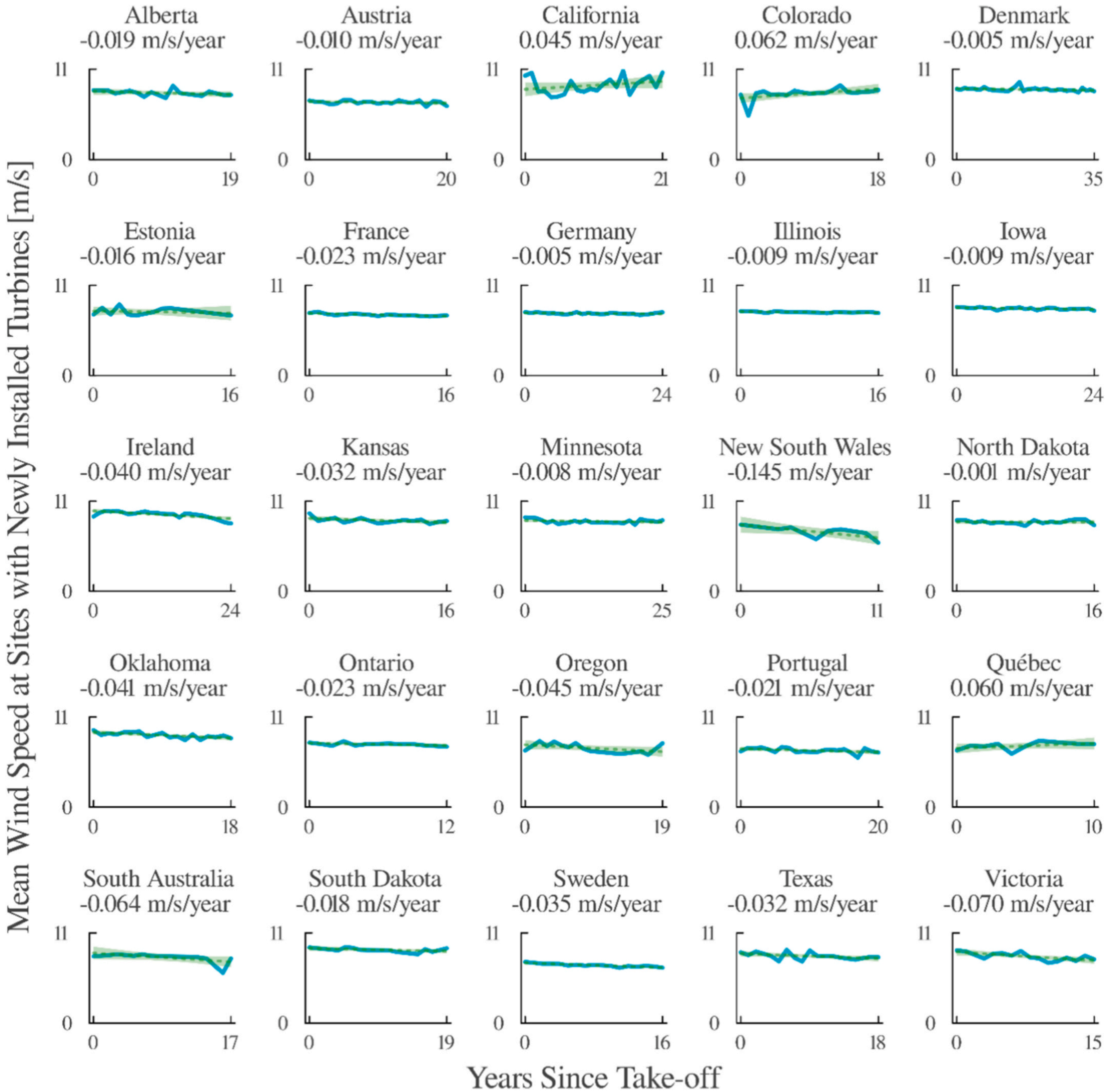

Fig. 5. The mean wind speeds at turbine sites for turbines installed each year since the take-off year. Each region has a linear fit whose inclination is shown below the region name. The green areas are 95 % confidence intervals.

above 6 m/s), and perform reasonably well across all regions. The conclusion holds when using another GoF measure like Mean Absolute Error, and when regions are weighted based on total installed wind capacity, total installed wind capacity divided by total area, or wind share of electricity demand (see Supplementary Tables D1-D4). We selected the heuristic with the lowest GoF value (labeled as "top-performing bracket heuristic") for evaluation alongside established allocation methods, as we deemed it representative of the top-ranking heuristics in Fig. 7.

3.5. Evaluation of allocation methods

To comprehensively assess the performance of existing wind power allocation methods in energy system models, we compared the historical deployment of wind power with four established allocation methods and with the top-performing heuristic calibrated across multiple regions from the *bracket method* (1st in Fig. 7). We use Colorado in Fig. 8 as an example to illustrate the results. The allocation method of Reichenberg et al. [4] sites turbines at windier sites than observed historically. Conversely, Schlachtberger et al. [31] deploy turbines to sites with lower wind speeds than the historical installations. The top-performing bracket heuristic matches the historical siting remarkably well for Colorado. However, this is not true for all regions (see Supplementary Figures E1-E25). The performance for all regions is summarized in Fig. 9, which shows the relationship between the weighted mean wind speed of existing turbine sites and the weighted mean wind speed of sites

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

Fig. 6. Allocation heuristics for each region expressed as the number of 10 %-multiples of installed capacity allocated to each wind speed bracket. The brackets are ranked based on wind speed, from wind speeds just above 6 m/s in the 1st bracket to the highest wind speeds in the 10th.

allocated by the tested methods. Reichenberg et al. [4] consistently locate turbines on windier sites compared to historical deployment, while the opposite is true for Schlachtberger et al. [31] and Plessman and Blechinger [29]. For most regions, the closest match to historical siting is observed for either the heuristic of Bogdanov and Breyer [30] or the top-performing bracket heuristic. This is not surprising as the heuristic of Bogdanov and Breyer (B&B) exceeds the minimum possible GoF value by only 3 %, see Fig. 7. Nonetheless, none of the allocation methods analyzed manage to represent the historical deployment consistently for all regions.

4. Discussion

4.1. Turbine siting with respect to wind speed

In this study, we assessed wind speeds at wind turbine sites and compared typical assumptions in energy system models regarding turbine siting with actual historical deployment patterns. The results show that wind turbines are typically located at sites that are windier than the regional mean wind speed. However, turbines have not been placed consistently in the windiest areas, contrary to what is commonly assumed in energy system models [4–7]. Interestingly, the average wind speeds at turbine sites are close to Normally distributed.

Jung and Schindler [26] claimed that wind turbines are being deployed at progressively worse sites due to the limited availability and

Table 3
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 bracket	NS	NS		0.128
2	10th bracket	NS		1.408*	0.229
3	10th & 9th brackets	NS	NS		0.147
4	10th & 9th brackets	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 in the table show that the corresponding independent variable is excluded from the model.

previous utilization of sites with high wind speeds. Our analysis contradicts this claim, showing that the average wind speeds at turbine sites have remained largely constant over time, with no discernible trend for the standard deviation. This finding may seem counterintuitive, as one might expect the favorable sites with high wind speeds and willing landowners to become scarcer as more turbines are installed. Yet, for large regions with relatively low population densities, such as Australian states and Canadian provinces, there is so much land that the favorable sites are nowhere close to running out. Furthermore, if turbines have been placed across a wide span of wind speeds from the start, which is the case for many of the regions, further deployment will not cause the sites with the highest wind speeds to run out first.

A multi-variable linear regression reveals a statistically significant positive relationship between the dependent variables, the share of installed wind power capacity in the top 10 or 20 percentiles of windiest sites above 6 m/s, and a land-use metric, population distribution coefficient. This suggests that regions with greater population concentration, which potentially have less competition over land, utilize their windiest sites more. In contrast, the other land-use metric, demand density, and the mean regional wind speed show no significant relationship. We initially hypothesized that a high demand density would indicate greater land-use competition, thereby restricting turbine siting. However, the lack of significance suggests that demand density is not a suitable metric for measuring land-use competition. A high demand density might, contrary to our hypothesis, reflect a strong incentive to install wind turbines at high wind speeds to meet local demand. Furthermore, it does

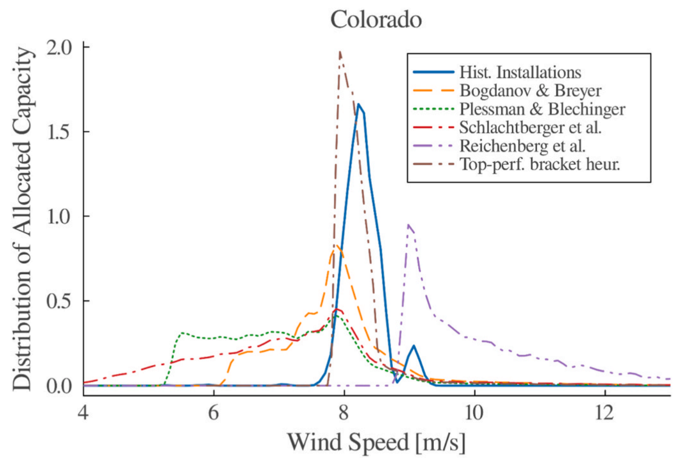

Fig. 8. Allocation of capacity with respect to wind speed for four existing allocation methods and the top-performing bracket heuristic compared to historical installations in Colorado.

Placement	1st-5th	6th	7th	8th	9th	10th	GoF Value	Share of min GoF
1st	0	0	0	4	5	1	0.40	1
2nd	0	0	0	3	6	1	0.40	1.00
3rd	0	0	1	2	6	1	0.40	1.00
4th	0	0	0	1	9	0	0.40	1.00
5th	0	0	0	9	2	2	0.40	1.00
6th	0	0	2	0	7	1	0.40	1.00
7th	0	0	0	7	1	2	0.40	1.00
8th	0	0	1	5	2	2	0.40	1.00
9th	0	0	1	0	9	0	0.40	1.00
10th	0	0	0	2	8	0	0.40	1.00
50th	0	0	1	3	4	2	0.41	1.01
100th	0	1	2	4	0	3	0.41	1.01
500th	1	1	1	1	3	3	0.41	1.03
1000th	1	1	3	2	0	3	0.42	1.04
B&B (505th)	0	1	1	2	3	3	0.41	1.03

Fig. 7. A selection of heuristics ranked according to their GoF value for the RMSD measure. In total, 92 378 possible heuristics were evaluated. B&B is the heuristic used by Bogdanov and Breyer [30].

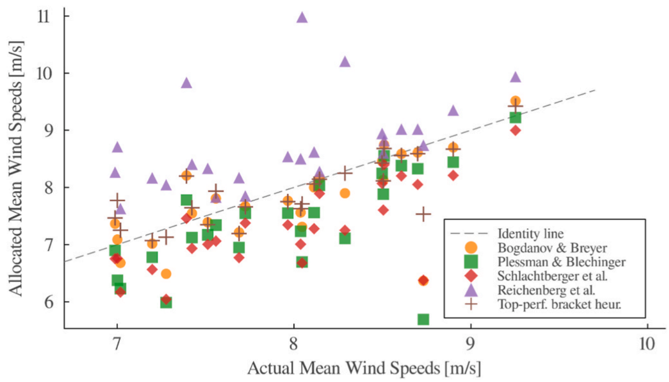

Fig. 9. The weighted mean of the wind speeds at sites with turbines allocated by the five allocation methods plotted against the mean wind speeds of sites with existing turbines. Each vertical set of five differently colored symbols represents one region in the sample. Symbols below the dashed line indicate that the allocation method places wind power capacity at lower wind speeds compared to historical installations. Conversely, for symbols above the dashed line.

not capture the heterogeneity of land-use competition. For instance, a single energy-intensive industry could create a high demand density without indicating significant land-use conflicts with wind power. As for the mean regional wind speed, we suggest the lack of significance stems from a consistent incentive to place turbines at windier sites regardless of the regional wind speed distribution. The statistical results suggest that the population distribution, and by extension land-use competition, might be correlated with the utilization of the windiest sites.

There are two primary limitations to our analysis. First, we cannot confirm if turbines are actually excluded from densely populated areas due to the variables being aggregated on the regional level. Second, the results require confirmation by more extensive statistical analyses. The relatively small sample size, where European countries consistently have more spread-out installations and less concentrated populations than the states and provinces in the U.S., Canada, and Australia (see Supplementary Figures B2-B3), limits the generalizability of our findings. Nevertheless, it is promising that the population distribution coefficient was significant even though the analysis did not exclude areas such as mountains. Excluding such areas would likely result in a strengthened correlation, as it would increase the share of capacity in the top brackets for regions like Austria and Québec while slightly increasing the population concentration. Given the lack of previous consensus on the exact factors influencing wind power deployment [9–11,17–19], the population distribution coefficient is a promising variable for predicting common patterns in global wind power deployment.

4.2. New heuristics to represent deployment patterns in ESMs

We developed a new heuristic method, the *bracket method*, which unlike previous heuristic allocation methods can represent any historical turbine siting with respect to wind speed. It divides land with wind speeds above 6 m/s into ten brackets ranked based on wind speed and allocates multiples of 10 % of the actual installed capacity to each bracket. The *bracket method* is calibrated based on historical data for individual and multiple regions to create allocation heuristics that can be used in energy system modeling. The heuristics for European countries tend to spread out the installed capacity across a wide range of wind speeds, whereas the heuristics for regions in Australia, Canada, and the U.S. tend to concentrate installations at higher wind speeds. The heuristics can be used directly by modelers to simulate future energy systems for these regions. Additionally, new heuristics can be calibrated based on the historical deployment patterns of regions not covered in our paper. If that is not possible, we suggest choosing a heuristic from another region with a similar population distribution coefficient, rather than relying solely on cost-optimal siting.

The best-performing heuristics calibrated on historical deployment patterns of all 25 regions tend to, as a rule of thumb, allocate 80–100 % of the wind capacity to the 8th and 9th brackets, corresponding to the 70th to 90th percentiles of windiest areas over 6 m/s. Although these heuristics do not capture the exact deployment patterns for a specific region, they can serve as a suitable option for siting turbines in energy system modeling for regions with poor turbine data. The allocation heuristics are ranked based on their Goodness-of-Fit (GoF) value. The Root Mean Squared Deviation (RMSD) was chosen as the GoF measure for ranking heuristics because it accounts for outliers, thereby minimizing the risk of poor performance in specific regions. While the exact ranking is sensitive to data changes and the choice of performance metric, our main results and conclusion hold, as additional analyses using alternative error measures (such as the Mean Absolute Error, MAE) and different regional weightings produced consistent outcomes (see Supplementary Tables D1–D4).

Still, the *bracket method* could be further improved. Because the calibration relies only on the mean wind speeds across allocated turbine sites, the heuristics for multiple regions tend to allocate turbines across a smaller range of wind speeds compared to actual installations. The heuristics also tend to place a small, isolated fraction of turbines at low wind-speed sites to lower the mean. Moreover, the method would ideally account for the temporal variability in wind speeds when siting turbines. In practice, the choice of turbine sites is also affected by the variability in wind speeds, not just the mean. However, our additional analysis showed that the change in wind power production from accounting for the temporal variability is relatively small and likely to decrease when considering variations in turbine designs (see Supplementary Section A and Fig. A1–A2). Thus, siting turbines based on average wind speeds is an acceptable simplification for energy system modeling.

4.3. Comparison of allocation methods

We evaluate three heuristic methods [29–31] and one cost-optimal approach [4] for siting wind turbines deemed representative of allocation methods used in energy system models at large. These methods are compared with historical siting and the heuristic that best matches historical deployment patterns for all regions derived through *bracket method.* Our results show that cost-optimal turbine siting [4–7] places turbines at sites with higher wind speeds compared to historical data. Among the existing heuristic methods, the heuristic employed by Bogdanov and Breyer [30], which assumes 60 % of wind power installations are concentrated in the 20 % windiest sites in a region, provides the closest match to historical data. The top-performing heuristic from the *bracket method* has a similar performance to the heuristic of Bogdanov and Breyer. If any difference can be noted, Figs. 7 and 9 show that this new heuristic is slightly more consistent in representing historical deployment patterns for all regions. Interestingly, Bogdanov and Breyer have since updated their heuristic to allocate wind power over the 25 % windiest sites, in part because their previous heuristic underestimated the full load hours for Finnish wind power (D. Bogdanov, personal communication, March 14, 2025). This update makes their method more closely aligned with the top-performing heuristics derived through the *bracket method.*

Although our implementation of the previous allocation methods differs slightly from their original versions, we believe these differences do not fundamentally affect our conclusions. If the deployment density, and therefore the wind potential, were lowered for all allocation methods, the cost-optimal approach [4] would allocate wind power capacity to lower wind speeds compared to our results and better match the historical installations for most regions. However, all evaluated allocation methods use higher deployment densities in their original studies than the one used here [30]. Constraints on land availability might improve the performance of the cost-optimal approach for specific regions, but for the tested allocation methods, the effect is likely small as the evaluated studies exclude relatively little land. Overall, we believe that our representation of existing allocation methods is fair and that the new heuristics improve upon previous allocation methods by grounding the analysis in historical data, thereby better capturing the actual deployment of wind power in energy system models.

4.4. Implications for energy system modelers

We used data from 25 regions, which represent a small but diverse set of countries, states, and provinces with substantial wind power installations. By analyzing wind speeds at turbine sites for all these regions, we found that wind power is spread out over the windier, but not windiest sites within a region, and that turbines are consistently placed at sites with similar average wind speeds over time, despite decades of deployment for some countries. Therefore, it is clear that the typical approach in energy system models, allocating wind power capacity to the windiest sites to minimize cost, does not match historical precedence.

We argue that this study provides compelling evidence for energy system modelers to reconsider how wind power deployment is represented in ESOMs and to account for historical deployment data. Otherwise, the importance of wind power in the future energy system might be misrepresented. Bogdanov and Breyer set a good precedent by updating their already well-performing heuristic in reaction to how well it captured the performance of Finnish wind power.

The question, however, remains whether the future deployment will continue to develop as it has in the past. New adopters of wind power might face unique social and institutional contexts that strongly influence the diffusion and deployment of wind power. Furthermore, the deployment of wind power might change as penetration rates further increase and laws evolve. Nevertheless, the observed consistency within regions, over time, to place turbines at sites with similar mean wind speeds across a wide range of institutional settings suggests that, unless there is a major shift in institutional, political, or social factors, wind power deployment patterns are most likely to continue following similar trends in the future.

5. Conclusions

In this study, we investigated the historical deployment of wind power with respect to wind speed, introduced a new heuristic method to represent historical wind power deployment patterns, and evaluated how energy system models allocate wind turbines compared to historical data. Based on an analysis of 25 regions, we found that.

- Wind turbines are typically deployed at sites with slightly higher wind speeds than the mean wind speed in the region.
- New turbines within a region are consistently sited at similar average wind speeds each year.
- Regions with more concentrated populations tend to utilize their windiest sites more.
- As a rule of thumb, the historical deployment patterns of wind power can be captured quite well for all regions by allocating 80–100 % of the wind capacity to the 70th to 90th percentiles of windiest areas.
- Out of four existing methods for allocating wind power capacity in ESOMs, the heuristic of Bogdanov and Breyer (2016) has the best match with historical deployment, whereas the other methods tend to deviate from actual siting regarding wind speed.

The results of energy system optimization models are widely used to inform policy and investment strategies for energy technologies. Our findings show that most ESOMs deviate from historical siting with respect to wind speed when allocating wind power. As a result, the potential contribution of wind power in future energy systems is likely to be misrepresented. Based on this evidence, we suggest that energy system modelers reconsider how wind power deployment is represented in ESOMs and incorporate historical deployment data. We anticipate future studies to assess the extent to which established allocation methods influence modeling outcomes, including overall system costs and the electricity supply mix.

Contributions

Niklas Jakobsson: Conceptualization, Data Curation, Software, Formal Analysis, Methodology, Writing – original draft. Carin Lundqvist: Data Curation, Software, Visualization, Formal analysis, Writing – original draft. Fredrik Hedenus: Conceptualization, Project administration, Methodology, Supervision, Funding acquisition, Writing – review and editing. Yodefia Rahmad: Methodology, Formal analysis, Writing – review and editing. Xiaoming Kan: Supervision, Writing – review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2025.101990.

Data availability

The authors do not have permission to share data.

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