Estimating National-Scale Wind Potential Using Spatially Explicit Turbine Layout Optimization

Anthony Lopez, P.J. Stanley, Owen Roberts, Trieu Mai, Travis Williams, Pavlo Pinchuk, Grant Buster, and Eric Lantz

National Renewable Energy Laboratory

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Contract No. DE-AC36-08GO28308

Technical Report
NREL/TP-6A20-85075
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Suggested Citation
Lopez, Anthony, P.J. Stanley, Owen Roberts, Trieu Mai, Travis Williams, Pavlo Pinchuk, Grant Buster, and Eric Lantz. 2023. *Estimating National-Scale Wind Potential Using Spatially Explicit Turbine Layout Optimization*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-85075. https://www.nrel.gov/docs/fy24osti/85075.pdf.

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15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

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This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

Acknowledgments

We are grateful to Mike Gleason, Dan Bilello, Donna Heimiller, and Brian Smith, for their helpful reviews, to Mike Meshek for editing support, to Billy Roberts for graphics, and Patrick Gilman and Gage Reber for their review and support. Any errors or omissions are the sole responsibility of the authors.

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Abstract

National renewable energy potential assessments play a broad and critical role in analysis of the clean energy transition by providing foundational estimates of developable clean resources. Common to all past wind potential assessments is an assumption that wraps the complexity of wind plant layout (i.e., the arrangement of turbines) into a single metric known as capacity density, or rated power capacity per unit of land area. Quite often, a singular capacity density or rotor diameter-driven capacity density is used in wind potential assessments across broad geographies despite the complexities of local drivers.

Here, we present a new wind technical potential assessment for the United States that leverages spatial optimization in lieu of the traditionally used uniform capacity density. The optimization approach is a spatially explicit method for determining the potential locations of individual wind turbines: it takes into account the turbine configuration, plant economics and losses, wind resource, and siting considerations. Our approach accounts for the interactions of wind technology design, wind plant layout, and the vast array of regulatory, land use and infrastructure conflicts with wind development.

Our results highlight the potential ability of larger and lower cost turbines to enable increased wind capacity, up to a point, and increased generation when siting turbines in and around spatial constraints; moreover, they demonstrate and capture the LCOE benefit of lower capacity densities and reduced wake losses when land is abundant. These insights provide foundational knowledge for the wind sector as it develops and pursues future turbine models and as wind energy markets expand in zero-carbon futures. Further, when applied in capacity expansion models, supply curves developed by these methods can provide detailed local insights about where wind turbines might be deployed given siting constraints for regions where wind energy is determined to be economic, thus providing critical nuance to local decision makers and stakeholders.

1 Introduction

National renewable energy potential assessments play a broad and critical role in analysis of the clean energy transition by providing foundational estimates of developable clean resources (Gagnon et al., 2023; Jenkins et al., 2021; Mai et al., 2021a). Previously, wind energy potential in the United States was believed to be sufficient to provide 10× or more the electricity required for the entire economy (Brown et al., 2016; Lopez et al., 2012; von Krauland et al., 2021). However, achieving deep decarbonization may require significantly more wind energy than previously thought, and though national potential is generally thought to be greater than demand, increasing spatial resolution of local siting constraints and drivers has illuminated regional variation in resource abundance (Lopez et al., 2021).

Wind capacity for any location is the product of a complex relationship between turbine cost scaling, wake losses, wind resource, and spatial arrangement of the land or the sea. One of the foundational elements common to past wind potential assessments is the use of capacity density (i.e., rater power capacity per unit of land area). This metric is conventionally used to convert a quantity of land into an amount of developable wind capacity. Quite often, a singular capacity density or rotor diameter-driven capacity density (Rinne et al., 2018) is used in wind potential assessments across broad geographies despite the complexities of local drivers. The capacity density assumption is rationalized by leveraging the many studies examining capacity density relationships through empirical analysis of existing wind facilities (Denholm et al., 2009; Enevoldsen and Jacobson, 2021; Harrison-Atlas et al., 2022, 2021; Miller and Keith, 2018, 2018). These studies are used to understand historical deployment and trends. They reveal aspects of wind expansion critical to studying the effects on ecological and social systems, and to date, have provided a means of quantifying overall wind potential for future deployment. Though these studies provide a means of deriving a capacity density, large regional variations in their results are often condensed into a national average for application in wind potential assessments. In addition, there is no standardized methodology for delineating the land associated with a wind plant when developing capacity density estimates. Some studies use a convex hull around the turbines to define the land area (Harrison-Atlas et al., 2022), some with adequate data use the lease area (Denholm et al., 2009), and still others use Voronoi polygons (Miller and Keith, 2018). This nonuniformity in the definition of land area has led to huge variations in the capacity density estimates reported by experts in the field. This point is demonstrated by several recent studies that report national average capacity densities ranging from 1.5 MW/km^2 to more than 20 MW/km^2 (Denholm et al., 2009; Enevoldsen and Jacobson, 2021; Harrison-Atlas et al., 2022; Miller and Keith, 2018; Rinne et al., 2018).

These empirically based capacity densities (often a single uniform density in all regions) are multiplied by the developable land area to derive wind capacity potential estimates. This method for estimating wind potential can be problematic for several reasons. First, the large variation in estimated capacity densities makes it challenging to select a single value. This variation also sends a mixed message about the technical potential of wind, making it challenging for decision makers to make correctly informed decisions.

Second, wind potential assessments apply spatial constraints or exclusions to the land to determine developable area, creating an area that is necessarily smaller than the total available within the boundaries of a wind plant. The smaller developable area is used when multiplying by a capacity density value to create the potential capacity estimate, which is problematic when there is a mismatch between the area used to define these two variables. This can result in an underprediction of the true capacity because empirical studies almost universally use total area and not developable area to define capacity density. Third, wind turbine technology is rapidly evolving (Wiser et al., 2022) and is intrinsically tied to policies that could affect the quantity and location of turbine installations. An example is provided by structural setback requirements, which dictate how close a turbine may be to a residence or other building and are most commonly a function of the turbines total height (Lopez et al., 2022). This creates a dynamic relationship between the turbine size and cost and the land available for development. Fourth, empirical studies, which are inherently retrospective, cannot adequately reveal how prospective turbine technologies might interact with such local siting conditions. For these reasons, reliance and application of historical trends to future deployment limits our ability to systematically evaluate the value proposition of technological advancements (e.g., are bigger turbines always better)?

Here, we present a new wind technical potential assessment for the United States that leverages a spatial optimization in lieu of traditionally used uniform capacity density. The optimization approach is a spatially explicit method developed by Stanley et al. (2022) for determining the potential locations of individual wind turbines; it takes into account the turbine configuration, plant economics and losses, wind resource, and siting considerations. Our approach accounts for the interactions between wind technology design, wind plant layout, and the vast array of regulatory, land use and infrastructure conflicts with wind development. We present this method as a new standard for estimating wind technical potential that will provide better estimates of regional and local capacity potential, enable exploration of wind turbine advancements, reveal interactions between turbine technology and local ordinances, and capture wind energy's ability to be sighted within complex environments.

2 Methodology

2.1 Geospatial supply curve modeling

Estimating deployable wind energy potential requires high-resolution modeling to account for the spatially varying wind resource, local land use, and other siting considerations. For this analysis, we use the geographic information system-based Renewable Energy Potential (reV) model to examine the cost, performance, and siting suitability of wind power plants (Buster et al., 2022; Maclaurin et al., 2019). reV subdivides the contiguous United States (CONUS) into roughly 57,000 11.5 km X 11.5 km wind sites and, for each site, estimates the deployable potential (MW), available hourly and annual generation (MWh), capital costs ($/kW), levelized cost of energy (LCOE, $/MWh), and grid connection costs ($/kW or $/MWh). These estimates are produced by combining high-resolution (2-km) wind resource data (Draxl et al., 2015), hourly wind generation modeling for seven weather years using the System Advisor Model (SAM) (Freeman et al., 2018), high-spatial resolution (90-m) representation of excluded areas, and wind turbine assumptions.

The choice of turbine affects many of the factors considered in reV. The cost of the turbines varies depending on configuration, which affects all cost-related metrics (e.g., LCOE). reV also models turbine-specific power curves and applies the wind resource corresponding to the turbine hub height. Furthermore, there are interactions between the turbine design and siting exclusions (Lopez et al., 2021). As noted above, some local ordinances apply height limits to turbines and setbacks to buildings and other infrastructure that are typically based on maximum tip heights. In general, larger turbines require larger setbacks and, thus, less available land for wind installations. In this paper, we model setbacks and other exclusions, which are discussed in Section 2.3.

The core geospatial modeling starts from the methods used by Lopez et al. (2021), but we advance this by modeling direct representation of *individual* turbine placements. Previously, reV assumed a capacity density (typically 3 MW/km^2), uniformly applied across all sites and for all technologies, to estimate the deployable potential after exclusions are removed. Such uniformity does not account for different spacing requirements, balance-of-system (BOS) costs or wake losses that could vary depending on turbine selection and turbine layout, as well as its interactions with the shape of the remaining land area and distribution of the wind resource.

2.2 An optimization approach to explicitly site wind turbines

Turbine siting availability is dictated by land constraints (e.g., national parks and existing highways) and interactions with ordinances (e.g., setback requirements and height restrictions). To reflect these factors, we apply a spatial optimization method developed by Stanley et al. 2022 within the reV geospatial model. Specifically, Stanley et al. 2022 demonstrate the turbine placement method for a single site or wind plant, whereas our application is for all 57,000 potential wind sites in the United States.

The optimization we implement in reV consists of two steps. First, we use a fast circle packing algorithm to determine the maximum number of turbines that could fit in a certain wind site and meet all the exclusion, setback, and minimum spacing requirements. This packing algorithm is computationally efficient, requiring < 1 second to complete, a critical requirement for national-scale assessments. This circle packing algorithm provides a set of possible turbine locations that can be used in the rest of the optimization process. Second, we use a genetic algorithm to determine at which of these possible turbine locations a turbine should actually be placed. This algorithm accounts for the costs and wake interactions between turbines to determine the best turbine configurations. This objective is discussed further in the following section.

Explicitly siting turbines in each of the wind sites gives the flexibility to vary capacity density in different sites. Sites that are highly restricted by exclusions and setbacks will typically benefit from placing as many turbines as possible. Less-restricted sites will typically not place a turbine in every possible location to reduce wake interactions.

Any design decision will be largely driven by the objective of the design. Realized wind power plant capacity, generation, and cost are dictated by the combination of several complex drivers: relationships between turbine siting availability, BOS, and wake losses.

Balance-of-system (BOS) costs refer to all the costs associated with installing a wind plant that are not associated with the capital costs or the operation and maintenance of the turbine. This includes permitting, labor, material, and equipment costs associated with site preparation, foundation construction, electrical infrastructure, and tower installation (Eberle et al., 2019). BOS costs increase with project size but decrease on a per-megawatt basis as project size increases (Wiser et al., 2021). BOS costs are also driven by turbine rating, hub height, and rotor diameter (Key et al., 2022). To capture these relationships, we develop BOS cost curves using a bottom-up process-based approached leveraging the Land-based Balance of System model, LandBOSSE (Eberle et al., 2019). When using an LCOE minimization objective function, these cost curves will counter the capacity minimizing effect of wake losses by promoting the installation of more turbines. Because the cost curve is steepest for smaller plants this countering effect is strongest in land-constrained sites.

Wake losses vary due to turbine physical locations and spacing, turbine-specific power, rotor diameter, coefficient of thrust, and wind resource. To capture these complex relationships, we use the Park (Jensen) wake model. Because the Park model as implemented in SAM underpredicts the coefficient of thrust relative to empirical thrust curves by an average value of 1.5 (Fields et al., 2021), we apply a wake loss multiplier of 1.5. Wake losses and BOS costs compete with each other during wind farm design, as wakes drive turbines farther apart to reduce losses, and BOS considerations drive a higher density to reduce costs.

The interaction of these considerations is visually presented in Figure 1, where the green curve represents LCOE as a function of capacity and is a combination of the orange and blue curves, which show the total plant cost and wake losses respectively. There is much justified discussion about better metrics beyond LCOE to evaluate wind farm performance (Mai et al., 2021b). For the present study, we decided to use LCOE as our evaluation metric due to the wide historical and present use of LCOE in wind plant design and the complexity of including cost models or projections for modeling profit or other more complex financial metrics. From an absolute cost perspective, lower capacity is more desirable as it requires fewer turbines resulting in lower capital and BOS costs. There are economies of scale associated with higher wind farm capacities, although there are diminishing returns as capacity increases. From an energy generation perspective, higher capacity is obviously more desirable as it results in higher absolute energy generation, although a higher turbine density for a given site results in higher wake losses. The optimal point from an

LCOE perspective is the inflection point where the cost economies of scale from adding additional capacity do not outweigh the wake losses associated with the added capacity.

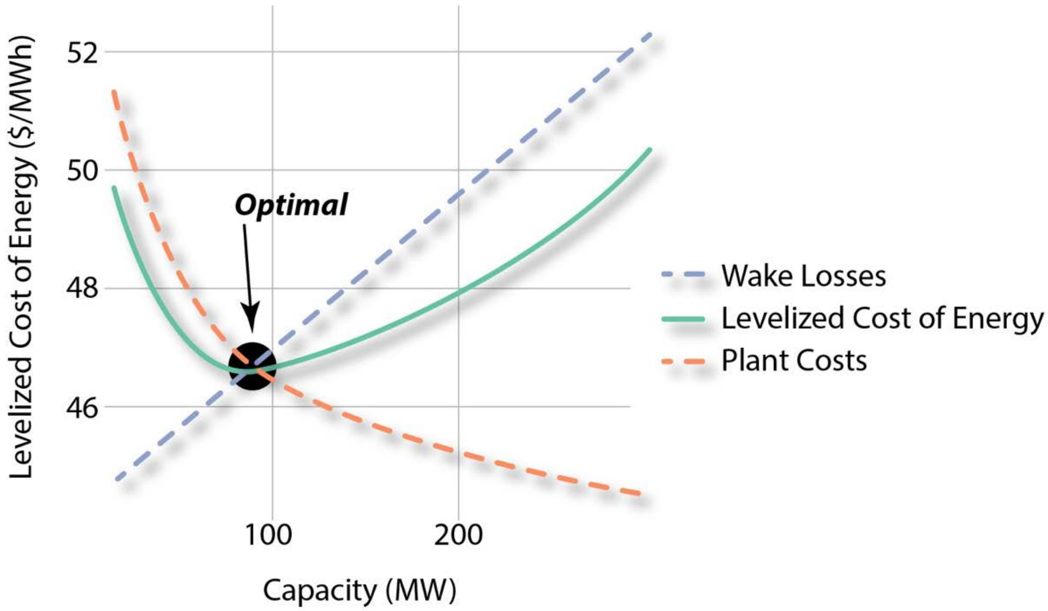

Figure 1. Conceptual diagram of wake loss, BOS cost, and levelized cost of energy optimization.

2.3 Turbine design, siting assumptions, and scenario matrix

We model three different turbine designs as inputs into the spatial optimization, based on assumptions from Lopez et al. (2021), to compare how technological advancements might impact the deployable wind potential. The range of turbine configurations—with distinct hub heights, rotor diameters, power curves, cost curves, and nameplate capacity ratings—are meant to capture plausible future designs and for comparison to a typical turbine installed in recent years. The Cost of Energy Review (COE) case represents the market average turbine in 2018, and the Annual Technology Baseline (ATB) Moderate and ATB Advanced cases represent plausible turbine design and costs in the year 2030. Table 1 shows the turbine assumptions for these cases.

Table 1. Assumed turbine design characteristics and costs.

Turbine Characteristic	COE Case (2018 Market Average)	ATB Moderate Case (2030)	ATB Advanced Case (2030)
Turbine rating (MW)	2.4	5.5	7
Rotor diameter (m)	116	175	200
Hub height (m)	88	120	135
Specific power (W/m^2)	227	229	223
Capital expenditures ($2018/kW)	$1,433	$1,161	$861
Fixed operation and maintenance ($2018/kW)	$45	$39	$34

Siting assumptions (regimes) are also taken from Lopez et al. (2021). Siting scenarios are meant to capture a plausible range of siting restrictiveness across the landscape. The Open Access siting regime is the least-restrictive regime; it restricts development on only legally or administratively protected lands (e.g., national parks and wilderness areas), and on land with existing infrastructure (e.g., houses or roads). The Reference Access regime applies additional constraints, includes documented local ordinances and, where feasible, applies best-management practices for wind development. Limited Access is the most restrictive regime, applying a combination of the most restrictive siting constraints. Details of each are shown in Table 2.

Table 2. Siting regimes and assumptions. *short-range radar / long-range radar

Siting Exclusion Category	Open Access Regime	Reference Access Regime	Limited Access Regime
Infrastructure			
Setbacks to transmission right-of-way, railroads, roads, building structures	Structure only, no setback	Setback = 1.1× tip height	Setback = 3× tip height
Urban areas and airports	Excluded	Excluded	Excluded
Radar	-	4-km NEXRAD, 9-km SRR/LRR*	NEXRAD and SRR/LRR* line-of-sight
Regulatory			
Documented state and county setback and height ordinances	-	Applied	Applied
Protected public lands and conservation easements	Excluded	Excluded	Excluded
Other federal lands	-	-	Excluded
Physical			
Slope >25%	-	Excluded	Excluded
Mountainous landforms and high (>9,000ft) elevation	Excluded	Excluded	Excluded
Water and wetlands (with 305-m buffer)	Excluded	Excluded	Excluded

Our scenario matrix is a combination of turbine design and siting regime to extract critical drivers of wind potential. We model the Moderate turbine against all siting regimes, and we model the Reference Access regime against all turbine cases.

3 Results

We first demonstrate how using our geospatial modeling with spatial plant layout optimization results in a wide range of turbine densities throughout the United States. Unless otherwise stated, we define capacity density as the available capacity (MW) per unit of *developable* area (km^2). The rationale is that our results are intended to guide wind potential assessments, which first apply siting constraints and then apply a capacity density to estimate capacity potential. We start by examining the results for the COE turbine case and Reference Access siting regime. These represent contemporary wind technology and siting assumptions that seek to mimic best-management siting decisions. We find that across the CONUS there are 7.8 TW of capacity and 21,151 TWh of generation potential. For context, the current installed wind capacity in the United States is 135 GW and the total capacity of the U.S. electric fleet is around 1,240 GW and total demand is roughly 4,150 TWh (EIA, 2022). The CONUS has just over 8 million km^2 of land and of this, roughly 3 million km^2 are deemed developable in the Reference siting regime. Nationally, this scenario results in a median capacity density of 2.9 MW/km^2.

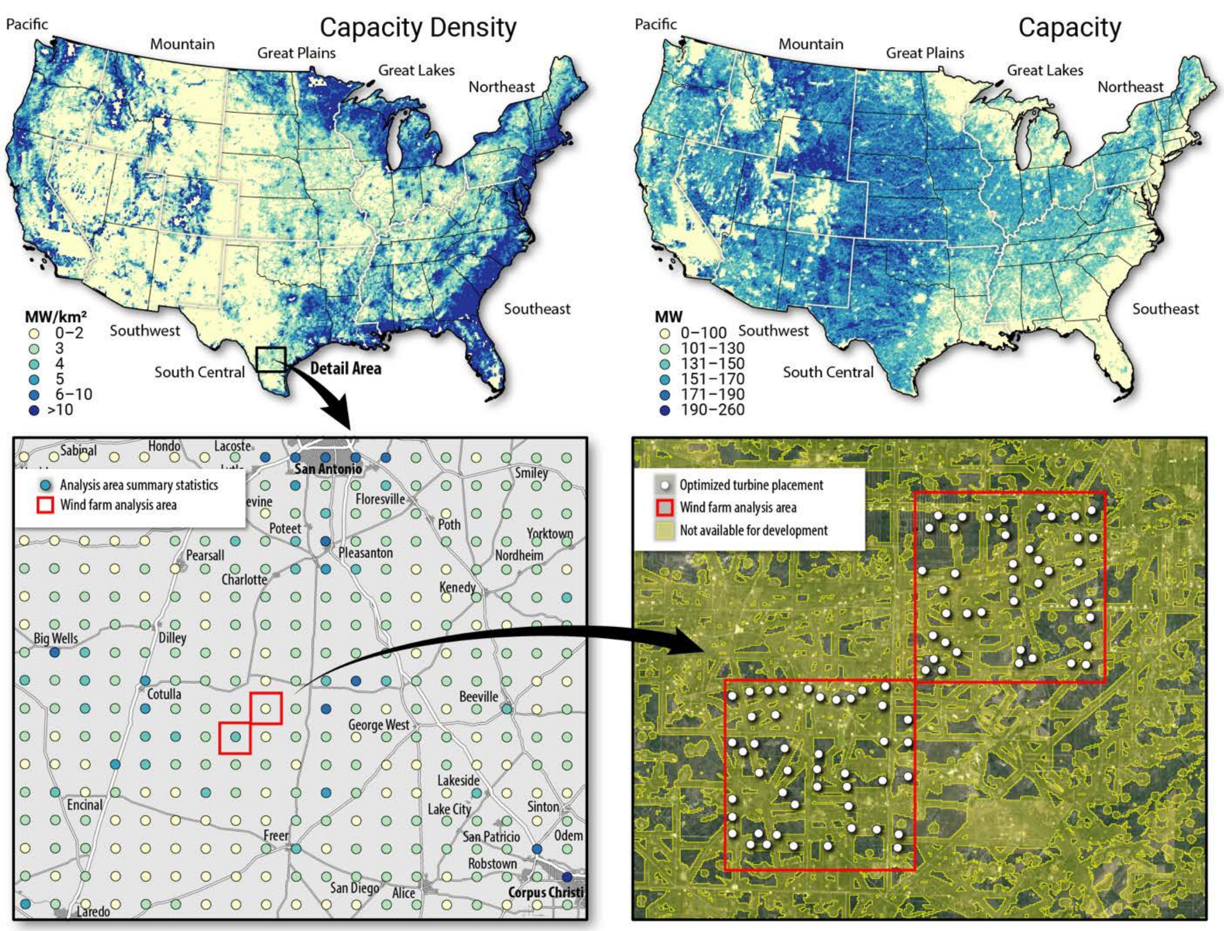

Figure 2. National capacity and capacity density results demonstrating the turbine placement detail at scale. Each colored dot represents a wind site and its resulting capacity density (upper left map) and capacity (upper right map) for Reference Access siting scenario and the COE turbine. The bottom left map shows the density of wind sites for a detailed area, while the bottom right map shows yet more detail and the optimized turbine locations as white dots.

As can be seen in the capacity map of Figure 2, there are strong regional variations in wind capacity, demonstrating how local siting exclusions can limit wind potential. In the Northeast, Southeast, and Pacific, dense infrastructure, population, and ordinances limit capacity. In the Great Lakes region, water bodies and wetlands limit capacity, while in the Mountain region, topographic constraints are the primary exclusion. There are also areas of high wind capacity due to relatively minimal siting constraints, as is seen in the South Central and Great Plains regions. While capacity is ample in these regions, they also have lower capacity densities (figure 2, capacity density map). The lower capacity density values are driven by an ability to flexibly reduce wake losses when the site is not land-constrained. Conversely, we see increased capacity density values where siting constraints are high. For these sites, turbine placement is highly restricted, resulting in few turbines being deployed on the limited land available. However, because few turbines can be deployed, the total site capacity is limited. Regionally (regions shown in Figure 2 and results listed in Table 3), median capacity densities vary between 1.9 MW/km^2 in the Southwest and 4.4 MW/km^2 in the Southeast and Northeast.

Table 3. Regional capacity density results for the COE turbine and Reference Access siting regime. Corresponding regions are visible in Figure 2.

Region	Capacity Density (MW/km^2) 25th Percentile	Capacity Density (MW/km^2) 50th Percentile	Capacity Density (MW/km^2) 75th Percentile
Great Lakes	2.7	4.0	8.5
Great Plains	2.2	2.7	3.7
Mountain	1.8	2.2	3.5
Northeast	3.1	4.4	8.3
Pacific	2.3	3.5	5.8
South Central	2.0	2.6	4.0
Southeast	3.0	4.4	9.6
Southwest	1.6	1.9	2.5

One overarching goal of national wind potential assessments is to evaluate the impacts of wind turbine technology advancement, as these assessments are routinely used in forward-looking energy planning models. As larger turbine options become available, the amount of developable land area decreases due to setbacks. For example, the ATB Moderate turbine has 433,314 km^2 less developable land area than the COE turbine (under the Reference Access siting regime). Yet we find that the CONUS wind potential for the ATB Moderate turbine could reach 11.9 TW of capacity and 38,475 TWh, which represents a 50% increase in capacity and an 82% increase in generation compared to the COE turbine. This result demonstrates that the larger machine can overcome less developable land with a larger nameplate and increased capacity factor. However, there is an inflection point for continued turbine scaling—at least from a national capacity perspective. Importantly, this inflection point is not observed for wind energy generation in this analysis. The ATB Advanced turbine, a significantly larger turbine than the ATB Moderate turbine (28-m greater tip height and a 1.5-MW greater nameplate), results in 0.5 TW less capacity. Still, the ATB Advanced turbine has slightly more generation potential than ATB Moderate (898 TWh), even though it has 170,000 km^2 less developable area and approximately 500,000 fewer turbines (Table 4).

Table 4. Siting regime and turbine technology wind technical potential. *Developable area capacity density is computed based on the results of the spatial optimization. ** Lopez at al. 2021 used a static capacity density of 3 MW/km^2 across the entire CONUS.

Siting Regime	Wind Technology Scenario	Capacity (TW)	Generation (TWh)	Developable Area (million km^2)	Turbines (million)	*Median Capacity Density (MW/km^2)	**Lopez et al. 2021 (TW)
Reference	COE 2018	7.8	21,151	3.05	3.2	2.9	9.1
Reference	ATB Moderate	12.0	38,475	2.62	2.18	5.6	7.8
Reference	ATB Advanced	11.4	39,373	2.45	1.63	5.9	7.3
Limited	ATB Moderate	5.6	18,828	0.76	1.02	15.8	2.2
Open	ATB Moderate	13.1	41,755	5.06	2.39	2.5	15.1

Siting constraint assumptions represent a critical dimension of wind potential assessments. Siting is highly dynamic and uncertain. To capture the uncertainty, wind potential assessments often develop scenarios to explore the impacts of the uncertainty. For the present study, we find that levels of siting restrictiveness impact overall wind potential capacity more significantly than turbine scale. The ATB Moderate turbine is modeled against three siting scenarios, Open, Reference, and Limited Access (described in Section 2.3). When siting restrictions are minimal (Open Access), our siting method results in lower median capacity densities (2.5 MW/km2). This result is driven by the model's ability to flexibly reduce wake losses by reducing turbine density. Though capacity densities are lower, the abundant land available for development (5.06 million km2) results in the Open Access regime having 13.1 TW of capacity potential—more than any other scenario. Where siting restrictions are high (Limited Access), our siting method estimates higher capacity densities (median 15.8 MW/km2) but with only 5.6 TW of national capacity potential. This represents only a 57% decrease in capacity potential despite an 84% reduction in developable land compared to the Open Access scenario. This demonstrates the optimization's ability to flexibly site individual turbines in a way that significantly increases overall capacity.

As stated earlier, we optimize roughly 57,000 wind sites across the CONUS. Figure 3 shows four of these sites that represent a cross section of low and high siting complexity and current and future wind turbine technology, thus contextualizing the drivers of our national results. In the low complexity site in Albany County, Wyoming, the two turbines (COE and Advanced) have roughly the same area (2.8 km2 difference) and similar capacity densities (≈1 MW/km2 difference). The difference in wind speed (≈1 m/sec) is a result of the taller (Advanced) turbine taking advantage of the positive wind shear. The Advanced turbine achieves more capacity (294 MW) than the COE turbine (220 MW) despite deploying 50 fewer turbines. This result highlights that although taller turbines require larger setbacks, have larger spacing between rotors, and produce larger wakes, these challenges can be overcome with larger, more advanced machines and the better wind resources higher in the atmosphere.

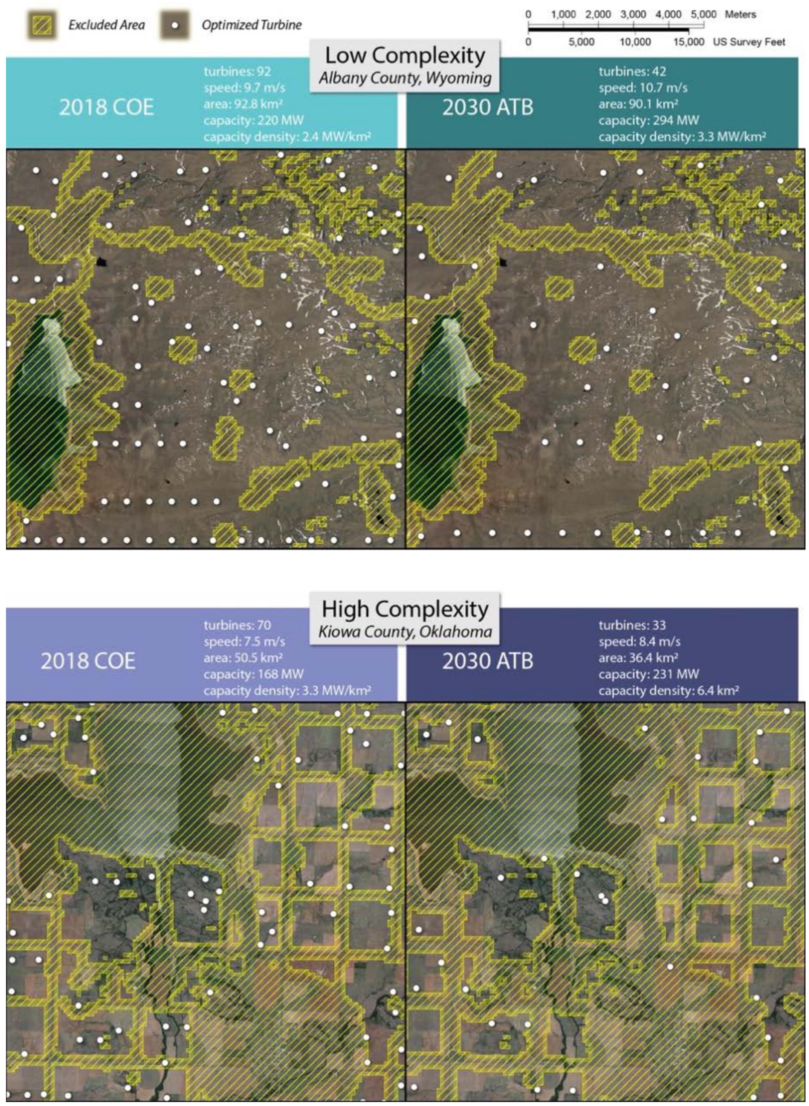

Figure 3. Cross section of wind site drivers showing a low complexity site and a high complexity site with different turbine assumptions. It may appear some turbines violate the spatial constraints; however, this is simply due to the scale of the image.

In the high complexity site of Kiowa County, Oklahoma, the two turbines have ≈14 km^2 of difference in developable land. This is a result of the Advanced turbine having larger setbacks from buildings, water, and roads as driven by its tip height. The resulting capacity (168 MW and 231 MW) and capacity densities of 3.3 MW/km^2 and 6.3 MW/km^2 for the COE and Advanced turbines respectively, demonstrate the siting advantages of the larger, more advanced turbine at this location.

Wind *supply curves* are another critical outcome of wind potential assessments. Supply curves integrate the cost of wind technology, including capital, operation and maintenance, BOS, spur-transmission, and point-of-interconnection costs with financing assumptions to derive an LCOE. The result is a curve representing the cumulative capacity available at different LCOE values. Figure 4 shows supply curves for our suite of siting and technology scenarios. Here, the blue lines represent the influences of different levels of siting restrictiveness on a single turbine (ATB Moderate). The results show an asymmetric relationship to siting. The Limited scenario increases in cost at around 1.5 TW of capacity relative to the Reference and Open scenarios, which do not start to deviate from one another until roughly 8 TW. Across the turbine technology dimension, we immediately see different starting points for the supply curves. This result is driven by the turbine costs, where the COE turbine is representative of costs in 2018 and the ATB turbines are representative of costs in the year 2030 to represent plausible turbine cost declines. The differences between the ATB turbines represent levels of cost reduction aggressiveness and result in a flattening of the supply curve.

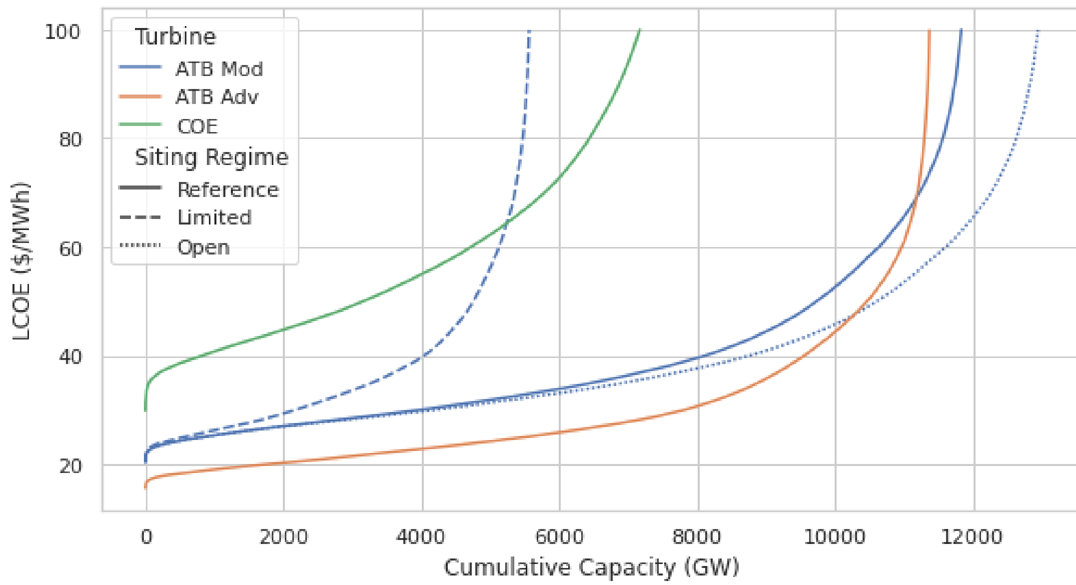

Figure 4. Wind supply curves showing cumulative capacity of wind potential and its associated LCOE. The results were limited to sites less than $100/MWh.

Although costs were synchronized as closely as possible with the static capacity density methods described in Lopez et al. 2021, there are small differences in LCOE and LCOT when using the site-optimization methods (Table 5). Differences were expected because of fundamental changes to the model, though a bias towards lower LCOEs was observed in the site-optimized outputs compared to those run with a static capacity density. While these LCOEs are close to those using a static density (within 1.27 to 1.97 $/MWh), they are consistently lower. Levelized costs of transmission (LCOT) do not show a similar bias with differences ranging from 1.1 $/MWh lower to 1.2 $/MWh higher compared to the static density method. The LCOE bias is mainly attributable to the objective function and the cost curves used in the optimization routine which reward larger farms with lower costs.

Table 5. Area weighted average site-based levelized cost of energy (LCOE), levelized cost of transmission (LCOT), and total LCOE with and without wind plant optimization.

Siting Regime	Plant Optimization	Wind Technology Scenario	Site-based LCOE ($/MWh)	LCOT ($/MWh)	Total LCOE ($/MWh)
Reference	yes	COE 2018	58.67	4.53	63.19
Reference	no	COE 2018	60.38	5.63	66.01
Reference	yes	ATB Moderate	36.49	4.89	41.38
Reference	no	ATB Moderate	38.43	4.33	42.76
Reference	yes	ATB Advanced	27.11	4.54	31.65
Reference	no	ATB Advanced	28.38	3.86	32.24
Limited	yes	ATB Moderate	35.48	4.25	39.73
Limited	no	ATB Moderate	37.24	3.05	40.29
Open	yes	ATB Moderate	36.99	4.36	41.35
Open	no	ATB Moderate	38.96	4.48	43.44

To contextualize our results, we compare them to three recent empirically based capacity density studies and one wind potential assessment. As mentioned previously, the capacity density studies use various methodologies to capture land area associated with the wind plant. However, all three studies include all area within the plant boundary in their capacity density equation. For our comparison, we use the COE turbine and the Reference Access siting regime. To help align our results, we compute a new capacity density from our results. To do so, we first buffer our optimized turbines by 300 m and then compute a convex hull for each of our wind sites (300 m is referenced from Atlas et al. 2022). Using the areas from these convex hulls in each site in the denominator, we estimate a hull capacity density for each site. These hull capacity densities range from 1.1 to 1.4 MW/km^2.

Our first comparison is to Harrison-Atlas et al. (2022) who observe a fleetwide capacity density of 4.3 MW/km^2 with regional variations between 3.1 and 7.6 MW/km^2. The authors also report on a yearly basis, finding that recently developed wind power plants have a national average of 2.2 MW/km^2—a lower capacity density trend the authors attribute to concentrated development in the traditionally low-density regions of South Central, Great Plains, and Great Lakes.

We next compare to Miller and Keith (2018) who observe a national average capacity density of 1.5 MW/km^2. Our results align most closely with Miller and Keith's results, who use Voronoi polygons to define the wind plant boundary. Though our results match closely their all-area capacity densities, their assertion that past studies are overestimating capacity density by 2–6X belies the fact that wind potential studies apply capacity densities *after* siting exclusions (Brown et al., 2016; Lopez et al., 2021, 2012; McKenna et al., 2014; Rinne et al., 2018; Ruhnau et al., 2022; Ryberg et al., 2018; von Krauland et al., 2021). Capacity densities for developable land after siting exclusions are removed are necessarily higher than full farm area estimates because they represent the same number of turbines on a smaller amount of land. As our results demonstrate, this developable area capacity density can be much greater than all-area capacity density, meaning the application of higher developable area capacity densities is appropriate.

We further compare our results to those found by Enevoldsen and Jacobson (2021) who observe and recommend application of 21.7 MW/km^2 to developable area to assess wind potential in the CONUS. They very narrowly define the boundary of a wind plant to include just the area around the turbines that includes a buffer size equal to their tip height. Their method is perhaps a good representation of density of wind energy in the context of studying co-uses (e.g., agriculture and ranching); however, in the context of wind potential assessments, this method has flaws. Namely, their method and densities ignore the importance of wakes (for both inter-wind and intra-wind plants) as a large variable driving overall plant design (Fields et al., 2021; Lundquist et al., 2019).

We conclude our comparisons by examining the differences between our national wind potential capacity results and those found by Lopez et al. (2021) who used a uniform capacity density of 3 MW/km^2—an identified limitation of their study. As mentioned earlier, our siting and turbine assumptions are aligned with Lopez et al. (2021), enabling us to demonstrate the importance of capacity density. Table 3 has a full set of scenario comparisons; however, we focus on a couple key differences. We find that given contemporary wind turbine technology (COE turbine) and standard siting (Reference Access regime), Lopez et al. (2021) estimate ≈17% more capacity than our results. This is a result of the turbine siting model's preference to spread turbines out, driving lower capacity density results in areas where land is abundant; when the capacity density results are summed to national levels, they fall below the constant 3 MW/km^2 assumptions. However, for a near-future turbine (ATB Moderate) also under the Reference Access siting regime, our capacity results are 52% higher than Lopez et al. (2021); with larger turbines, more capacity can be placed in areas with less-abundant land, boosting the national potential estimate. Further, with a near-future turbine (ATB Moderate) under difficult siting (Limited Access), our capacity results are 155% higher than Lopez at al. (2021). This is again the result of the larger turbine's ability to enable more capacity when siting considerations are more restrictive. Overall, because the actual area available for wind power was held constant between studies, these differences demonstrate the limitations of a singular capacity density assumption extrapolated across diverse areas. In other words, using the uniform 3 MW/km^2 capacity density and applying it to the available area after exclusions are applied double counts the impact of the exclusions as the empirically based 3 MW/km^2 was derived from the total lease area and not just from remaining suitable land area. The spatial optimization method applied here highlights the potential ability of larger turbines to enable increased wind capacity and generation when siting turbines in and around spatial constraints, and the energy generation value of lower capacity densities and reduced wake losses when land is abundant.

4 Discussion

To overcome challenges in wind technical potential assessments, we developed an approach that leverages spatial optimization in lieu of the traditionally use uniform capacity density. The optimization approach is a spatially explicit method for determining the potential locations of individual wind turbines; it takes into account the turbine configuration, plant economics and losses, wind resource, and siting considerations. Our approach accounts for the interactions between wind technology design, wind plant layout, and the vast array of regulatory, land use and infrastructure conflicts with wind development.

We find strong regional variations in capacity density: 1.9 MW/km^2–4.4 MW/km^2 when considering a single turbine design and siting regime. We also find strong variations in national capacity density (2.5 MW/km^2–15.8 MW/km^2), as driven by the interactions between turbine technology and siting restrictiveness. Additionally, we find these varying capacity densities lead to large variations in estimates of national wind technical potential (5.6 TW–13.1 TW) and generation potential (18,828 TWh–41,755 TWh).

Our results highlight the potential ability of larger turbines to enable increased wind capacity, up to a point, and increased generation when siting turbines in and around spatial constraints; moreover, they demonstrate and capture the LCOE benefit of lower capacity densities and reduced wake losses when land is abundant. These insights provide foundational knowledge for the wind sector as it develops and pursues future turbine models and as wind energy markets expand in zero-carbon futures.

In demonstrating the sensitivity of wind potential to prospective turbine technology, we identify the limitations of using retrospective studies to inform national wind potential assessments, which limits our ability to quantify the value proposition of technological advancement. Further, it limits our ability to capture local siting opportunities, especially in difficult siting environments. This is particularly problematic when retrospective wind potential is used within capacity expansion models, as is often done, because they miss the critical nuance needed by local decision makers and stakeholders and thus mislead about the land required for decarbonization.

Though our work here advances the state of the wind potential literature, we acknowledge there is still much work to be done.

An increasing number of siting ordinances based on height limits or setbacks might also limit the technology options available in some locations (Lopez et al., 2023). Given these regional factors, assessments of wind technical potential and deployment scenarios would benefit from considering a broad range of wind technologies and their interactions with these siting factors.

Siting is a highly dynamic topic and not all siting considerations are present in this analysis. Viewshed, sound propagation, shadow flicker, Federal Aviation Administration and U.S. Department of Defense airspace considerations, as well as ecological sensitivities require integration into the present analysis.

Future research leveraging the work presented here could also advance the literature by examining wind turbine innovations such as wake steering, construction cost variability due to terrain and site complexity, and the capture of intra-wind site resource variability and topological effects.

Wind technical potential is not a static estimate; it is ever evolving alongside our changing human and natural landscapes and is influenced by technological innovation and adaptation. Our ability to capture nuances of wind plant layouts and siting broadly is critical for estimating wind potential and ultimately understanding wind energy's role in decarbonizing the United States.

References

Brown, A., Beiter, P., Heimiller, D., Davidson, C., Denholm, P., Melius, J., Lopez, A., Hettinger, D., Mulcahy, D., Porro, G., 2016. Estimating Renewable Energy Economic Potential in the United States. Methodology and Initial Results (No. NREL/TP-6A20-64503, 1215323). https://doi.org/10.2172/1215323

Buster, G., Rossol, M., Pinchuk, P., Spencer, R., Bannister, M., Benton, B.N., Williams, T., Stanley, P.J., 2022. NREL/reV: PySAM 3 Support. https://doi.org/10.5281/zenodo.7301491

Denholm, P., Hand, M., Jackson, M., Ong, S., 2009. Land Use Requirements of Modern Wind Power Plants in the United States (No. NREL/TP-6A2-45834, 964608). https://doi.org/10.2172/964608

Draxl, C., Clifton, A., Hodge, B.-M., McCaa, J., 2015. The Wind Integration National Dataset (WIND) Toolkit. Appl. Energy 151, 355–366. https://doi.org/10.1016/j.apenergy.2015.03.121

Eberle, A., Roberts, J.O., Key, A., Bhaskar, P., Dykes, K.L., 2019. NREL's Balance-of-System Cost Model for Land-Based Wind (No. NREL/TP-6A20-72201, 1569457). https://doi.org/10.2172/1569457

EIA, 2022. Electric Power Annual 2021.

Enevoldsen, P., Jacobson, M.Z., 2021. Data investigation of installed and output power densities of onshore and offshore wind turbines worldwide. Energy Sustain. Dev. 60, 40–51. https://doi.org/10.1016/j.esd.2020.11.004

Fields, M., Optis, M., Perr-Sauer, J., Todd, A., Lee, J., Meissner, J., Simley, E., Bodini, N., Williams, L., Sheng, S., Hammond, R., 2021. Wind Plant Performance Prediction Benchmark Phase 1 (Technical Report) (No. NREL/TP-5000-78715, 1826665, MainId:32632). https://doi.org/10.2172/1826665

Freeman, J.M., DiOrio, N.A., Blair, N.J., Neises, T.W., Wagner, M.J., Gilman, P., Janzou, S., 2018. System Advisor Model (SAM) General Description (Version 2017.9.5) (No. NREL/TP--6A20-70414, 1440404). https://doi.org/10.2172/1440404

Gagnon, P., Brown, M., Steinberg, D., Brown, P., Awara, S., Carag, V., Cohen, S., Cole, W., Ho, J., Inskeep, S., Lee, N., Mai, T., Mowers, M., Murphy, C., Sergi, B., 2023. 2022 Standard Scenarios Report: A U.S. Electricity Sector Outlook. Renew. Energy.

Harrison-Atlas, D., Lopez, A., Lantz, E., 2022. Dynamic land use implications of rapidly expanding and evolving wind power deployment. Environ. Res. Lett. 17, 044064. https://doi.org/10.1088/1748-9326/ac5f2

Harrison-Atlas, D., Maclaurin, G., Lantz, E., 2021. Spatially-Explicit Prediction of Capacity Density Advances Geographic Characterization of Wind Power Technical Potential. Energies 14, 3609. https://doi.org/10.3390/en14123609

Jenkins, J.D., Mayfield, E.N., Larson, E.D., Pacala, S.W., Greig, C., 2021. Mission net-zero America: The nation-building path to a prosperous, net-zero emissions economy. Joule 5, 2755–2761. https://doi.org/10.1016/j.joule.2021.10.016

Key, A., Roberts, O., Eberle, A., 2022. Scaling trends for balance-of-system costs at land-based wind power plants: Opportunities for innovations in foundation and erection. Wind Eng. 46, 896–913. https://doi.org/10.1177/0309524X211060234

Lopez, A., Cole, W., Sergi, B., Levine, A., Carey, J., Mangan, C., Mai, T., Williams, T., Pinchuk, P., Gu, J., 2023. Impact of siting ordinances on land availability for wind and solar development. Nat. Energy. https://doi.org/10.1038/s41560-023-01319-3

Lopez, A., Levine, A., Carey, J., Mangan, C., 2022. U.S. Wind Siting Regulation and Zoning Ordinances [WWW Document]. OpenEI. URL https://data.openei.org/submissions/5733 (accessed 1.21.23).

Lopez, A., Mai, T., Lantz, E., Harrison-Atlas, D., Williams, T., Maclaurin, G., 2021. Land use and turbine technology influences on wind potential in the United States. Energy 223, 120044. https://doi.org/10.1016/j.energy.2021.120044

Lopez, A., Roberts, B., Heimiller, D., Blair, N., Porro, G., 2012. U.S. Renewable Energy Technical Potentials. A GIS-Based Analysis (No. NREL/TP--6A20-51946, 1219777). https://doi.org/10.2172/1219777

Lundquist, J.K., DuVivier, K.K., Kaffine, D., Tomaszewski, J.M., 2019. Costs and consequences of wind turbine wake effects arising from uncoordinated wind energy development. Nat. Energy 4, 26–34. https://doi.org/10.1038/s41560-018-0281-2

Maclaurin, G., Grue, N., Lopez, A., Heimiller, D., Rossol, M., Buster, G., Williams, T., 2019. The Renewable Energy Potential (reV) Model: A Geospatial Platform for Technical Potential and Supply Curve Modeling (No. NREL/TP-6A20-73067, 1563140, MainId:13369). https://doi.org/10.2172/1563140

Mai, T., Lopez, A., Mowers, M., Lantz, E., 2021a. Interactions of wind energy project siting, wind resource potential, and the evolution of the U.S. power system. Energy 223, 119998. https://doi.org/10.1016/j.energy.2021.119998

Mai, T., Mowers, M., Eurek, K., 2021b. Competitiveness Metrics for Electricity System Technologies (No. NREL/TP--6A20-72549, 1765599, MainId:6148). https://doi.org/10.2172/1765599

McKenna, R., Hollnaicher, S., Fichtner, W., 2014. Cost-potential curves for onshore wind energy: A high-resolution analysis for Germany. Appl. Energy 115, 103–115. https://doi.org/10.1016/j.apenergy.2013.10.030

Miller, L.M., Keith, D.W., 2018. Observation-based solar and wind power capacity factors and power densities. Environ. Res. Lett. 13, 104008. https://doi.org/10.1088/1748-9326/aae102

Rinne, E., Holttinen, H., Kiviluoma, J., Rissanen, S., 2018. Effects of turbine technology and land use on wind power resource potential. Nat. Energy 3, 494–500. https://doi.org/10.1038/s41560-018-0137-9

Ruhnau, O., Eicke, A., Sgarlato, R., Tröndle, T., Hirth, L., 2022. Cost-Potential Curves of Onshore Wind Energy: the Role of Disamenity Costs. Environ. Resour. Econ. https://doi.org/10.1007/s10640-022-00746-2

Ryberg, D.S., Robinius, M., Stolten, D., 2018. Evaluating Land Eligibility Constraints of Renewable Energy Sources in Europe. Energies 11, 1246. https://doi.org/10.3390/en11051246

Stanley, A.P.J., Roberts, O., Lopez, A., Williams, T., Barker, A., 2022. Turbine scale and siting considerations in wind plant layout optimization and implications for capacity density. Energy Rep. 8, 3507–3525. https://doi.org/10.1016/j.egyr.2022.02.226

von Krauland, A.-K., Permien, F.-H., Enevoldsen, P., Jacobson, M.Z., 2021. Onshore wind energy atlas for the United States accounting for land use restrictions and wind speed thresholds. Smart Energy 3, 100046. https://doi.org/10.1016/j.segy.2021.100046

Wiser, R., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G., Darghouth, N., Gorman, W., Jeong, S., Mills, A., Paulos, B., 2021. Land-Based Wind Market Report: 2021 Edition.

Wiser, R., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G., Darghouth, N., Gorman, W., Jeong, S., Paulos, B., 2022. Land-Based Wind Market Report: 2022 Edition.