Variability in Wind Energy Generation across the Contiguous United States

S. C. Pryor, F.W. Letson, and R. J. Barthelmie

Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, New York
Sibley School for Mechanical and Aerospace Engineering, Cornell University, Ithaca, New York

ABSTRACT: ERA5 provides high-resolution, high-quality hourly wind speeds at 100 m and is a unique resource for quantifying temporal variability in likely wind-derived power production across the United States. Gross capacity factors (CF) in seven independent system operators (ISOs) are estimated using the location and rated power of each wind turbine, a simplified power curve, and ERA5 output from 1979 to 2018. Excluding the California ISO, the marginal probability of a calm (zero power production) is less than 0.1 in any ERA5 grid cell. When a calm occurs, the mean co-occurrence across wind-turbine-containing grid cells ranges from 0.38 to 0.39 for ISOs in the Midwest and central plains [Midcontinent (or Midwest) ISO (MISO), Southwest Power Pool (SPP), and the Electric Reliability Council of Texas (ERCOT) region], increasing to 0.54–0.58 for ISOs in the eastern United States [Pennsylvania–New Jersey–Maryland interconnection (PJM), New York ISO (NYISO), and New England ISO (NEISO)]. Periods with low gross CF have a median duration of ≤6 h, except in California, and are most likely during summer. Gross CF exhibit highest variance at periods of 1 day in ERCOT and SPP; on synoptic scales in MISO, NEISO, and NYISO; and on interannual time scales in PJM. This implies differences in optimal strategies for ensuring resilience of supply. Theoretical scenarios show adding wind energy capacity near existing wind farms is advantageous in areas with high existing installed capacity (IC), while expanding into areas with lower IC is more beneficial to reducing ramps and the probability of gross CF falling below 20%. These results emphasize the benefits of large balancing areas and aggregation in reducing wind power variability and the likelihood of wind droughts.

KEYWORDS: Wind; Reanalysis data; Diurnal effects; Interannual variability; Seasonal variability; Renewable energy

1. Introduction and objectives

Currently, 18% of gross final energy consumption in Europe derives from renewable energy sources, and renewables, including biofuels, contribute almost 30% of European electricity supply (Brodny and Tutak 2020). Renewable energy sources provide over half of national electricity supply in Sweden (Brodny and Tutak 2020). Thus, individual countries and power system control areas have adapted to efficiently accommodate these variable generation sources (Brodny and Tutak 2020; Holttinen et al. 2011).

Measures to innovate the electricity supply and transmission network to accommodate fluctuating power sources while maintaining a reliable and secure electricity supply are aided by improved understanding of the sources and magnitude of expected variability and accurate forecasts of electrical power production (Collins et al. 2018; Das et al. 2020; Deetjen et al. 2017; Nottton et al. 2018). Research to better quantify and predict variability in wind generation potential is particularly valuable for areas with a weak or highly fractured electricity grid and for electricity supply systems with high penetration of variable renewable energy generation sources (e.g., wind and solar) (Bakke 2016; Grams et al. 2017). Accurate estimates of the probability that a given network will simultaneously experience little or no wind generation capacity, and the duration of such periods, are useful inputs to decisions regarding the need for storage (Denholm and Mai 2019; Ziegler et al. 2019). Such information may also provide guidance on where projected new capacity or storage could be added to smooth out variations in supply or optimal mixes of generation sources (Cassola et al. 2008; Roques et al. 2010). For example, there is some evidence of synergies gained by co-deploying wind turbines and solar photovoltaics since power production from these sources is largely anticorrelated at frequencies below a few weeks (Nikolakakis and Fthenakis 2011; Ziegler et al. 2019) and on seasonal time scales within the contiguous United States of America (Shaner et al. 2018).

The need for improved understanding of variability in wind power production is increasingly pressing in the United States. Wind energy provided 7% of the national electricity supply during 2019 [American Wind Energy Association (AWEA) 2020; Hamilton et al. 2020], and there are suggestions that wind turbines (WTs) may contribute 20% of the national electricity supply by 2030 [National Renewable Energy Laboratory (NREL) 2008; Pryor et al. 2020a]. There are already examples of the benefits to modifying the transmission network to enable efficient transfer of wind generated electricity to load centers, and to reduce the need for wind curtailment that may arise due to bottlenecks in the transmission network. For example, a project to expand transmission in the Electric Reliability Council of Texas (ERCOT) region decreased the rate of wind curtailment from 17% to 1.2% (Jang 2020).

A range of different scales and phenomena contribute to the variability in power generation from WTs (Troccoli et al. 2014). These range upward from the smallest (α and β) microscales

ORCID: 0000-0003-4847-3440.
ORCID: 0000-0001-9275-0359.
ORCID: 0000-0003-4847-3440.

Corresponding author: S. C. Pryor, sp2279@cornell.edu

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(length scales from 30 m to 3 km) that are associated with surface-layer and boundary layer turbulence (Stull 2017). The corresponding decorrelation length scales are also relatively small, and thus such variability is readily "smoothed out" by increasing the number of WTs or the area of wind farms (Nanahara et al. 2004). The energy content of the wind also typically exhibits variability at mesoscales. Variation over length scales from 3 to 700 km and time scales from <1 to 12 h [meso-γ (3–30 km), meso-β (30–300 km), and meso-α (300–700 km)] is associated with phenomena such as orographically forced gap and downstream winds and squall lines (Stull 2017). One analysis of 20 wind plants in Texas found that variability of power production on time scales below 24 h was reduced by 87% by interconnecting four wind power plants, and it further suggested that the temporal correlation of power production at wind power plants separated by 200 km is half that of collocated plants (Katzenstein et al. 2010). Wind speed and power production variability also occurs on synoptic scales with horizontal length scales from 700 up to 4000 km and time scales from a few hours to multiple days. Variability at this scale results from transitory midlatitude frontal cyclones and anticyclones, plus tropical cyclones (Stull 2017). It tends to dominate the variance in wind speed and power production at midlatitude sites (Mehrens et al. 2016; Pryor et al. 2012; Pryor et al. 2018).

As a result of major research initiatives such as the “development of a next generation wind resource forecasting system for the large-scale integration of onshore and offshore wind farms” (“Anemos”) suite of projects (Giebel and Kariniotakis 2017) and the Wind Forecast Improvement Project (WFIP) and the Second WFIP (WFIP2) (Bianco et al. 2019; Wilczak et al. 2015; Wilczak et al. 2019b), short-term variability of wind power production is increasingly predictable. Tremendous strides have been made toward achieving the high degree of accuracy of short-term forecasts (from <1- to 36-h time horizons) (Akish et al. 2019; Anastasiades and McSharry 2013; Bianco et al. 2019; Qian et al. 2019; Wilczak et al. 2019a) necessary to (i) reduce the need for spinning reserve power, (ii) enable efficient grid operation, and (iii) maximize market purchase price for wind farm operators (AWEA 2019; Collet et al. 2018; Ortega-Vazquez and Kirschen 2009; Purvins et al. 2011).

The need for, and magnitude of, spinning reserve required is a function of the penetration of intermittent electricity supply sources, volatility of supply and demand, and factors such as the accuracy and uncertainty in load and wind power production forecasts (Ortega-Vazquez and Kirschen 2009). Wind ramps (i.e., steep gradients in wind-generated power production) are typically manifest in the mesoscale range but are frequently associated with the frontal passages from mid-latitude cyclones (Bossavy et al. 2013; Cutler et al. 2007; Vincent and Trombe 2017), although other mechanisms may be more important in complex terrain (Bianco et al. 2019). One analysis of data from 2008 to 2010 over the ERCOT region of the United States (Fig. 1) suggests that large systemwide perturbations in power production associated with wind ramps appear to be declining in magnitude due to the geographic diversification of WTs, but at the hourly time scale, wind ramps can generate up to 10% changes in electricity production (Holttunen et al. 2010). Optimal strategies for compensating for ramps in wind generation and the implications for system frequency regulation are highly dependent on the direction of change, plus the speed (ramp rate), duration, magnitude, and timing of the ramp (Ela and Kemper 2009; Gong et al. 2017). Negative ramps (rapid declines in wind power) are usually more challenging to grid operators because they require short-term provision of power from other sources to replace the decrease from wind energy and keep generation and consumption balanced, mitigate volatility in voltage and ensure grid stability (Ackermann 2012; Mohandes et al. 2019).

Spatial correlations and/or coherence functions for wind speeds and power production generally exhibit exponential forms with horizontal separation (Mehrens et al. 2016; Nanahara et al. 2004; Pryor et al. 2014). The coefficients that determine the decorrelation length scale (i.e., the separation distance at which those time series become minimally or uncorrelated) have implications of power fluctuations and reliability and vary substantially in space as a result of variations in the meteorological regime such as the frequency of transitory cyclone passages (St. Martin et al. 2015).

Wind climates also exhibit low-frequency (monthly to interannual and interdecadal) variability due to the action of internal climate modes, such as the Pacific–North American index (PNA), El Niño–Southern Oscillation (ENSO), and North Atlantic Oscillation (NAO) (Klink 2002; Pryor et al. 2018; Schoof and Pryor 2014). Power production data from individual wind farms in the U.S. Great Plains (i.e., in the ERCOT and SPP independent system operators, Fig. 1) indicate the interquartile range of annual values is 6%–12% of the median (Pryor et al. 2018). This implies substantial year-to-year variability in the wind resource and thus wind power production due to the action of these internal climate modes (Pryor et al. 2020c).

An increasing share of variable sources in the power supply system raises questions about reliability and the potential for “energy droughts” (Raynaud et al. 2018). Times with low wind-derived power production are referred to as “wind droughts” and arise due to extended episodes of low wind speeds (Lledo et al. 2018; Raynaud et al. 2018). An analysis of data from Europe used a definition of 0.2 times the mean daily production as a severe energy production drought for solar, wind, and hydroelectric production. That study found that in Norway, Germany, and Andalusia (a region of Spain) the mean duration of severe wind droughts was < 2 days. Severe wind energy droughts had a shorter mean duration for solar power and were longer but less frequent for hydropower (Raynaud et al. 2018). As discussed further below, a wind drought impacted the western United States during the first quarter (Q1: January–March) of 2015 (Lledo et al. 2018).

The objectives of research presented herein are as follows:

1) Characterize the dominant scales of temporal variability, across a range of time scales from hourly to interannual, in wind speeds and wind power production estimates across different regions of the United States.

2) Characterize key aspects of power production of relevance to grid integration and system reliability such as the cooccurrence
and temporal duration of low power production periods and the occurrence of power ramps.

3) Perform a semiconstrained analysis of the theoretical potential efficiency/reliability gains from geographical diversification of wind power production plants.

An evaluation of the validity of power production estimates derived using the ERA5 reanalysis is also performed. Throughout this analysis capacity factors (CF) are used to describe the efficiency of electrical power production from wind turbines relative to that achievable if all WTs operated at their rated capacity. Observational estimates of power production efficiency from operating wind farms and or clusters of wind farms computed in this way are referred to as net CF because they include power losses that derive from WT curtailment (Bird et al. 2014), WT wakes (Barthelmie et al. 2013; Staid et al. 2018), WT operations and maintenance (O&M) (Carroll et al. 2017; Olauson et al. 2017), and electrical losses (Lumbreras and Ramos 2013). Modeled estimates of power production are referred to as gross CF because they exclude these factors and are solely a function of the wind speed in each grid cell and the assumed WT power curve. A further key concept that is employed herein is the capacity value of wind. In brief, the capacity value of any electrical power production unit is used to quantify the contribution to meeting electricity demand and thus system reliability targets (Milligan et al. 2017) or the fraction of the installed capacity that can be counted on during peak demand (Keane et al. 2010).

2. Data and methods

a. The U.S. electric power transmission network

The electric power transmission network in the contiguous United States comprises three main interconnections that largely operate independently with only limited transfers of electricity between them (Blume 2016). The three interconnections are as follows: 1) eastern, which covers the area east of the Rocky Mountains and a small portion of Texas; 2) western, which covers the area west of the Rocky Mountains; and 3)
ERCOT, which covers most of Texas (Bakke 2016) (Fig. 1). There are 66 “balancing authorities” that oversee regional operation of the electric grid system including seven that cover the majority of the WT assets in the United States and are considered herein (Table 1, Fig. 1) (Borenstein and Bushnell 2015). These entities are referred to as regional transmission operators or independent system operators (ISOs) and differ in terms of the total generation capacity, the area and number of customers served, and penetration of wind energy into the electricity supply (Table 1, Fig. 1). Wind energy penetration is highest in ERCOT, but as of April 2020 all seven ISOs considered herein have at least 1.4 GW of installed wind energy capacity (Table 1).

Because of difficulties associated with precisely allocating WT to specific ISOs and the fluidity of the ISOs (Pollitt 2012), state-based approximations of each ISO are used herein (Table 1). As an example, ERCOT is wholly contained within Texas. It currently covers 75% of the land area of Texas serves 85% of the state’s electric load and has 87% of the state’s generation capacity (Jang 2020). Herein ERCOT is defined as covering all WT assets in the state of Texas. The analyses presented here are thus an abstraction from the actual generation, and transmission networks that are currently operating with the United States. For example, where we present information with regard to gross CF within a given ISO, we are implicitly assuming the ISO has a perfectly efficient and interconnected transmission network. However, analysis at this scale permits direct comparison with observational data and the approximations are relatively close to the actual ISO areas in terms of WT deployments.

b. Power production data from the U.S. EIA

U.S. Energy Information Administration (EIA) datasets of monthly electricity generation and annual estimates of installed capacity (IC) by electricity generation source and state for September 2014 to December 2019 are merged to estimate the monthly net CF from wind in each of the ISO as approximated using the state-based definitions summarized in Fig. 1 and Table 1. These net CF (Fig. 2) are rendered conservative due to use of the IC in each state at the end of each calendar year as reported by the EIA. These data are used to illustrate low-frequency variability in net CF and to evaluate monthly ISO-wide gross CF computed from ERA5 during 2018.

c. Data from the NREL Wind Prospector

Two modeled datasets from the NREL Wind Prospector are used herein for evaluation of gross CF derived from ERA5: the Eastern Wind Dataset and the Western Wind Dataset (3TIER 2010; Brower 2009; Pennock 2012). These datasets contain modeled net CF estimates at potential wind farm locations across the eastern and western United States, respectively, based on the climate of 2004–06 as simulated using the Weather Research and Forecasting (WRF) Model applied at approximately 2-km grid spacing. The procedure used to derive these estimates employs 10-min modeled wind speeds, theoretical (standardized) power curves for representative WT and adjustments made using empirical correction factors to account for factors such as wake loss, WT and plant availability, and adjust for model errors in the diurnal variability of wind speeds (Brower 2009). In the analysis presented here, the net CF at each of these 34,689 georeferenced locations is allocated to the appropriate ERA5 grid cell and compared with gross CF computed using the method described herein. Some ERA5 grid cells contain multiple estimation locations from the Eastern and Western Wind Datasets. The coefficient of variation (COV) of net CF of those estimates is used to provide an estimate of the variability that is subgrid scale in ERA5:

$$\text{COV} = \frac{\sigma(\text{netCF}_{j,L,n})}{\text{netCF}_{j,L,n}} \times 100. \quad (1)$$

d. Wind turbine locations in the contiguous United States

Wind turbine locations employed herein (Fig. 1) derive from a database of the latitude, longitude, and rated capacity of WTs in the United States (Rand et al. 2020). The states included in this analysis have approximately 88.2 GW of installed WT capacity from the national total in April 2020 of approximately 105 GW (Table 1). These georeferenced WTs are allocated to the appropriate ERA5 reanalysis grid cell for calculations of gross CF (Fig. 1). The mean IC in ERA5 grid cells containing one or more WT is 9 MW. The maximum IC in any ERA5 grid cell is 2.34 GW. This is equivalent to an installed capacity density of 2.6 MW km$^{-2}$.

e. ERA5 reanalysis

Wind speed data used herein cover a 40-yr period (1979–2018) and the area from 65° to 126°W and from 24° to 54°N (Fig. 1). They are derived from the European Centre for Medium Range Weather Forecasts (ECMWF) ERA5 reanalysis product (Hersbach et al. 2020). The wind components at 100 m AGL are nominally instantaneous at the time step of the reanalysis model, which is 20 min, and are at a disjunct frequency of hourly. The spatial resolution is 0.25° × 0.25° (Fig. 3a). ERA5 has been subject to a wide array of validation analyses, and has been reported to exhibit relatively high fidelity for wind speeds (Jourdier 2020; Kalverla et al. 2019, 2020; Olauson 2018; Pryor et al. 2020b; Ramon et al. 2019).

The 40-yr time series of hourly wind speeds $U$ from ERA5 are used to compute the long-term mean wind speed in each grid cell, and the marginal probability (i.e., overall probability) of “calms” ($U$ at 100 m AGL < 4 m s$^{-1}$) when there is little/no electrical power production from a typical WT. The mean duration of calms in hours and maximum duration of calms in any period from 1979 to 2018 in each ERA5 grid cell are also calculated. Data from ERA5 grid cells with one or more WT present accord to the USGS database are additionally used to quantify the co-occurrence (or conditional probability) of calms across space and the Spearman (rank) correlation of hourly wind speeds with other ERA5 grid cells in the same ISO that also contain WT. The co-occurrence of calms does not convey information about the probability of a calm in a given grid cell. Rather it is a measure that describes, when a calm is detected in a grid cell, what fraction of the other WT-containing grid cells in that ISO region are also calm.
Table 1. Independent system operators in the contiguous United States, their spatial extent, the abbreviations used, and the approximate number of customers served and total generation capacity (GW) in 2017 (IRC Markets Committee 2017). The five rightmost columns show the ISO approximations used herein, wind turbine installed capacity in each ISO as of April 2020, number of ERA5 grid cells in each ISO that contain WT, co-occurrence of calms, and the Spearman correlations of hourly wind speeds for all ERA5 grid cells within each ISO that contain WT. The statistics reported for co-occurrence of calms and Spearman correlation are the range from minimum to maximum values for individual ERA5 grid cells and the spatial mean computed across all grid cells.

<table>
<thead>
<tr>
<th>Name</th>
<th>Abbreviation used herein</th>
<th>No. of customers served (and generation capacity; GW) in 2017</th>
<th>Coverage</th>
<th>Approximation used herein</th>
<th>Approximate WT IC (GW) based on the USGS WT dataset as of April 2020</th>
<th>No. ERA5 grid cells with WT in each ISO</th>
<th>Mean co-occurrence of calms (range from min to max)</th>
<th>Mean spearman correlation with wind speeds from other WT-containing grid cells (range from min to max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>California ISO</td>
<td>CAISO</td>
<td>30 million (71.7)</td>
<td>Most of CA</td>
<td>All WT in CA</td>
<td>5.76</td>
<td>34</td>
<td>0.74 (0.64–0.84)</td>
<td>0.42 (0.25–0.52)</td>
</tr>
<tr>
<td>Electricity Reliability Council of Texas</td>
<td>ERCOT</td>
<td>24 million (86.0)</td>
<td>Most of TX</td>
<td>All WT in TX</td>
<td>28.2</td>
<td>189</td>
<td>0.39 (0.20–0.49)</td>
<td>0.51 (0.22–0.62)</td>
</tr>
<tr>
<td>Midcontinent (or Midwest) ISO</td>
<td>MISO</td>
<td>48 million (190.5)</td>
<td>All of IA, MI, MN, ND, and WI; parts of AR, IL, IN, LA, MS, MO, MT, SD, and WY; the province of Manitoba</td>
<td>All WT in AR, IL, IN, IA, LA, MI, MN, MI, MO, ND, and WI</td>
<td>28.9</td>
<td>369</td>
<td>0.38 (0.25–0.47)</td>
<td>0.45 (0.17–0.57)</td>
</tr>
<tr>
<td>New England ISO</td>
<td>NEISO</td>
<td>14.7 million (30.5)</td>
<td>CT, ME, MA, NH, RI, and VT</td>
<td>All WT in CT, ME, MA, NH, RI, and VT</td>
<td>1.49</td>
<td>67</td>
<td>0.58 (0.43–0.61)</td>
<td>0.66 (0.53–0.71)</td>
</tr>
<tr>
<td>New York ISO</td>
<td>NYISO</td>
<td>19.5 million (38.8)</td>
<td>NY Parts of DE, IL, IN, KY, MD, MI, NJ, NC, OH, PA, TN, VA, WV, and DC</td>
<td>All WT in NY</td>
<td>1.99</td>
<td>36</td>
<td>0.58 (0.39–0.65)</td>
<td>0.66 (0.42–0.74)</td>
</tr>
<tr>
<td>Pennsylvania–New Jersey–Maryland interconnection</td>
<td>PJM</td>
<td>65 million (176.5)</td>
<td>Parts of DE, IL, IN, KY, MD, NJ, NC, OH, PA, TN, VA, WV, and DC</td>
<td>All WT assets in DE, KY, MD, NJ, NC, OH, PA, VA, and WV</td>
<td>3.29</td>
<td>75</td>
<td>0.54 (0.38–0.60)</td>
<td>0.58 (0.32–0.66)</td>
</tr>
<tr>
<td>Southwest Power Pool</td>
<td>SPP</td>
<td>18 million (83.5)</td>
<td>All of the states of KS and OK, and portions of NM, TX, AR, LA, MO, NM, SD, ND, MT, MN, IA, WY, and NE</td>
<td>All WT in KS, MT, NE, NM, OK, and SD</td>
<td>18.6</td>
<td>223</td>
<td>0.38 (0.22–0.46)</td>
<td>0.42 (0.07–0.56)</td>
</tr>
</tbody>
</table>
Three-hourly output from ERA5 for mean sea level pressure fields from 1979 to 2018 are also subject to a transitory cyclone and anticyclone identification and tracking detection algorithm (Hodges et al. 2011) using a spectral filter of T63. The resulting statistics are given in Figs. 3b and 3c and provide context for the time-scale analysis of wind power variability. Note that the low frequency of anticyclonic activity over the southwestern United States derived in this analysis (Fig. 3c) is because the algorithm is not designed to record semipermanent features such as ridging associated with the subtropical high (Sheppard et al. 2002).

f. Estimating gross CF from ERA5

Estimates of gross CF from each ERA5 grid cell where WTs are located are derived using hourly wind speeds and a simplified theoretical power curve. This WT power curve has zero power production for all wind speeds below 4 m s\(^{-1}\) increases linearly (by 11% for each 1 m s\(^{-1}\)) to a nominal rated wind speed of 12 m s\(^{-1}\) and remains constant until the cut-out wind speed of 25 m s\(^{-1}\). A single simplified power curve is used to focus on spatial variability in the wind resource rather than differences arising from spatial variations in adopted technologies. The amount of power produced in each hour is weighted by the total IC of WTs in each ERA5 grid cell to derive gross CF. This procedure assumes the wind speed at 100 m AGL is representative of the flow impinging on the rotor disk. During 2019 ~ 53% of new wind energy IC was associated with WT that have hub heights of 80–90 m, ~38% was in WT with hub heights of 90–100 m, and nearly 8% of new IC was in WT with hub heights above 100 m (AWEA 2020). Use of gross CF also neglects power losses. Observed levels of curtailment over the eastern United States were \(\leq 4\%\) during 2007–12 (Bird et al. 2014). During 2018 across all ISOs wind energy curtailment was 2.2%, while in ERCOT it was 2.5% (Wiser and Bolinger 2019). Wake losses for onshore wind farms are typically \(\leq 5\%\) (Staid et al. 2018), and WT availability typically exceeds 98% (Carroll et al. 2017). Thus, the expectation is that gross CF will exceed net CF by 4–10 percentage points.

The advantage of deriving gross CF from the ERA5 reanalysis output over use of data from EIA and/or other estimates of net CF is the ability to examine variability over a large range of temporal frequencies in the absence of confounding issues as curtailment and O&M activities. Further, this analysis approach enables examination of spatiotemporal variability across regions for which net CF data are not available and to undertake analyses of scenarios of wind energy expansion.

Hourly gross CF estimates are used to analyze the temporal scales of variability computed using fast Fourier transform
and are presented as power spectra across a range of periods from 2 h to 1000 days. These gross CF estimates are also used to compute the probability of ISO-wide power ramps of different magnitudes and gross CF duration curves, and to characterize seasonal and diurnal variability of gross CF.

### g. Scenarios of WT expanded IC

Four theoretical scenarios are used to provide geophysically consistent and, to some degree, engineering-constrained storylines of expanded WT IC. In all of these scenarios the IC in each ISO is increased by 50% over the baseline of April 2020 (baseline) values (Table 1). Thus, under these scenarios an additional 2.9 GW is added to the California ISO (CAISO), 24.1 GW to ERCOT, 14.5 GW to the Midcontinent (or Midwest) ISO (MISO), 0.75 GW to the New England ISO (NEISO), 1 GW to the New York ISO (NYISO), 1.65 GW to the Pennsylvania–New Jersey–Maryland interconnection (PJM), and 9.3 GW to the Southwest Power Pool (SPP). The scenarios differ in terms of where the additional IC is added. In scenario 1 the additional capacity is installed in the top 20% of grid cells in terms of

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**FIG. 3.** (a) Orography in the ERA5 model plotted at the model output resolution of 0.25° by 0.25° (for the latitudes of the contiguous United States this is approximately 30 km by 30 km). Note that for legibility the color bar is truncated at 3500 m but there are some grid cells with elevations above that level. Also shown is the mean annual frequency of transitory (b) cyclones and (c) anticyclones as identified using a detection algorithm developed by K. Hodges (Hodges et al. 2011) applied to 3-hourly output for mean sea level pressure fields from ERA5 for 1979–2018. The results are computed for each ERA5 grid cell but are presented herein averaged over 3 by 3 gridcell areas.
### 3. Results

**a. Month-to-month variability in wind-derived electrical power derived using EIA data**

Mean net CF in each ISO computed from EIA data from January 2015 to December 2019 are 26% (CAISO), 34% (ERCOT), 28% (MISO), 27% (NEISO), 25% (NYISO), 28% (PJM), and 36% (SPP) (Table 2). Maximum monthly net CF by ISO are 40%, 44%, 42%, 38%, 40%, 44%, and 46% for CAISO, ERCOT, MISO, NEISO, NYISO, PJM, and SPP, respectively (Table 2). Net CF estimates for each ISO approximation derived from the 2018 Wind Technologies Report (Wiser and Bolinger 2019) are 28.5% (CAISO), 38.0% (ERCOT), 32.6% (MISO), 29.1% (NEISO), 24.3% (NYISO), 30.6% (PJM), and 40.0% (SPP) (Table 2). Differences between these two sets of net CF may reflect interannual variability and are also due to trends toward increased net CF for more recently deployed WT (Hamilton et al. 2020; Wiser and Bolinger 2017). Previous reports have indicated net CF for WTs deployed within the United States during 1988–2001 of approximately 25.4%, whereas those deployed in 2004–2011 had net CF of 32.1%, and WTs deployed in 2014 and 2015 had net CF of 42.5% (Wiser and Bolinger 2017). The ISO to ISO variability in the net CF estimates derived from the EIA data may also be partly a response to differences in the age of the WT fleet, with a larger fraction of the WT fleet in CAISO being more than 20 years old (AWEA 2020; Hamilton et al. 2020).

The maximum net CF from monthly EIA data is slightly over 46% (Table 2). It is derived for the SPP and occurred during October 2017 (Fig. 2). The minimum net CF in any month and ISO derived from the EIA was 5% and is derived based on data from CAISO during January 2015 (Fig. 2). This month was part of the “wind drought” (Q1 of 2015) over parts of the United States (Lledo et al. 2018). As shown in Fig. 2, this “wind drought” was observed in only two of the ISOs considered herein. Net CF computed from EIA generation data during January to March of 2015 is 70% of the 5-yr mean for Q1 in CAISO, 81% in ERCOT, 117% in MISO, 125% in NEISO, 135% in NYISO, 132% in PJM, and 94% in SPP. Thus, over a large fraction of the United States, and in ISOs with substantial IC (e.g., MISO; Table 1) net wind generation was above the 5-yr mean for Q1 in CAISO, 81% in ERCOT, 117% in MISO, 125% in NEISO, 135% in NYISO, 132% in PJM, and 94% in SPP. Therefore, over a large fraction of the United States, and in ISOs with substantial IC (e.g., MISO; Table 1) net wind generation was above the 5-yr mean for Q1 (Fig. 2). This reemphasizes the limited spatial extent of “production droughts” and the value in a distributed network of wind power generation facilities and a highly interconnected distribution network in reducing variability of electrical power production on long time scales.

Minimum three-month running net CF according to the EIA data were reported in December 2014–February 2015 (CAISO), January–March 2015 (ERCOT), June–August 2015 (MISO), July–September 2015 (NEISO), July–September 2015 (NYISO), and June–August 2015 (SPP), consistent with observations that the summer months are generally characterized by lowest wind speeds and wind power generation over most of the contiguous United States (Shaner et al. 2018; Fig. 2, see also section 3c).

**b. Wind climates in the ISOs derived using ERA5**

Long-term (1979–2018) mean wind speeds $U$ at 100 m AGL computed using 1-hourly output of the two horizontal wind...
components from the ERA5 reanalysis exhibit good accord with estimates from other sources, with highest values in the central plains and upper Midwest (Pryor et al. 2020b) (Fig. 4a), consistent with the high penetration of wind energy in these regions (Fig. 1 and Table 1). However, estimates from ERA5 lack some of the spatial variability in wind energy resources derived from higher spatial resolution model output that can be visualized using the NREL Wind Prospector (https://maps.nrel.gov/wind-prospector) and/or that are present in point observations. For example, while some regions of Wyoming exhibit annual mean wind speed at 100 m AGL in excess of 10 m s\(^{-1}\) in the Wind Prospector, no land-based grid cell in ERA5 exhibits a mean wind speed in excess of 9 m s\(^{-1}\) (Fig. 4a). Wind speeds at 100 m AGL from ERA5 exhibit a systematic low bias over much of the western United States relative to estimates from the NREL Wind Prospector and long-term WRF simulations. Negative wind speed bias in ERA5 is also reported for high elevation areas of France (Jourdier 2020) and may reflect excess orographic drag in the ERA5 reanalysis model (Pryor et al. 2020b,c) (see Fig. 3a for the ERA5 orography). These biases result in a high marginal probability of calms (i.e., the frequency with hours of wind speed below 4 m s\(^{-1}\); Fig. 4b), plus a high mean and maximum duration of calms in most grid cells west of the Rocky Mountains (Figs. 4b,c). For example, wind speed data from some grid cells in the western United States exhibit mean duration of calms of 1 day (24 h) and a maximum duration of up to 15 days (360 h). For this reason, extreme caution should be used in use of ERA5 over the western contiguous United States, and while for completeness gross CF estimates are given herein for CAISO they must be viewed as having relatively low credibility.

Over most of the areas with high wind energy penetration (see Fig. 1), such as the central plains (in areas covered by ERCOT and SPP), the Midwest (covered by MISO), and the northeastern United States (covered by NEISO, PJM, and NYISO), the marginal probability of a calm is less than 0.1 (Fig. 4b). That is fewer than 1 hour in 10 will, on average, experience \(U < 4 \text{ m s}^{-1}\). Over the central plains (in areas covered by ERCOT and SPP) and much of MISO the mean duration of calms in individual ERA5 grid cells is below 6 h, while much of the southeast experiences lower wind speeds and a longer mean duration of calms (Fig. 4). East of the Rocky Mountains and excepting the higher elevation areas of the Appalachian Mountains, the maximum duration of any calm period computed for all hours during 1979–2018 is below 100 h (<4 days) and the higher wind energy penetration areas of the Great Plains and Texas typically have maximum durations of calms of <50 h (Figs. 4b,c).
The joint probability of calms across an ISO is an indicator of the capacity value of wind plants to that ISO (Milligan et al. 2017). A low co-occurrence of calms across different wind farms within an ISO indicates that wind plants are doing more to offset the need to build and maintain other power plants and/or storage to efficiently meet demand. The co-occurrence of calms is low in the ERCOT, SPP and MISO regions (Fig. 5b, Table 1). In these ISOs the spatially averaged mean co-occurrence of calms \( (U < 4 \text{ m s}^{-1}) \) is 0.39, 0.38, and 0.38, respectively, indicating that if a calm occurs in one WT-containing ERA5 grid cell, on average it will simultaneously impact 38% of other grid cells in a given ISO that contain one or more WT. The probability of calms affecting multiple WT-containing ERA5 grid cells in CAISO is substantially higher (Fig. 5b) in part due to the high marginal probabilities of low wind speeds (Fig. 4b, Table 1). The spatially averaged co-occurrence of calms in the PJM, NYISO, and NEISO are 0.54, 0.58, and 0.58 (Table 1), indicating that when calms occur, they impact more of the WT fleet within those ISOs. These results imply the capacity value of wind plants is higher in ERCOT, SPP and MISO than the other ISOs.

The co-occurrence of calms is generally low in ERCOT and MISO but is locally high in the central areas of Texas and in the state of Iowa due to the high density of wind farms within a relatively short distance (Fig. 5b). This implies there may be diminishing returns in terms of capacity value by adding IC in these areas and/or that these areas would benefit maximally from enhanced grid integration, integration with other decorrelated generation sources, or storage to allow the penetration of wind energy to continue while ensuring minimal disruptions to supply.

Spearman (rank) correlation coefficients \( r \) of wind speed time series from ERA5 output in grid cells that contain one or more WT indicate highest coherence of wind speeds in the northeastern states, that is, NYISO, NEISO, and to some degree PJM (Fig. 5a, Table 1). This is consistent with the relatively small area of NYISO and NEISO, the geographical concentration of WT in the northern part of PJM and the dominance of the synoptic scale in terms of wind speed and gross CF variability in these ISOs (see section 3c). Spatially averaged (mean) Spearman correlation coefficients \( r \) for NYISO, NEISO, and PJM are 0.66, 0.66, and 0.58, respectively (Table 1).

Grid cells in the center of the ERCOT ISO and in the state of Iowa (in MISO), which also has a high density of WT installation (Fig. 1), also exhibit high correlations \( (r > 0.6) \) in the wind speed time series. Moderate correlations \( (r \sim 0.5) \) are observed in ERA5 wind speed output from grid cells within CAISO, and lowest spatially averaged Spearman correlation coefficients are observed in the SPP (mean \( r = 0.42 \) Table 1). Thus, lowest correlation coefficients between hourly wind speed time series are observed in the largest ISO with the most spatially distributed WT IC (MISO and SPP, Fig. 1), and that have spatial extents along their longest axis of over 2000 km and that extend south–north across the major cyclone genesis areas and storm tracks in the United States (Fig. 3b).

c. Wind turbine power production variability across scales derived using ERA5

The mean gross CF computed from ERA5 output is 36% for the entire contiguous United States, 14% for CAISO, 41% for ERCOT, 38% for MISO, 27% for NEISO, 29% for NYISO, 27% for PJM, and 40% for SPP (Table 2). The systemwide gross CF thus agree with reported values for net CF during 2019 of 35% (Fig. 6a). Due to the biases reported above in ERA5 wind speeds over the complex terrain of the western United States, gross CF estimates are substantially below the observed net CF for CAISO (of 23%–28.5%) (Table 2).

Agreement is considerably better between the net CF from EIA and the Wind Technologies Report given in section 3a for the other ISOs. For example, mean gross CF for ERCOT derived using the ERA5 output is 41%, while the net CF are in the range of 30%–38%. Similar comparisons for MISO are 38% (gross CF) and 32%–35% (net CF), and for SPP the results are 40% (gross CF) and 32%–40% (net CF) (Table 2). Gross CF is higher than net CF from EIA in every ISO than CAISO because it represents wind power production without curtailment, wake, and O&M losses. In MISO, NEISO, NYISO, and PJM gross CF is 2%–6% higher than net CF, consistent with losses from small to medium-size wind farms with moderate wake losses that are rarely curtailed and indicate ERA5 wind speed inputs are at least broadly representative of the observed wind resource. Greater differences in SPP (8%) and ERCOT (11%) may reflect larger wind farms with higher wake losses and more frequent curtailment in these ISOs (Bird et al. 2016).

An analysis of gross CF estimates from ERA5 relative to estimated net CF from model-derived wind speeds indicates that, with the exception of locations in CAISO, some of the spatial variability within ISO is reproduced (Fig. 6b). Estimates for 34 ERA5 grid cells in CAISO indicate the mean gross CF from ERA5 is 2.8 times that derived from the estimated (adjusted) net CF from the NREL model experiment, indicating that gross CF from ERA5 are on average 36% of the value from the NREL modeled-based assessment. This is consistent with other analyses presented here that suggest substantial negative bias in ERA5 wind speeds at 100 m AGL over that state. The ratios of gross CF from ERA5 to adjusted (net) CF from the NREL data for the other ISOs lie in the range from 0.93 to 1.3. Five of the six ISO regions have ratios above 1 consistent with the expectation that gross CF will exceed net CF (Fig. 6b). Linear fits of gross CF from the ERA5 data to monthly net CF from the EIA data from 2018 with forced zero intercept exhibit slope values of 0.92–1.3, except for CAISO where again, there is evidence of negative bias in gross CF from ERA5 (Fig. 6c). For a mean net CF of 38%, a regression slope value of 1.2 implies that mean power losses due to WT wakes, and so on, are approximately 7–8 percentage points, consistent with a priori expectations articulated above.

The grid spacing at which numerical models are applied has important implications for resolved features and the derived wind resource (Dörenkämper et al. 2020). The COV for modeled net CF from the NREL Eastern Wind Dataset and the Western Wind Dataset within a common ERA5 grid cell
have a mean value of 11% in CAISO, 3% in ERCOT
and <2% in the other ISOs. This implies that variability not
resolved (subgrid scale) at the 30 km grid spacing in ERA5,
but present in net CF estimated using output from the WRF
Model applied at 2 km, is substantial in the complex terrain
of the western United States (CAISO) but is relatively modest
elsewhere.

Consistent with observed net CF (Fig. 2, Table 2) and the
high WT installed capacities (Table 1), according to the ERA5
data set and the simple approximations used here ERCOT,
MISO, and the SPP ISO exhibit the “best” overall wind power
production potential with 17%–20% of hours exhibiting gross
CF > 60% (Fig. 6a). Normalized generation duration curves
for 20 ERCOT interconnected wind plants in 2008 found 10% of
hours in a year exhibited gross CF in excess of 75% of total
IC (Katzenstein et al. 2010), while estimates for the entirety of
the ERCOT region derived from ERA5 output shown in
Fig. 6a are achieved in 8% of hours. Based on Fig. 6a, WT in
NEISO and PJM are also estimated to exhibit gross CF > 60%
for approximately 8% of hours.

Gross CF from ERA5 derived using the method presented
here capture both a substantial amount of the geospatial and

FIG. 5. Mean (a) Spearman correlation coefficient \( r \) for hourly wind speeds in each ERA5 grid cell that contains one or more WT with all
ERA5 grid cells within a given ISO that also contain WT. If a grid cell is shown as having a mean \( r \) ((Spearman \( r \)) of 0.6 it indicates that the
mean correlation coefficient between hourly wind speeds in that ERA5 grid cell with all other grid cells containing WT in the ISO is 0.6.
(b) Co-occurrence of calms. The values plotted in (b) indicate, if a given ERA5 grid cell experiences a calm \((U < 4 \text{ m s}^{-1}\)) the probability
that other WT-containing ERA5 grid cells within the same ISO will simultaneously also experience a calm, computed using hourly wind
speeds at 100 m AGL from 1979 to 2018. A mean co-occurrence of 0.4 indicates that on average 40% of ERA5 grid cells containing one or
more WT will experience a calm when a calm is observed in the ERA5 grid cell at which the information is plotted. The shading of the
states used to approximate the ISOs is as in Fig. 1.
month-to-month variability manifest in observed ISO-wide power production, approximate the ISO-wide mean net CF and capture some of the spatial variability in net CF estimates included within the NREL prospector datasets. They are thus deemed sufficient for use in analyses to determine the dominant time scales of variability, probability of ramps and potential efficiency/reliability gains from geographical diversification of wind power production plants.

Probability distributions of hour-to-hour gross CF ramp-up and ramp-down in each ISO computed using the ERA5 output, and an assumption of complete power connectivity of the electrical transmission network within each ISO, are summarized in Fig. 7a. Consistent with past research (Kiviluoma et al. 2016), ramps in excess of 10% of gross CF are rare (Fig. 7a) because in all ISOs the WT are distributed over relatively large geographic areas, and it takes time for phenomena such as fronts to transit over all of them. Large magnitude ramp-ups (i.e., hour-to-hour increases in ISO-wide gross CF of ≥ 15%) are most frequent in ERCOT and NYISO (probabilities of 0.198% and 0.226%, respectively) (Fig. 7a). The frequency of large magnitude fluctuations in gross CF are thus, as expected, largest in the ISOs with the smallest geographic extents (Milligan and Kirby 2008). ERCOT exhibits almost a 4 times higher frequency of hour-to-hour ramps in gross CF of ≥10% than MISO (marginal probabilities of 0.72% and 0.2%, respectively) (Fig. 7a). The marginal probability of gross CF
ramps derived in this way for ERCOT are comparable to the observed frequency of 1 h + 10% wind power ramps in ERCOT of slightly over 1% (Kiviluoma et al. 2016).

The probability distributions of hour-to-hour changes in gross CF exhibit asymmetric forms. As in observed data (Kiviluoma et al. 2016), ramp-ups are more frequent than ramp-downs of a given magnitude (Fig. 7a). For example, in MISO a +10% change in gross CF between consecutive hours has a marginal probability of 0.2%, whereas a −10% change from one hour to the next has a probability of 0.16% (Fig. 7a).

Understanding dominant time scales of variability (including seasonal; Lledó et al. 2019) can be used to target efforts to improve the accuracy of forecasts at scales that will benefit both owner operators of wind plants and assist with integration to the electricity supply system (Torralba et al. 2017). Power spectra of gross CF in each ISO indicate that variability on the diurnal time scale is most pronounced in ERCOT and SPP (Fig. 7b), consistent with the presence of a high frequency of nocturnal low-level jets over the U.S. Great Plains (Aird et al. 2020; Shapiro and Fedorovich 2010; Storm and Basu 2010; Storm et al. 2009). Transient anticyclones have highest frequency in Texas and the southeast where diurnal variability dominates wind variability (Fig. 3c). Variability at synoptic scales is most pronounced in the NYISO, NEISO, and SPP consistent with the presence of these ISOs under major storms tracks with high transient cyclone frequencies \( f \) (Fig. 3b). Variability on seasonal time scales is largest in SPP and MISO, while seasonal to interannual variability (i.e., \( f \sim 2-4 \times 10^{-3} \) day\(^{-1}\)) is largest in PJM, NYISO, and NEISO (Fig. 7b).

Consistent with the generally low marginal probability of calms within individual ERA5 grid cells (Fig. 4b), all ISOs except CAISO exhibit only short duration periods when gross CF < 10% (Fig. 8). The mean and median duration of such periods is < 10 h for PJM, NEISO, and NYISO and < 6 h for MISO, ERCOT, and SPP. The maximum duration of such “wind power droughts” is \( < 100 \) h in MISO, ERCOT, SPP, and \( < 150 \) h in NEISO and NYISO (Fig. 8). Inferences from analyses using ERA5 output thus emphasize that the wind drought of January–March 2015 is exceptional. The maximum duration of gross CF < 10% (the value estimated from EIA power production data during January 2015, Fig. 2) is 300 h (or 12 days) according to analyses based on wind speeds from ERA5. ERCOT shows the shortest duration of relatively low gross CF, followed by SPP, MISO, NYISO, PJM, and NEISO (listed in order of length of duration, Fig. 8). The mean and median duration of gross CF < 50% in ERCOT are 28 and 14 h, respectively, while comparable values for MISO are 44 and 20 h, in NEISO are 70 and 32 h, in NYISO are 51 and 21 h, in PJM are 67 and 20 h, in SPP 51 and 32 h, and in SPP they are 34 and 17 h. Conversely, the mean duration of periods with gross CF > 90% is 8 h in MISO; 6 h in ERCOT, NEISO, and SPP; and 5 h in NYISO and PJM (Fig. 8).

The gradient of the gross CF duration curves provides an indication of the likelihood of transitioning between different gross CF levels, or alternatively stated it is a measure of the volatility in gross CF. For example, over the range of gross CF from 10% to 80% the slope of the mean duration curves from ERCOT is 1.7 h per 1 percentage point change in gross CF. The slope is nearly 2 times as steep for NYISO and almost 3 times as steep for MISO. Thus, the mean time spent at each level of gross CF value is twice as long in NYISO as ERCOT and nearly 3 times as long in MISO. Alternatively stated there is more hour-to-hour variability in gross CF from ERCOT. The shallow slope of gross CF curves for ERCOT (Fig. 8) are likely due to the relatively small geographic extent of ERCOT. Thus, although ERCOT is characterized by high average gross CF, there is also comparatively large hour-to-hour variability in wind power production. Estimated duration curves for gross CF in NYISO also exhibit a relatively shallow gradient, again indicating relatively frequent transitions between different gross CF levels. This is due to the relatively small geographic area of the ISO, concentration of WT assets in the west of the state (Fig. 1) and the high temporal correlation of hourly wind speeds within the ISO (Fig. 5a). Conversely, the gradient in the mean and median gross CF curves for MISO and PJM are relatively steep indicating low gross CF volatility (Fig. 8).

Gross CF for each ISO conditionally sampled by hour of the day and calendar month exhibits the expected signature of lowest values during the summer months consistent with summertime minimum net CF in most ISOs (cf. Figs. 2 and 9).
(Schwartz et al. 1993). Excluding CAISO, the amplitude of the seasonal variability in gross CF is smallest in NEISO and SPP and is largest in PJM (Fig. 9). Conversely, electricity demand in each ISO is generally maximized in during summer, although the amplitude of the seasonal variability in demand differs substantially between ISOs and is smallest in MISO and SPP (Fig. 9). Gross CF in all months in all ISOs is projected to occur between 0000 and 1200 UTC, which is during the nighttime hours in all ISOs (Fig. 9). There is evidence of the strongest seasonality and diurnal variability in ERCOT and SPP (Fig. 9). Both ISOs exhibit highest power production potential centered around 0600 UTC (i.e., close to midnight local time) during the spring months and late fall early winter and decoupling of high mean power production from demand (Fig. 9). ERCOT, MISO, NEISO, NYISO, PJM, and SPP all exhibit lowest gross CF during summer and particularly in the 1200–1800 UTC periods, which equate to early morning to midday local times. All ISOs also indicate the highest probability of extended periods with gross CF < 20% during the summer months (Fig. 9), which reemphasizes the benefits of a mixed portfolio of generation types to maximize system reliability.

d. Assessing scenarios of expanded WT IC

The impact of increasing IC by 50% relative to the baseline (current IC) in each ISO on mean gross CF, probability of ramps (ramp-up or ramp-down in gross CF of > 10%) and probability of gross CF < 20% according to the four deployment scenarios is summarized in Fig. 10. Also shown are the values of those parameters for the current WT IC within each ISO (approximations as in Table 1) that are labeled “baseline.”

Naturally, there are additional constraints on systemwide optimization that are not considered here (Roques et al. 2010), and introduction of large-scale energy-storage technologies in conjunction with increased penetration of renewable energy sources may transform the electricity supply and transmission network. Nevertheless, the scenarios considered herein indicate there is benefit in terms of increased gross CF from
increased geographic concentration of WT IC in ERCOT, MISO, and SPP (Fig. 10). Indeed, for ERCOT and SPP scenario 1 (which has the greatest concentration of WT) actually leads to small increases in gross CF relative to the baseline. For ERCOT this scenario only modestly increases the risk of a gross CF ramp of $6 \times 10^{-3}$ from 0.024 to 0.026 (Fig. 10). This is consistent with prior research focused on the ERCOT region that examine changes in net load (demand minus intermittent renewable generation) and found that while “adding 15.7 GW of wind power had insignificant effects . . . Adding 14.5 GW of solar to the ERCOT grid increases maximum 1-h ramp rates by 135%” (Deetjen et al. 2017).

For NEISO, NYISO, and PJM, scenario 3 results in the highest gross CF. However, concentration of additional WT on these areas with currently highest WT installed capacity density uniformly leads to increased probability of substantial hour-to-hour variability in gross CF and the probability of gross CF $< 20\%$. In accord with a priori expectations and past research (Milligan and Kirby 2008), ramp events are least pronounced with an increasingly distributed WT fleet (scenario 4), but for NYISO and PJM, scenario 3 leads to the overall lowest probability of gross CF $< 20\%$ and substantially reduces the probability of experiencing gross CF $< 20\%$ relative to the baseline (Fig. 10). This suggests that if the goal is to increase the resiliency of electricity supply in PJM there may be benefit to enhanced distribution of WT across areas with existing capacity and that could be achieved with no penalty to mean gross CF and indeed small magnitude increases in this parameter relative to the baseline.

4. Concluding remarks

Observed electrical power production data from wind turbines within U.S. regional system operator zones (referred to herein as ISOs) indicate the presence of substantial month-to-month differences in WT-derived electrical power. However,
operational data on wind-derived electricity generation are typically not available at sufficiently high frequency and/or long duration to fully characterize all scales of variability. There is also very limited availability of in situ wind speed measurements at heights of relevance to WTs. Thus, this research employs output from a high-resolution reanalysis (ERA5, 0.25° × 0.25°) to characterize the spatial and temporal scales of variability in wind speeds and gross capacity factor from WTs within major U.S. regional grid systems.

Gross CF computed as herein are not equivalent to observed net CF from operating wind turbine arrays and wind climates exhibit variability on scales smaller than the grid resolution of ERA5. Nevertheless, gross CF estimates derived using a simplified WT power curve and hourly output from ERA5 exhibit similar spatial and temporal variability to observed net CF from contiguous U.S. wind plants and regional electric system operators and to independent modeled estimates of net CF, except over the western United States. ERA5-derived gross CF estimates are strongly negatively biased relative to both sets of net CF for CAISO (Table 2). For all other ISOS gross CF computed from 40 years of hourly ERA5 output lie within −4 and +5 percentage points of net CF for each ISO. Also shown are the values of those parameters computed for the current WT IC within each ISO (approximations as in Table 1), labeled “baseline.” In scenario 1, the additional capacity is installed in the top 20% of grid cells in terms of current IC. In scenario 2, the additional capacity is installed in the top 40% of grid cells in terms of current IC. In scenario 3, the additional capacity is installed in grid cells with the lowest 40% in terms of current IC. In scenario 4, the additional capacity is installed in grid cells with the lowest 20% in terms of current IC. Grid cells highlighted in red indicate the scenario associated with “worst” performance in terms of the parameter under consideration, and cells highlighted in green indicate the scenario with “best” performance. Values that are underlined indicate performance that is “better” than the base case for the parameter under consideration (e.g., higher mean gross CF than the baseline).

Fig. 10. Impact of increasing IC by 50% relative to the baseline (current IC) on mean gross CF, probability of ramps (ramp-up or ramp-down in excess of 10%), and probability of gross CF below 20% in each ISO. Also shown are the values of those parameters computed for the current WT IC within each ISO (approximations as in Table 1), labeled “baseline.” In scenario 1, the additional capacity is installed in the top 20% of grid cells in terms of current IC. In scenario 2, the additional capacity is installed in the top 40% of grid cells in terms of current IC. In scenario 3, the additional capacity is installed in grid cells with the lowest 40% in terms of current IC. In scenario 4, the additional capacity is installed in grid cells with the lowest 20% in terms of current IC. Grid cells highlighted in red indicate the scenario associated with “worst” performance in terms of the parameter under consideration, and cells highlighted in green indicate the scenario with “best” performance. Values that are underlined indicate performance that is “better” than the base case for the parameter under consideration (e.g., higher mean gross CF than the baseline).

Variability in gross CF, and thus approximate electricity production from wind power plants in the ISOS, is dominated by the diurnal time scale in ISOS within the central plains (ERCOT, SPP), by synoptic time scales in the Northeast and Midwest (NEISO, NYISO, and MISO) and by interannual variability in PJM. Large magnitude changes in power production on hour-to-hour time scales have important implications for grid integration particularly for rapid declines in power production. ISO-wide gross CF ramp-up events of a given magnitude are more common than ramp-down events and ramp events of ≥±10% are most frequent in ERCOT where they have a marginal probability of 0.024, which is in good accord with previously published empirical estimates (Kiviluoma et al. 2016). The probability of low gross CF and duration of low production negatively impacts the capacity value for wind. These probabilities are lowest in the ERCOT, SPP, and MISO, indicating greatest benefit from wind turbines in those regions. All ISOS except CAISO indicate low marginal probability and mean and median duration of gross CF < 10% of less than 10 h (Fig. 8).

A theoretical, but constrained, analysis of scenarios of increased wind energy IC indicates that continued geographic concentration of WTs in ERCOT and MISO yields greatest benefit in terms of mean gross CF and is associated with only small increases in the probability of gross CF ramps and/or the frequency of occurrence of periods with low wind-derived electricity generation. In NEISO, NYISO, and PJM, there may be greater benefit from increased geographic diversification in terms of gross CF, gross CF volatility, and probability of a ramp in gross CF of >10%.

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**Data availability statement.** ERA5 data are available at https://climate.copernicus.eu/climate-reanalysis (https://doi.org/10.24381/eds.adbb2d47). The WT locations as reported by the USGS are available at https://eerscmap.usgs.gov/uswtdb/. The transmission network shown in Fig. 1 is available at https://hub.arcgis.com/datasets/geoplatform:electric-power-transmission-lines?page=8975. EIA data with regard to demand by ISO (shown in Fig. 9) are available at https://www.eia.gov/realtime_grid. EIA data with regard to power supplied to the grid and WT installed capacity by state (shown in Fig. 2) are available at https://www.eia.gov/electricity/data/state/. Estimates of adjusted CF from the Eastern Wind Dataset and the Western Wind Dataset are available at https://maps.nrel.gov/wind-prospector.

**REFERENCES**


