Title
Limitations of reanalysis data for wind power applications

Journal
Wind Energy, 25(9)

ISSN
1095-4244

Authors
Davidson, Michael R
Millstein, Dev

Publication Date
2022-09-01

DOI
10.1002/we.2759

Peer reviewed

Received: 30 October 2021 | Revised: 20 May 2022 | Accepted: 23 May 2022

DOI: 10.1002/we.2759

SHORT COMMUNICATION

WILEY

Limitations of reanalysis data for wind power applications

Michael R. Davidson[1,2] | Dev Millstein[3]

[1]Department of Mechanical and Aerospace Engineering, University of California San Diego, San Diego, California, USA

[2]School of Global Policy and Strategy, University of California San Diego, San Diego, California, USA

[3]Lawrence Berkeley National Laboratory, Berkeley, California, USA

Correspondence

Michael R. Davidson, Department of Mechanical and Aerospace Engineering, University of California San Diego, 9500 Gilman Dr, San Diego, CA 92093-0411, USA.
Email: mrdavidson@ucsd.edu

Dev Millstein, Lawrence Berkeley National Laboratory, 1 Cyclotron Rd, Berkeley, CA 94720, USA.
Email: dmillstein@lbl.gov

Abstract

Wind energy resource estimates commonly depend on simulated wind speed profiles generated by reanalysis or weather models due to the lack of long time series measurements with sufficient coverage at relevant heights (roughly 90 m above ground). However, modeled data, including reanalyses, can be noisy and display a wide range of biases and errors, variously attributed to terrain effects, poor coverage of assimilated inputs, and model resolution. Wind generation records, if available at high temporal and geographical resolution, can provide a proxy for wind measurements and allow for evaluation of reanalyses and weather model wind time series. We use a 7-year-long data set of hourly, plant-level generation records from over 100 wind plants across Texas to evaluate two commonly used reanalysis data sets (MERRA2 and ERA5). Additionally, we use 1-year of records (2019) to evaluate an operational, high-resolution regional weather modeling product (HRRR v3). We find that across the region, and across all modeling products, the modeled representation of wind generation (i.e., wind speeds at hub heights passed through a power curve) has relatively small mean errors when aggregated daily, but that accuracy and hourly correlation have a strong diurnal sensitivity. Accuracy and correlation systematically decline through the evening and markedly improve after sunrise. These diurnal patterns persist even in the highest resolution model tested (HRRR v3). We hypothesize the nighttime decline in accuracy is mostly due to poorly represented boundary layer conditions, perhaps related to model representation of stability, while other uncertainties (such as wake effects) play a secondary role.

KEYWORDS

boundary layer, reanalysis, wind power, wind resource assessment

1 | INTRODUCTION

Net-zero emissions energy systems will rely upon large increases in wind and solar energy, whose intermittency characteristics create challenges for power systems planning and operations. Measurements of relevant renewable energy availability metrics (e.g., wind speeds at wind turbine hub heights, ~90 m above ground) are generally sparse geographically and limited in time coverage, necessitating the use of simulated renewable energy profiles generated by weather models. Planning exercises to manage continent-scale renewable energy and accompanying infrastructure expansion depend upon not only aggregate availability but also the temporal effects of spatial deployment.[1] For the case of wind, however, there is little consistency in the generation profiles and models adopted by various studies, and frequently little to no validation is done.[2] Examination of simulated and actual wind power output at high spatial and temporal granularity shows significant biases and errors across a wide range of weather models and geographies.[3]

Validation and error correction of these inputs, if performed at all, are often limited to aggregate correction factors such as country-wide adjustments.[2] Sophisticated correction methodologies are sometimes used,[4–6] but these approaches would benefit from enhanced validation of the relevant meteorological models. In general, error-correction approaches can capture persistent, long-term biases in the input weather data and, to some extent, shorter-term phenomena, though necessarily moderated by the effects of aggregation.

Renewable energy analyses have largely relied upon two types of weather models: assimilation-based reanalysis and numerical weather prediction (NWP). Reanalysis models construct a physically consistent model of the atmosphere driven by an underlying physical model and constrained by a wide range of historical observations from both the surface and satellites.[7] Their primary advantages lie in the global coverage and long historical record (exceeding four decades in some cases). NWPs simulate and forecast the atmosphere in real time from a set of initial conditions, though they can also incorporate assimilation processes of available observations.[8] NWPs generally have higher geographic resolution and are more computationally intensive, thus limiting them to specific regions and a shorter historical record.

Key to the challenge of estimating spatially and temporally granular wind power profiles is the representation of the boundary layer, the slice of the atmosphere from the ground up to where synoptic flows become dominant. In the boundary layer, friction with the ground and varying thermal stratification (or stability) complicate the description of vertical wind profiles.[9] Two commonly used formulae to extrapolate wind speeds to different heights (e.g., turbine hub height) both rely upon boundary layer parameterizations in terms of wind shear: the “log law” derived from Monin–Obukhov similarity theory and neutral stratification assumptions (wind shear parameter $= 1$) and the “power law” heuristic with a wind shear exponent commonly assumed to be 0.14 for neutral conditions.[10,11] Generalizations of the “log law” to nonneutral conditions incorporate a wind shear parameter that varies with turbulence or vertical heat flux and, in some cases, empirically determined stability functions to account for further discrepancies.[12] Model performance of strongly stratified nocturnal regimes is highly dependent on land–surface interactions.[13] Low-lying jets, for example, are challenging to predict and can result in coherent wind conditions over large areas[14] and impact wind speeds at wind energy relevant heights.[15,16]

Validations of reanalysis surface wind fields are frequently limited by data availability to low heights (e.g., 10 m) where boundary layer parameterization errors would be less pronounced.[17] Validation of higher fields has shown stability is a predictor of mean errors.[18] Recent work has also found that interannual variability in recorded wind generation is only weakly correlated with observed surface wind speeds, suggesting that wind turbines are subject to meteorological phenomena above the surface boundary layer.[19] Furthermore, ground observations of surface heat fluxes (an important diurnally varying signature of stratification) do not provide sufficient geographic coverage to usefully constrain reanalysis models.[20] Together, these points indicate that while reanalysis outputs, such as wind speed, are most often validated at the surface (∼10 m above ground), that surface validation may not provide much insight into accuracy at wind turbine heights as different phenomena affect meteorology at hub heights.

The lack of validation of reanalysis wind speeds at wind plant hub heights represents a research gap for the wind energy community. To address this gap, we use a unique set of plant-level, hourly generation records across more than a hundred wind plants in Texas to assess the ability of two commonly used reanalysis models to represent wind speeds at relevant heights for wind energy. Though not direct measurements of wind speed, recorded generation here provides useful observational data at many locations and, importantly, reflects winds well above ground that impact wind generation but cannot necessarily be observed from ground-based anemometers. To compare reanalysis data to recorded generation, we convert reanalysis wind speeds to energy generation using manufacturer power curves. Though this conversion adds some uncertainty, differences between recorded and estimated generation are dominated by variation in the underlying wind speed estimates, not from the power curve conversion.

We examine two reanalysis products: MERRA-2 and ERA5. MERRA2 is produced by the National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office (GMAO), and ERA5 is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF).[7,21] In order to explore issues related to model resolution, we also assess recent data (from 2019) from the High-Resolution Rapid Refresh (HRRR) v3 NWP of the National Oceanic and Atmospheric Administration (NOAA) Global Systems Laboratory (GSL) and Earth System Research Laboratories (ESRL).[22]

2 | MATERIALS AND METHODS

2.1 | Wind generation data

Plant-level, hourly wind generation data were provided directly by ERCOT. For each plant, ERCOT provided both records of hourly generation sold to markets along with estimates of generation had curtailment not been applied. It is the latter set of records that we compare to reanalysis-based generation estimates. These generation records have been used in prior publications and provide some of the only hourly, plant-level generation records that are publicly available in the United States.[5,23] Minimal data cleaning was conducted to remove sites with incomplete records and to truncate capacity factors at nominal power capacity (i.e., CF ≤ 1).

Characteristics of wind plants in the ERCOT region were defined based on the US Wind Turbine Database. Characteristics of interest include project centroid, average turbine hub height, overall plant capacity, and turbine manufacturer and type.[24]

2.2 | Wind reanalysis construction

We use hub-height wind speeds from three meteorological/reanalysis models: MERRA2, ERA5, and HRRR v3. We combine these wind speeds with a manufacturer's power curve, specific to each plant, to estimate hourly generation implied by the meteorological model. Power curves were selected to match the dominant technology at each wind plant (i.e., either all turbines were the same, or we selected a turbine that matched the majority of turbines within a plant). A database of power curves was purchased from "thewindpower.net," and in the rare case where a direct match of manufacture and type was not found for a power curve, we selected an alternate power curve based on the physical characteristics of the turbines, based on matching rotor diameter and turbine capacity.

MERRA2 provides hourly wind speeds at 2, 10, and 50 m above ground. We first matched each plant centroid to the closest MERRA2 grid cell. To extrapolate winds from 50 m to hub heights of 80–90 m (depending on the plant), we used a log law to estimate the scaling factor for each location and hour, following the approach used by Staffell and Green.[25] We then applied the power curve to these hub-height wind speeds to develop plant-level generation estimates.

ERA5 provides hourly, three-dimensional files which include wind speed at multiple heights. We matched each plant centroid to the closest ERA5 grid cell. We then interpolated between vertical layers, using a cubic spline function, to find the hub-height wind speed at each hour. The ERA5 grid cell layers, at the heights of interest, ranged from 20 to 40 vertical meters. We note that the interpolation introduces less uncertainty compared with the extrapolation that was necessary with the MERRA2 data, as the ability to incorporate wind speed estimates above and below the hub heights of wind plants ensured that the results were internally consistent with the wind shear represented by the ERA5 model.

For HRRR, we also matched each plant centroid to the closest HRRR grid cell. Given the higher resolution of HRRR, wind plants often span a larger area than the HRRR grid cells themselves (this is not the case for ERA5 and MERRA2). Thus, matching to a single grid cell includes a simplifying assumption that the grid cell corresponding to the centroid of each plant is generally representative of the overall plant conditions. HRRR provides hourly wind speeds at 80 meters above ground. We used this output directly, and, to maintain computational tractability, we did not adjust for the relatively small differences that would be caused by the adjustment from 80 meters to actual wind plant hub heights (usually between 80 and 90 meters of height).

2.3 | Error and correlation analysis

We evaluate weather data against actual generation along three main dimensions: mean error, correlation coefficient, and root mean squared error (RMSE). To maintain focus on errors inherent in modeled estimation of wind speed, we have chosen to neglect explicit modeling of a generation loss factor, which would substantially expand the scope of analysis. Typically, a loss factor would be used to account for mechanical losses, wind plant wake effects, and maintenance and other downtime.[3,26] We expect neglecting losses to result in a small positive bias and higher RMSE, but a minor or negligible impact on correlation.

We also introduce a new variable for solar time (*SolTime*), which translates timestamps according to local sunrise ($SolTime = 0$). This allows us to highlight the impact of diurnal weather cycles and indeed show much stronger effects compared to typical approaches by hour of day. We group times into hourly *SolTime* bins for the purposes of generating statistics.

2.4 | Capacity factor definition

Capacity factor (CF) represents a plant's realized generation divided by the total possible generation assuming the plant was operating at full capacity in all hours, expressed as a percentage. Throughout, when evaluating CF errors, we use % CF to refer to capacity factor percentages, not percentage deviations from an absolute wind generation level or relative to a given capacity factor. For example, the difference between a model-estimated CF of 32% and an actual CF of 35% is 3%. We do this for two reasons: (a) to compare wind plants of different sizes and (b) to account for power system operators' primary concerns resting with biases and errors in total energy delivered (hence, percentage point differences) as opposed to relative biases, which would tend to exaggerate the impact of small differences at low wind output.

3 | RESULTS AND DISCUSSION

We find that both ERA5 and MERRA2 represent average levels of the wind resource accurately, with small mean errors (i.e., bias) of 1.1% CF and 6.4% CF, respectively. We expect that inclusion of loss factors would push both models toward small negative average mean errors but that the rough characterization of "small" average bias would remain acceptable.

Averaging over time dampens differences between modeled and recorded capacity factors. Daily capacity factors, for example, show a similar positive bias as hourly, but with a tighter distribution. Hourly (daily) standard deviations of MERRA2 and ERA5 errors are 21.5% CF (6.9% CF) and 19.0% CF (7.0% CF), respectively, as shown in Figure 1. Hourly errors for both ERA5 and MERRA2 show a strong peak at 0% CF, corresponding to a zero mode in both actual and estimated generation when wind speeds are below the cut-in speed of the turbines (see Figure 1). The larger spread away from 0% error for hourly versus daily comparisons shows that a substantial amount of the mean error derives from diurnal fluctuations that are averaged out when aggregating to the daily level. For example, the probability that the estimated CF is within ±20% CF of actual hourly (daily) for MERRA2 and ERA5 is 70.3% (97.0%) and 78.0% (99.1%), respectively.

Evidence of the pivotal role of the diurnal cycle to reanalysis model representation of wind energy resources is given by examining three evaluation metrics in terms of solar time (see Figure 2). In particular, RMSE and correlation coefficients show a rapid improvement following sunrise (compared to the nighttime hours). For example, ERA5 RMSE falls from 21.7% CF 4 h prior to sunrise to 15.7% CF 5 h after. Similarly, ERA5

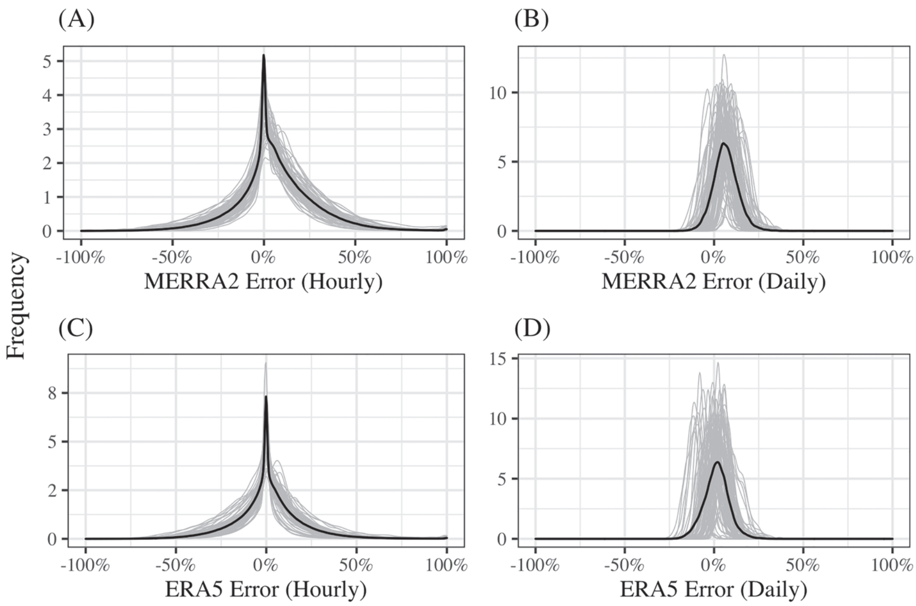

FIGURE 1 Hourly and daily mean CF errors by location (gray) and entire sample (black). CF error is calculated as model (%CF) minus recorded generation (%CF)

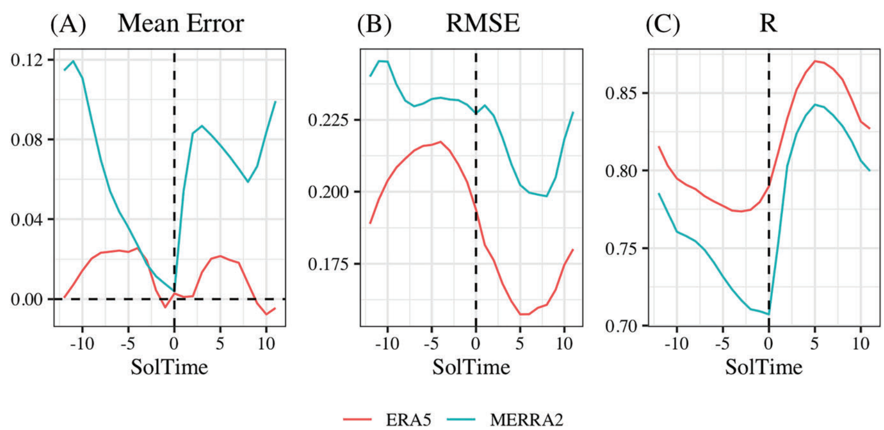

FIGURE 2 Diurnal mean error, RMSE, and correlation coefficient in local solar time (sunrise = 0)

correlation coefficients rise from 0.78 just prior to sunrise up to 0.87 at 5 h after sunrise. MERRA2 shows even larger improvements following sunrise. A potential explanation for this diurnal pattern is that reanalysis models systematically underestimate nighttime stability in the boundary layer, as discussed in Section 4.

The diurnal cycle of mean error is a bit harder to interpret within this context, but we do see that ERA5 has a limited range of mean error over the day, while MERRA2 shows a strong diurnal trend. Again, when incorporating loss factors, we would expect mean error to shift downward; thus, the fact that the mean error for both MERRA2 and ERA5 is close to zero in the hours before sunrise (Figure 2) suggests that both models underestimate wind speeds in those hours. We note the improvement to RMSE and correlation coefficients that occurs after sunrise, suggesting that issues related to the nighttime representation of the surface boundary layer impact the models' ability to produce accurate wind energy resource estimates.

Further separating the data into season, in Figure 3, we find that MERRA2 and ERA5 perform worse (as measured by the correlation coefficient) at nighttime compared to daytime across all seasons. Both models tend to perform worse during summer nighttime compared to winter nighttime, while seasonal variations in daytime remain somewhat smaller.

One hypothesis for the improved model performance in winter over summer is the possible correlation of model performance with wind speed. If the models' performance improved at higher wind speeds compared to lower wind speeds, then the increased frequency of high wind speed hours during winter, compared with summer, could explain the improved model performance during the winter. However, we find that while model performance improves with the highest wind speeds during winter daytime and nighttime hours (as evidenced by declining RMSE with high CF; Figure 4), the opposite relationship is found during summer nighttime hours (high CF summer night hours have some of the highest levels of RMSE during summer; Figure 4). Here, daytime is defined as times between 1 and 8 h after sunrise, and night is defined as 8 to 1 h before sunrise. This seasonal pattern is intriguing, as seasonal meteorological differences might provide further clues as to what is driving model performance, but a focused study with a larger set of atmospheric variables would be required to fully explore the causes of this seasonal pattern.

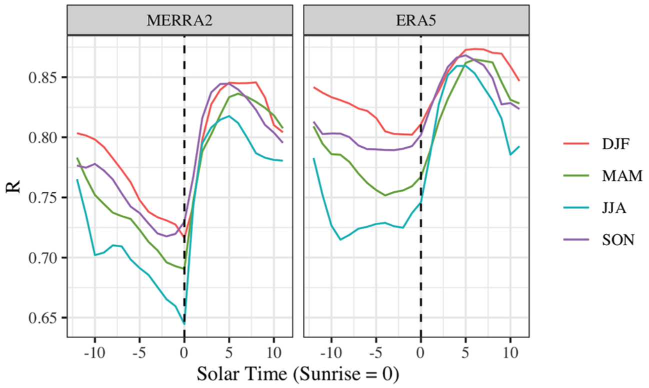

FIGURE 3 Diurnal correlations by season in local solar time (sunrise = 0)

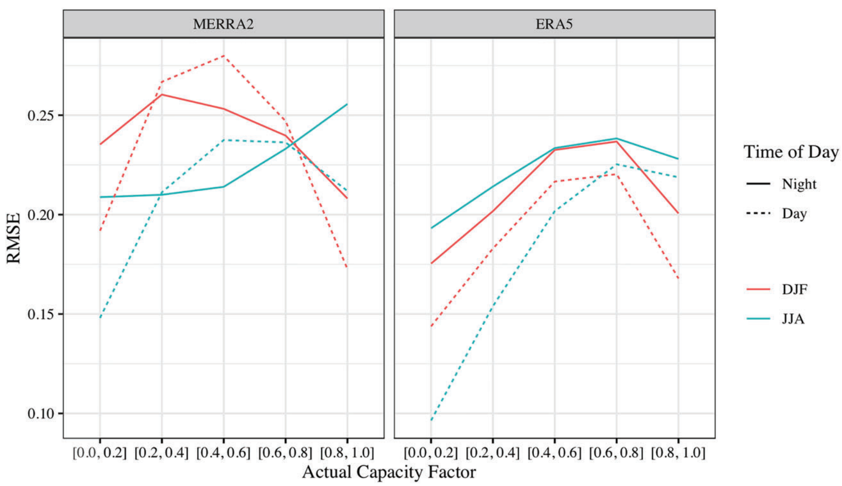

FIGURE 4 RMSE as a function of recorded CF bins for winter (DJF) and summer (JJA) and nighttime (8–1 h before sunrise) and daytime (1–8 h after sunrise)

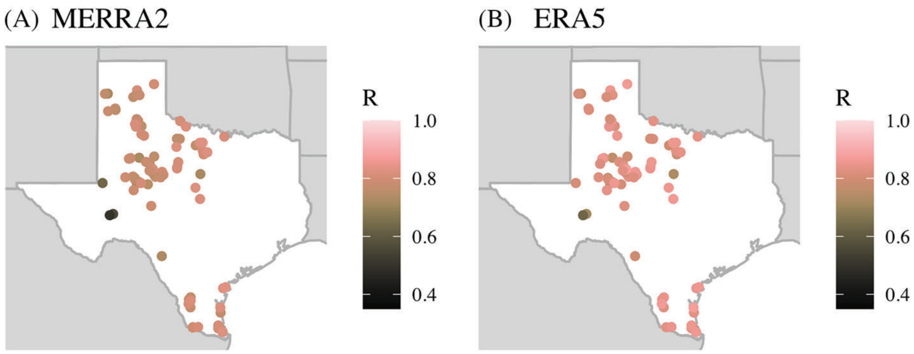

FIGURE 5 Correlation coefficients by location

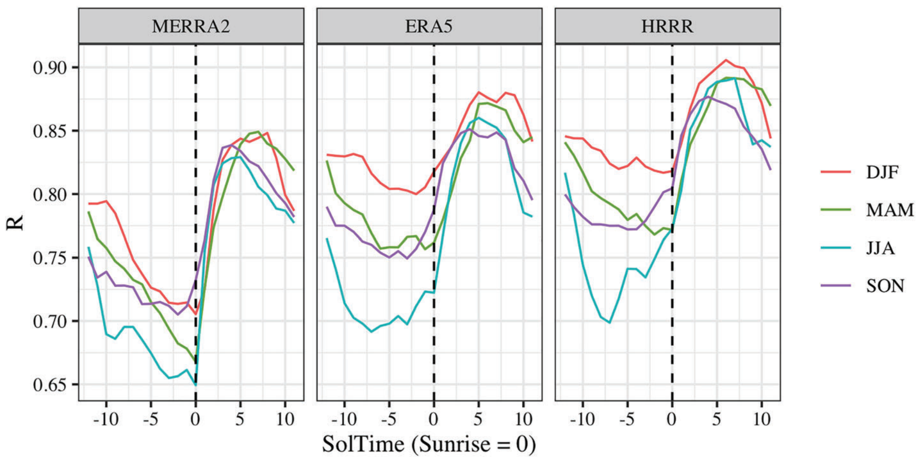

FIGURE 6 Diurnal correlations by season in solar time (sunrise=0) for MERRA2, ERA5, and HRRR (2019)

Geographic variation among plants in terms of correlation coefficients was somewhat muted. ERA5 correlation coefficients range from 0.63 to 0.88, and MERRA2 correlation coefficients range from 0.50 to 0.83 (see Figure 5). Besides slightly higher correlation coefficients at the coastal wind plants, there is no clear geographic explanation for this variation. Elevation and rough terrain increase further north into the Texas panhandle, but this is not the main driver for variation in correlation coefficients or the other metrics.

One potential concern of using MERRA2 and ERA5 wind speeds to estimate wind generation is the coarse model resolution (~50 and ~30 km, respectively). This resolution is improved compared to past global reanalysis products, but is still coarse compared to regional meteorological modeling products. To address the potential influence of model resolution, we analyzed for year 2019 the output of the HRRR v3 model at a resolution of 3 km. Hourly correlations between recorded and modeled generation are indeed improved in HRRR compared to the lower-resolution global analysis models. Nevertheless, a similar decline in HRRR hourly correlations occurs during nighttime hours (Figure 6).

4 | CONCLUSION

We use a unique data set of hourly, plant-level, wind generation records across the ERCOT region in Texas to validate wind speeds at relevant hub heights from three weather models commonly used in power system studies. We find that, in this region, RMSE and hourly correlation is dominated by diurnal patterns while errors are reduced substantially with daily averaging. Furthermore, after converting to solar time (setting the origin at local sunrise), we identify a strong nighttime/daytime sensitivity to all evaluation metrics, with models performing worse in the hours before sunrise than after. Notably, all models regardless of whether we extrapolate or interpolate to hub height, or use a fixed model layer near hub height, show the same behavior, indicating systemic errors that affect using derived wind speeds for hourly energy modeling. Enhancing grid resolution (e.g., moving from ~50 km in MERRA2 to 3 km in HRRR v3) does improve evaluation metrics. That said, HRRR nighttime, though improved over MERRA2 and ERA5 nighttime, still has worse hourly correlation coefficients than the relatively low-resolution MERRA2 does during daytime, implying that the diurnal pattern in errors is still an important issue despite the improved resolution of HRRR.

We hypothesize, but do not prove, that the nighttime decline in accuracy of NWP and reanalysis models is due to the incomplete characterization of boundary layer phenomena, an issue previously identified as a challenge for meteorological modeling. Though nighttime model performance is worse than daytime across all seasons, models performed worse during summer nighttime hours. This seasonal difference may be influenced by model performance at high wind speeds. For example, we found that though model performance (measured by RMSE) improves with higher wind speeds during winter daytime and nighttime hours, this is not the case during summer nighttime, where RMSE was particularly high during high wind speed hours. Worse performance at nighttime could be due to an underestimation of stable conditions and poor representations of phenomena such as low-lying jets in state-of-the-art meteorological models. Small-scale variations in the nocturnal boundary layer driven by topography could decrease wind speed correlations.[27] Furthermore, atmospheric stability and turbulence can directly impact power output even while holding hub-height wind speeds constant.[28,29]

Our simple approach for modeling generation from reanalysis, or NWP, wind speeds has limitations. Our modeled generation estimates do not account for issues such as wake losses, shutdowns due to extreme cold, air density changes, and precipitation impacts. We found that correlations were higher during winter than summer, suggesting that extreme cold, at least, was not a dominant driver of RMSE. We hypothesize that the simplicity of our modeling approach does not drive the diurnal or seasonal trends in RMSE and correlation and that more complicated modeling efforts would find similar results.

As the wind energy community seeks to answer increasingly difficult questions about power systems operations under high penetration scenarios, more attention should be paid to the renewable resource profile inputs. Annual bias correction and plant-specific loss factors can improve the utility of weather model-derived wind speeds, but this work points to more challenging structural deficiencies in the weather models that are not easily removed through simple correction factors or improved model resolution. The multi-decadal trend toward taller towers and longer blade sizes[23] means that wind turbines tips are reaching ever higher heights, in some case above 200 m,[30] and thus more frequently interact with winds above the surface boundary layer. In order to best serve the wind energy community, providers of global and regional weather models should, in the short term, work toward outputting hourly variables at multiple heights to eliminate the potential for extrapolation-based errors. For the longer term, directing research toward improving the representation of nighttime surface boundary layer and wind flows at wind energy relevant heights (i.e., order of 100 m) would be helpful in improving overall representation of wind energy resources.

ACKNOWLEDGEMENTS

The authors thank Seongeun Jeong and Amos Ancell of Lawrence Berkeley National Laboratory for assistance with preparation of the meteorological data. The authors thank ERCOT for sharing plant-level generation data. Michael Davidson would like to thank Graduate Climate Conference participants and American Geophysical Union Annual Meeting attendees for providing feedback on earlier versions of this work and the MIT Joint Program on the Science and Policy of Global Change and Tianyu Qi for early inspiration. Support for the work of author Dev Millstein was provided by the US Department of Energy's Office of Energy Efficiency and Renewable Energy under Lawrence Berkeley National Laboratory contract no. DE-AC02-05CH11231. The US Government retains, and the publisher, by accepting the article for publication, acknowledges, that the US Government retains a non-exclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1002/we.2759

DATA AVAILABILITY STATEMENT

MERRA2, ERA5, and HRRR meteorological data are freely available to the public. Recent, plant-level, hourly generation records in ERCOT are publicly available, but the long-term generation records used in this analysis were provided directly to Lawrence Berkeley National Laboratory from ERCOT. Additionally, manufacturer power curves were purchased via license from thewindpower.net. Therefore, not all of the data used can be posted publicly. However, to the extent possible, datasets will be made available upon request. Please contact author Dev Millstein (dmillstein@lbl.gov) for information related to generation and meteorological data and author Michael Davidson (mrdavidson@ucsd.edu) for information related to validation scripts.

ORCID

Michael R. Davidson https://orcid.org/0000-0002-5035-8209
Dev Millstein https://orcid.org/0000-0002-8091-0535

REFERENCES

1. Grams CM, Beerli R, Pfenninger S, Staffell I, Wernli H. Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nat Clim Change*. 2017;7(8):557-562. doi:10.1038/nclimate3338

2. Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*. 2016;114:1224-1239. doi:10.1016/j.energy.2016.08.068
3. Jourdier B. Evaluation of ERA5, MERRA-2, COSMO-REA6, NEWA and AROME to simulate wind power production over France. *Adv Sci Res*. 2020;17:63-77. doi:10.5194/asr-17-63-2020
4. Olauson J, Bergkvist M. Modelling the Swedish wind power production using MERRA reanalysis data. *Renew Energy*. 2015;76:717-725.
5. Millstein D, Wiser R, Mills AD, Bolinger M, Seel J, Jeong S. Solar and wind grid system value in the United States: the effect of transmission congestion, generation profiles, and curtailment. *Joule*. 2021;5(7):1749-1775. doi:10.1016/j.joule.2021.05.009
6. Wiser R, Millstein D, Bolinger M, Jeong S, Mills A. The hidden value of large-rotor, tall-tower wind turbines in the United States. *Wind Eng*. 2021;45(4):857-871.
7. Gelaro R, McCarty W, Suárez MJ, et al. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *J Climate*. 2017;30(14):5419-5454. doi:10.1175/JCLI-D-16-0758.1
8. Alexander C, Dowell DC, Hu M, et al. Rapid refresh (RAP) and high resolution rapid refresh (HRRR) model development. In: 100th American Meteorological Society Annual Meeting. AMS; 2020.
9. Emeis S. *Wind Energy Meteorology*. Springer; 2013. Accessed October 30, 2014. http://link.springer.com/10.1007/978-3-642-30523-8
10. Jacobson MZ. *Fundamentals of Atmospheric Modeling*. Cambridge University Press; 2005.
11. Ll L, Torralba V, Soret A, Ramon J, Doblas-Reyes FJ. Seasonal forecasts of wind power generation. *Renew Energy*. 2019;143:91-100. doi:10.1016/j.renene.2019.04.135
12. Optis M, Monahan A. Vertical wind profiles above the surface layer under stable conditions-an analysis of existing model performance. In: European Wind Energy Association; 2012. Accessed November 1, 2014. http://proceedings.ewea.org/annual2012/allfiles2/1464_EWEA2012presentation.pdf
13. Baas P, van de Wiel BJH, van der Linden SJA, Bosveld FC. From near-neutral to strongly stratified: adequately modelling the clear-sky nocturnal boundary layer at Cabauw. *Boundary-Layer Meteorol*. 2018;166(2):217-238. doi:10.1007/s10546-017-0304-8
14. Heppelmann T, Steiner A, Vogt S. Application of numerical weather prediction in wind power forecasting: assessment of the diurnal cycle. *Meteorol Z*. 2017;26(3):319-331. doi:10.1127/metz/2017/0820
15. Banta RM, Newsom RK, Lundquist JK, Pichugina YL, Coulter RL, Mahrt L. Nocturnal low-level jet characteristics over Kansas during xases-99. *Bound-Lay Meteorol*. 2002;105(2):221-252. doi:10.1023/A:1019992330866
16. Vanderwende BJ, Lundquist JK, Rhodes ME, Takle ES, Irvin SL. Observing and simulating the summertime low-level jet in central Iowa. *Mon Weather Rev*. 2015;143(6):2319-2336. doi:10.1175/MWR-D-14-00325.1
17. Carvalho D. An assessment of NASA's GMAO MERRA-2 reanalysis surface winds. *J Climate*. 2019;32(23):8261-8281. doi:10.1175/JCLI-D-19-0199.1
18. Rose S, Apt J. Quantifying sources of uncertainty in reanalysis derived wind speed. *Renew Energy*. 2016;94:157-165. doi:10.1016/j.renene.2016.03.028
19. Millstein D, Bolinger M, Wiser R. What can surface wind observations tell us about interannual variation in wind energy output? *Wind Energy*. 2022;25(6):1142-1150. doi:10.1002/we.2717
20. Draper CS, Reichle RH, Koster RD. Assessment of MERRA-2 land surface energy flux estimates. *J Climate*. 2017;31(2):671-691. doi:10.1175/JCLI-D-17-0121.1
21. Hersbach H, Bell B, Berrisford P, et al. The ERA5 global reanalysis. *Q J Roy Meteorol Soc*. 2020;146(730):1999-2049. doi:10.1002/qj.3803
22. Benjamin SG, Weygandt SS, Brown JM, et al. A North American hourly assimilation and model forecast cycle: the rapid refresh. *Mon Weather Rev*. 2016;144(4):1669-1694. doi:10.1175/MWR-D-15-0242.1
23. Wiser R, Bolinger M, Hoen B, et al. Land-based wind market report: 2021 edition. 2021.
24. Rand JT, Kramer LA, Garrity CP, et al. A continuously updated, geospatially rectified database of utility-scale wind turbines in the United States. *Sci Data*. 2020;7(1):15. doi:10.1038/s41597-020-0353-6
25. Staffell I, Green R. How does wind farm performance decline with age? *Renew Energy*. 2014;66:775-786. doi:10.1016/j.renene.2013.10.041
26. Clifton A, Smith A, Fields M. Wind plant preconstruction energy estimates. Current practice and opportunities. National Renewable Energy Lab; 2016.
27. Mahrt L, Pfister L, Thomas CK. Small-scale variability in the nocturnal boundary layer. *Boundary-Layer Meteorol*. 2020;174(1):81-98. doi:10.1007/s10546-019-00476-x
28. Wharton S, Lundquist JK. Atmospheric stability affects wind turbine power collection. *Environ Res Lett*. 2012;7(1):014005. doi:10.1088/1748-9326/7/1/014005
29. St. Martin CM, Lundquist JK, Clifton A, Poulos GS, Schreck SJ. Wind turbine power production and annual energy production depend on atmospheric stability and turbulence. *Wind Energ Sci*. 2016;1(2):221-236. doi:10.5194/wes-1-221-2016
30. Veers P, Dykes K, Lantz E, et al. Grand challenges in the science of wind energy. *Science*. 2019;366(6464):eaau2027. doi:10.1126/science.aau2027

How to cite this article: Davidson MR, Millstein D. Limitations of reanalysis data for wind power applications. *Wind Energy*. 2022;1-8. doi:10.1002/we.2759