Assessing the stability of wind resource and operating conditions

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Abstract. Wind energy is both a key potential mechanism to reduce climate forcing and a ‘weather-dependent’ energy source. Thus, while wind energy is making an increasing contribution to mitigation of human-induced climate change, climate variability and change have the potential to induce changes in both the average (expected) wind resource, the inter-annual variability in power production and the conditions in which wind turbines will operate. We present simulations with the Weather Research and Forecasting (WRF) model conducted at 12 km grid-spacing (resolution) over the eastern USA and use them to quantify the spatiotemporal variability in one aspect of wind turbine operating conditions (extreme wind speeds) and possible changes in the magnitude and interannual variability of expected wind power generation. We also discuss possible approaches that can be applied to assess the differential credibility of model-derived assessment of these properties at different locations using examples drawn from the eastern US.

1. Introduction

Wind contributed approximately 6.5% of US national electricity supply in 2018 [1]. As of the end of the first quarter of 2019 installed capacity in the USA exceeded 97 GW and a further 39 GW were either in construction or advanced development [1]. Proposed generation and retirements by December 2021 in the USA include net capacity additions from wind of 90 GW [2]. Achieving the goal of 20% of US electricity generation from wind by 2030 thus seems increasingly feasible [3].

Wind conditions vary across a wide array of spatial and temporal scales [4,5]. Despite the transformations of the energy sector that have been achieved to date and the resulting mitigation of climate change [6], climate variability due to moderate to low-frequency modes (e.g. El Niño Southern Oscillation, ENSO; Arctic Oscillation, AO; Pacific-North American, PNA, and the North Atlantic Oscillation, NAO, modes) and non-stationarity of the climate system due to rising concentrations of greenhouse gasses are inevitable. Both impose substantial long-term (annual to decadal) variability and changes on wind climates in the mid-latitudes [7-11]. This prompts questions regarding both (a) the current magnitude and variability of wind resources (and annual energy production (AEP) from wind turbines) and operating conditions and (b) the potential for future changes in wind resources and operating conditions (e.g. extreme wind speeds) and the consequences of that variability and change for the levelized cost of energy from wind turbines (WTs) [12,13].

Global Climate or Earth-System Models (GCMs or ESMs) are applied at resolutions inappropriate...
to capturing wind resources and operating conditions [14]. Thus, the only viable mechanism for addressing questions regarding how global climate change and variability will impact the wind energy industry is application of limited area (regional) models (LAM) nested within global models. Conceptually the approach is simple. Regional models are applied at higher spatial resolution (i.e. using smaller grid cells) than is possible with global models and thus add fine scale details to the large-scale flow that is described by the global model and provided to the limited area model in the form of lateral boundary conditions (LBC) [15]. Many parameterizations of key dynamical and physical processes are available for LM which can be optimized to address specific research questions [16,17], or employed to explore model sensitivities and potentially build an ensemble of possible future wind resources/operating conditions that can be used to quantify uncertainty and rank sources of uncertainty [18,19]. The fidelity of LAM simulations for applications to the renewable energy sector and the credibility of inferences drawn therefrom are fundamentally constrained by a range of factors such as:

- The ability of LAM to capture phenomena responsible for dictating wind resources and extreme wind speeds. LAM are applied at finite resolutions and employ Reynolds-Averaged Navier Stokes equations. Thus, although regional models clearly exhibit added-value (i.e. enhanced skill) over the global models [20] (e.g. via improved treatment of land surface heterogeneity), the ‘skillful scale’ for models is often considered to be approximately 8 times 8 grid cells [21]. Even simulations conducted at a grid spacing of a few km exclude scales of variability of relevance to wind resources and extreme wind conditions. Hence, wind resource estimates from such models will not be equally valid everywhere and not all causes of extreme wind speeds will be treated with equal fidelity [4].

- The presence or absence of ‘mixed wind climates’ wherein the large magnitude wind speeds derive from different sources (meteorological conditions) and thus have different parent probability distributions. This leads to violations of the assumptions implicit in use of generalized extreme value (GEV) theories to derive wind speeds at given return periods [22,23].

Here we provide preliminary results from research designed to address three inter-linked questions:

1. What are the spatial patterns of gross annual energy production (AEP) and inter-annual variability (IAV) of AEP in the contemporary climate, and how might that change in the future?

2. What are estimates of the extreme (50-year return period, $U_{50}$) wind speeds at wind turbine relevant hub-heights in the contemporary climate, and how might they change in the future?

3. How should we assign differential credibility [24] to model-derived estimates of current and possible future AEP and $U_{50}$ in different regions of the eastern USA? Is it possible to quantify how differential credibility depends on factors such as the dynamical causes of, and context for, extreme wind speeds across the eastern USA and thus the likelihood that such features are reproduced with fidelity for a given model grid formulation/spacing/duration?

2. Methods

2.1 Model simulations

Our analyses are predicated on moderate-resolution limited-area numerical simulations with the Weather Research and Forecasting (WRF, v3.8.1 [25,26]) for the eastern two-thirds of the continental USA at 12 km horizontal grid spacing:

1. The contemporary climate (2001-2016) using LBC from the ERA-Interim reanalysis [27]. ERA-Interim (ERA-I) has an approximate resolution of 80 by 80 km.

2. The contemporary climate (1980-2005) and projected future climate (2075-2099) conducted using LBC from the Max Planck Institute Earth System Model at low-resolution (MPI-ESM-LR, [28]). MPI-ESM-LR has an approximate horizontal resolution of 1.87° by 1.88°. The LBC from MPI-ESM-LR used here represent a high climate forcing scenario; Representative Concentration Pathway (RCP) 8.5. In this scenario the atmospheric concentration of radiatively active gases is projected to exceed 1200 ppm of carbon-dioxide equivalent by the end of the twenty-first century, resulting in a radiative forcing at that time of 8.5 Wm$^{-2}$ above the 1850 estimated value [29].

These WRF simulations are conducted for a grid spacing at the lower end of what is typical within the climate science community (i.e. at comparatively high resolution) but the grid spacing is coarse relative
to, for example, simulations conducted for wind atlas development (e.g. 3 km in the New European Wind Atlas, NEWA) [5,19]. As shown in Table 1, the simulations share many common properties (e.g. resolution, land-surface model, cumulus parameterization, land use classification, time step) but employ different planetary boundary layer (PBL) and the surface layer physics schemes. Wind speeds near typical WT HH exhibit sensitivity to PBL scheme due to differences in how the schemes respond to surface roughness and atmospheric stability conditions [5]. The MYJ scheme is a local, 1.5 order turbulent closure scheme. Higher order schemes (e.g. MYNN level 2.5 scheme) employ more complex turbulence closure schemes but have higher computational costs [30]. In the NEWA project, use of the MYNN parametrization was shown to result in closer agreement (i.e. lower bias) with observed wind speeds near to WT hub-heights than the MYJ scheme at least in flat terrain [5]. Surface layer physics schemes are designed to describe the properties of the lowest approximately 10% of the atmospheric boundary layer and thus the exchange between the atmosphere and underlying surface and also to provide a lower boundary condition for the PBL scheme. The two schemes employed in this work both rely of applications of Monin-Obukhov similarity theory with phi-functions to account for the flux dependence on stability and employ roughness lengths specified by land use class. They differ in terms of the form of the empirical stability correction functions. Surface layer physics packages generally have a lesser impact of wind speeds at wind turbine relevant heights than PBL schemes [5,19].

The dynamical solver used in WRF employs a terrain-following hydrostatic-pressure vertical coordinate system (sigma). Sigma varies from 1 at the ground surface to 0 at the upper boundary, and varies in space due to the terrain and in time due to variations in the thermal structure of the atmosphere [31]. For the analyses presented here to be relevant to WT hub-height, the WRF-MPI simulations output on the modelled sigma levels bracketing 100-m (typically both were within 40-m of 100-m) are vertically interpolated to 100-m a.g.l. in each time step and each grid location using the base state and perturbation geopotential values and the grid cell mean topography. The WRF-ERA-I simulation output is used directly from the 3rd model layer which has an average height above ground level ~ 100-m. To provide consistent estimates of wind speeds and projected AEP from the three sets of WRF output, output from the WRF-ERA-I simulations are down-sampled to the frequency of output from simulations from WRF-MPI for the contemporary and possible future climate (i.e. disjunct at once every 6-hourly). Also, because WRF-ERA-I simulations were conducted for a smaller domain than those with WRF-MPI, the output from the MPI-nested simulations was clipped to cover the same simulation domain.

2.2 Data analyses
Evaluation of wind speeds at 100-m a.g.l. from the WRF simulations is conducted relative to the recently released ERA5 reanalysis [32]. ERA5 has a nominal resolution of 30 km, and is thus higher resolution than most reanalyses that are currently available. The comparison is undertaken both subjectively at the nominal resolutions of the two datasets and quantitively using Taylor diagrams by remapping the 12 km WRF output to the 30 km ERA5 output grid. Taylor diagrams are a standard tool used to assess three aspects of model performance [33] but in brief; the azimuth angle depicts the correlation between two spatial fields, the distance along the radial axis shows the ratio of the spatial standard deviations and the distance from the origin (at a standard deviation ratio of 1 and a correlation of 1) is the root mean square difference between the fields. A qualitative assessment is also conducted relative to the annual average wind speed at 100-m map disseminated by the National Renewable Energy Laboratory (NREL).

Time series of wind speeds at the nominal wind turbine hub-height (HH = 100-m) from each WRF simulation are applied to a standard power curve for a 1.6 MW WT (Figure 1) located at the center of each model grid cell to derive an estimate of gross AEP in each year of the simulations and a mean gross AEP over each simulation period. Gross AEP computed in this way represents the raw resource magnitude and differences in gross AEP computed from two different periods are due solely to variations in the wind speed regime. There is no accounting for wake effects and/or curtailment and/or operations and maintenance that influence actual power production from an operating wind turbine array. The difference in mean gross AEP from the MPI nested simulations for the contemporary and future climates are computed for each grid cell as the future period minus the contemporary period.
Thus, positive numbers indicate higher values at the end of the current century. This analysis is designed to evaluate the degree to which the expected power production might evolve as a result of warming of the global climate.

Analyses pertaining to extreme wind speeds (i.e. wind speeds with a return period of 50 years, i.e. are expected to occur once in a 50 year period) close to WT HH are as follows:

1) Annual maximum wind speeds are extracted from each WRF grid cell and are subject to application of the Gumbel distribution derive an estimate of $U_{50}$ (and uncertainties thereon) [34]. In brief, assuming the tail of the wind speed distribution is exponential, the accumulated probability of extreme winds is double exponential:

$$P(U_{\text{max}}) = \exp \left( - \exp \left[ \frac{(U_{\text{max}} - \beta)}{\alpha} \right] \right)$$  \hspace{1cm} (1)

Where: $U_{\text{max}}$ = Maximum wind speeds (m s$^{-1}$) calculated for some time interval (in this case annually), and the distribution coefficients $\alpha$ and $\beta$ are derived using maximum likelihood fitting. The wind speed ($U_T$) for a given return period (T) can then be determined from:

$$U_T = \frac{-1}{\alpha} \ln \left( \ln \left( \frac{T}{T-1} \right) \right) + \beta$$  \hspace{1cm} (2)

2) Analyses of the seasonality of the occurrence of annual maximum wind speeds and the consistency in the timing of the occurrence of annual maximum wind speeds.

Point 1) is applied to output from all simulations using once every six-hour output. Point 2) is only applied to WRF-ERA-I output to illustrate consideration of differential credibility. These analyses are conducted as follows: The annual maximum wind speed is found for each year of the simulation in each grid cell. The decimal year-day-time of the occurrence is noted. Thus, if the highest value in a year is simulated on 18 June (i.e. the 169th day of the year) at 13:20 UTC, then a value of 169.5555 is recorded. An index of when the annual maxima occur in a given grid cell is derived along with an assessment of the variability in the timing of the annual maxima. Using probability theorem the number of unique combinations of two individual years in a sample of 15 years is; $15!/(2!(15-2)!)$ = 105. The time series of 15 annual maximum values (i.e. one for each year during 2002-2016) is then evaluated to determine if >50% of all those 105 possible unique combinations (date in year 1 versus date in year 2, date in year 7 versus date in year 10) fall within < 60 calendar days of each other while accounting for the discontinuity at the beginning and end of the calendar years. Year day values from simulation years that fall within 60 calendar days of each other are then averaged to derive an estimated year date that represents the center of gravity of the timing of high wind speeds at that location. Otherwise a value of ‘NaN’ is reported and the grid cell is identified as potentially exhibiting a mixed wind climate that is likely to result in high uncertainty in $U_{50}$. The results for the dominant year day are examined to determine if there is spatial consistency and also as a first indirect assessment of the likely atmospheric context of the high wind speeds.

**Figure 1.** Nominal power curve (representative of a GE1.6 MW WT) used to quantify gross AEP.
3. Results

3.1 Annual mean wind speeds

Mean wind speeds from WRF-MPI exhibit lower values than the WRF-ERA-I (cf. Figure 2(a) v. (b)) consistent with the differences in the PBL schemes employed (see discussion above) [5]. Remapping of WRF-MPI to the ERA5 grid in order to conduct the statistical skill analysis relative to ERA5 has little impact on the wind speeds (cf. Figure 2(a) and (c)). Annual mean wind speeds from WRF-MPI simulations are biased high relative to ERA5 (Figure 2). This bias is ~0.8 ms\(^{-1}\) on the spatial mean with larger differences in regions of complex terrain (cf. Figure 2(c) and 2(d)). The Taylor diagram (Figure 2(e)) indicates the spatial mean wind speed fields from WRF-MPI (remap) and ERA5 are correlated (r > 0.8), but WRF-MPI exhibits lower overall spatial variability due in part to the very low wind speeds from ERA5 over the Rocky Mountains (Figure 2(d)). Note, data from ERA5 are shown in Figure 2 for an area beyond the WRF simulation domain to emphasize the spatial extent of low winds over and west of the Rocky Mountains. A similar result was also found in the New European Wind Atlas (NEWA) project where over areas with terrain ERA5 was found to exhibit substantial negative bias of > 0.5 ms\(^{-1}\) over the Alps, most of Norway, Italy and the Pyrenees in the long-term mean wind speed at 100-m relative to observations and simulations with WRF, and negative bias of up to 0.5 ms\(^{-1}\) over almost all grid cells in Europe. This negative bias in ERA5 is hypothesized to be linked to the terrain drag applied in the reanalysis model. Output from the MPI-ESM-LR is not equivalent to those from observationally constrained reanalyses (ERA5 or ERA-Interim). While the GCM nested simulation is for a nominal time period of 1980-2005 this does not correspond to those specific calendar years, and thus the comparison can only be conducted under the assumption that a random 26 year period in the contemporary climate is sufficient to capture the true mean climatology. Further, some of the discrepancies in wind climates derived from WRF-MPI and those from ERA5 and WRF-ERA-I might reflect differences in synoptic scale systems advected into the WRF domain through the LBC or differences in the simulation period duration (15 years for WRF-ERA-I, versus 26 years for WRF-MPI and ERA5) and thus the impact of the internal climate modes as discussed above. Thus, WRF-MPI and WRF-ERA-I exhibit closer accord with wind resource estimates from NREL (cf. Figure 2 and Figure 3). For example, all three indicate large swaths of the central Great Plains to have annual mean wind speeds of 8 to 9 ms\(^{-1}\). Based on these and other quality control assessments WRF-MPI was deemed sufficient to provide a preliminary assessment of the potential change in AEP and U\(_{50}\).

### Table 1. Precis of the WRF simulations.

| Abbreviation used → | WRF-ERA-I | WRF-MPI |
|---------------------|-----------|---------|
| Simulation period   | 2001-2016 | 1980-2005 & 2075-2099 |
| LBC                 | ERA-Interim [27] | MPI-ESM-LR [28] |
| Output freq. 3-D wind comp. | 10-minutes | 6-hourly |
| Land use description | USGS (24 categories) | |
| Microphysics        | Eta (Ferrier) [35] | WRF-single-moment-microphysics classes 5 (WSM5) [36] |
| Longwave radiation  | Rapid radiative transfer model (RRTM) [37] |
| Shortwave radiation | Dudhia [38] | Goddard [39] |
| Surface layer physics | MM5 similarity scheme [40] | Eta similarity [41] |
| Land surface physics | Noah land surface model [42] |
| Planetary boundary layer | Mellor-Yamada-Nakanishi-Niino 2.5 (MYNN2.5) [43] | Mellor-Yamada-Janjic (MYJ) [44] |
| Cumulus scheme      | Kain-Fritsch [45] |
| Horizontal grid size (resolution) | 12 km by 12 km |
| Vertical levels     | 41 (3rd level used here) | 45 |
| Time step           | 72 seconds |

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Figure 2. Annual mean wind speeds at approximately 100-m a.g.l. from; WRF-MPI (a) at the native resolution of 12 km and (c) remapped to ERA-5 resolution, (b) WRF-ERA-I at the native resolution of 12 km and (d) ERA5 (at a grid resolution of 30 km). Also shown is (e) a Taylor diagram of the WRF-MPI output remapped to ERA-5 resolution and ERA5 mean wind speeds (i.e. wind speeds from panels (c) and (d)). The comparison of WRF-MPI and ERA5 is for the same nominal period; 1990-2005 but GCMs to do simulate specific calendar years but rather a plausible time evolution. The values above each map show the spatial means for the common domain.

Figure 3. Annual mean wind speeds at 100-m a.g.l. over the contiguous USA. Figure obtained from https://www.nrel.gov/gis/images/100m_wind/awstwspd100onoff3-1.jpg. The duration of the simulations that underpin these estimates is not reported.

3.2 Annual energy production

Inter-annual variability (IAV) of gross AEP from WRF-MPI in each grid cell is characterized using two metrics. The first is a non-parametric estimate described as the ratio of inter-quartile range of annual gross AEP (i.e. 25th to 75th percentile, p25 to p75) to the median value (50th percentile, P50); IQR(AEP)/P50(AEP). This estimate expresses the range of gross AEP in the half of estimates closest to the median value. Half of gross AEP estimates are expected to fall within IQR(AEP) of the P50(AEP). The second descriptor of uses the standard deviation (σ) of annual gross AEP values to the mean; σ(AEP)/mean(AEP). Under the implied assumption that the AEP estimates within a given grid cell are Gaussian distributed, two-thirds of gross AEP values should fall within ± 1σ(AEP) of the mean. The modal value of these two metrics from all land-based grid cells that have high wind resource (i.e. AEP: 4 to 5.2 x10^3 MWh) is used as an estimator of the typical IAV in AEP for resource rich areas of the eastern USA. The modal value of ratio of IQR(AEP)/P50(AEP) ~ 6.5%, while the modal value for IAV derived using σ(AEP)/mean(AEP) is ~ 4.5% (Figure 4).
Figure 4. Histograms showing two metrics of the inter-annual variability (IAV) of gross AEP from WRF-MPI output in the contemporary climate for all land-based grid cells that have a high wind resource (Gross AEP > 4 to $5.2 \times 10^3$ MWh). (a) Ratio of IQR(AEP) to median(AEP). (b) Ratio of $\sigma$(AEP) to mean(AEP).

Figure 5. Mean gross annual energy production (AEP) for the contemporary and possible future climate derived WRF-MPI. The lower panels show the difference in AEP from the two periods (future minus contemporary) expressed as a difference in mean AEP in MWh (left) and as a percentage of the mean AEP in the contemporary climate (right).

Gross AEP from WRF-MPI simulations of the future and contemporary climate indicate some differences in mean AEP. Eight-percent of grid cells exhibit a difference in mean AEP that exceeds 4.5% of the mean gross AEP in the current climate, and thus exceeds the typical current IAV. Gross mean AEP in the future period is, on average, higher in the southern Great Plains (by upto 8%) (Figure 5). Conversely, mean gross AEP in the latter period is, on average, slightly lower over parts of the upper Midwest (Figure 5). These differences appear to be the result of changes in the intensity of the Great Plains low-level jet and small shifts in the prevailing cyclone tracks, in the response to very large applied climate forcing (RCP8.5).

3.3 Extreme wind speeds
Preliminary estimates of approximately 72-second (i.e. model time step) $U_{50}$ at a nominal height of 100-m a.g.l. from the contemporary climate as simulated using WRF-ERA-I are shown in Figure 6(a). These estimates are consistent with a priori expectations and exhibit similar spatial patterns to estimates of extreme winds from 10-m a.gl. observations [46,47]. Very high values (approx. 40 ms$^{-1}$) are found for the steep terrain of the Rocky Mountains, and off the east coast in regions with very intense atmospheric
phenomena such as tropical cyclones [48] and/or Nor’-easters [49]. The seasonality of occurrence of the annual maximum wind speeds also exhibits important spatial variability (Figure 6(b)): (i) High wind speeds in the Rocky Mountains are dominated by early-winter (November and December), as are annual maxima across much of the Midwest. These high winds are likely to result from strong mid-latitude cyclones. Although the topographic complexity of the Rocky Mountains may lead to enhancement of wind speeds (e.g. via gap-flow) these are unlikely to be manifest at scales below those represented in simulations at 12 km. (ii) Along the east coast (and offshore) there is a dominance of early fall (August and September) for maximum winds consistent with the peak Atlantic hurricane season [50]. (iii) Through parts of the southern Great Plains (i.e. regions with high current WT installed capacities) extreme wind speeds are most likely to occur in April to June (year days 91-213) during the peak season for mesoscale convective systems [51]. Given the different spatial scales of the driving phenomena of these high wind speeds one can begin to develop a hierarchy of the likely fidelity of the extreme wind speeds in these different areas. Conceptually, this credibility analysis would assign highest fidelity in the areas where synoptic-scale systems (e.g. mid-latitude cyclones with cold fronts manifest over hundreds of kilometres) dominate the occurrence of extreme wind speeds (e.g. Illinois), since these features are likely to be well-represented by WRF simulations at 12 km resolution. Lowest credibility would be assigned where either topographic forcing or meso-scale convection (and the downdrafts associated there with) dominate the occurrence of extreme winds (e.g. Oklahoma).

**Figure 6.** (a) Preliminary estimates of $U_{50}$ (ms$^{-1}$) from the WRF-ERA-I simulations for the contemporary climate. (b) Mean day of year on which the annual maxima used to derive $U_{50}$ were obtained. If the grid cell is shown as white there is no consistency from year-to-year.

Preliminary estimates of $U_{50}$ from the WRF-MPI simulations under the contemporary and future climate are shown in Figure 7. Consistent with the higher wind speeds from WRF-ERA-I than WRF-MPI (Figure 2) extreme wind speeds for the contemporary climate are also lower in the WRF-MPI runs (Figure 7) than in the WRF-ERA-I simulations (Figure 6, note the same color bar scale is used in Figure 6(a) and Figure 7). Differences between $U_{50}$ from the future (end of century) and contemporary climate are on average positive over most land areas; indicating increased values at the end of the twenty-first century. But there is substantial grid-cell to grid-cell variability, and when only land-based grid cells that have high wind resource (i.e. AEP: 4 to 5.2 ×10$^3$ MWh) are selected the mean difference in $U_{50}$ (future minus contemporary) is -0.24 ms$^{-1}$ and the median value is -0.25 ms$^{-1}$. The maximum value in any grid cell from the high resource areas is 3.7 ms$^{-1}$, and the minimum value is -4.9 ms$^{-1}$. Areas of spatial coherence in the sign of difference in $U_{50}$ are observed in the southern Great Plains. However, the differences in $U_{50}$ estimates from the future and contemporary climate for WRF-MPI are generally smaller than the difference in the two estimates of $U_{50}$ in the contemporary climate (i.e. estimates from WRF-ERA-I and WRF-MPI). Further, they are in an area where the annual maxima in the current climate likely derive from mesoscale structures (Figure 6(b)) and thus that may not be well reproduced simulations at 12 km. Hence, low credibility must be assigned to the implied differences in $U_{50}$.
Figure 7. Estimates of $U_{50}$ (ms$^{-1}$) from the WRF-MPI simulations for the contemporary and future climate. The lower panel shows the difference in $U_{50}$ (in ms$^{-1}$) from the two periods (future minus contemporary). Positive numbers indicate high values at the end of the current century.

4. Concluding remarks
This manuscript presents initial results from a project designed to assess the potential for evolution of wind resource and WT operating conditions and to develop a transparent and robust workflow for assigning credibility to those assessments. Differential credibility assessments are urgently needed for climate science in the service of stakeholders (such as the wind energy industry) because they go beyond simply assessing statistical skill relative to a target in the contemporary climate to understanding the degree to which the processes that lead to an ‘outcome’ are correctly reproduced by a given model. They can thus be seen as an important part of any model verification and validation (V&V) exercise for computational models used to make engineering predictions with quantified confidence.

Here we illustrate aspects of differential credibility analyses and present new projections of possible changes in wind resources and operating conditions over the eastern two-thirds of the USA. In these analyses we apply a relatively long time horizon (i.e. the future resource and $U_{50}$ estimates are for the end of the current century) and the strong climate forcing applied (RCP8.5). Nevertheless, simulated changes from the WRF-MPI model chain in terms of expected gross annual energy production from wind turbines and extreme wind speeds are comparatively modest. Specifically, few grid cells exhibit evidence for a difference in mean gross AEP at the end of the current century that lies beyond the current mean ± the current inter-annual variability. Further, differences in the estimated 50-year return period wind speed at 100-m a.g.l. from the contemporary and possible future climate are of small magnitude. There is weak evidence for increased $U_{50}$ over parts of the Southern Great Plains, but the credibility of these projections is comparatively low because of the challenges inherent in simulating the Mesoscale Convective Systems that are likely to be responsible for extreme winds in this region.

Key aspects that will be addressed in future work within the project are:
- Enhancing the simulation duration to ensure improved sampling of low-frequency modes of climate variability.
- Conducting the climate change simulations for the near-term climate that is of greatest value to the wind energy industry (i.e. for a time horizon to 2050).
- Developing an enhanced ensemble of simulations to examine model sensitivities and further explore why use of the MYNN2.5 PBL scheme results in substantially higher wind speeds over the eastern USA than use of the MYJ PBL scheme.
Further development of the framework for assigning credibility to projections of operating conditions and resource magnitude using preliminary concepts advanced herein.

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