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What can reanalysis data tell us about wind power?

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ABSTRACT

Reanalysis data sets have become a popular data source for large-scale wind power analyses because they cover large areas and long time spans, but those data are uncertain representations of "true" wind speeds. In this work we develop a model that systematically quantifies the uncertainties across many sites and corrects for biases of the reanalysis data. We apply this model to 32 years of reanalysis data for 1002 plausible wind-plant sites in the U.S. Great Plains to estimate variability of wind energy generation and the smoothing effect of aggregating distant wind plants. We find the coefficient of variation (COV) of annual energy generation of individual wind plants in the Great Plains is 5–12%, but the COV of all those plants aggregated together is 3.0%. The year-to-year variability (of interest to system planners) shows a maximum step change of ~10%, and the wind power varies by ±7.5% over a 32-year period. Similarly, the average variability of quarterly cash flow to equity investors in a single wind plant is 29%, but that can be reduced to 18–21% by creating small portfolios of two wind plants selected from regions with low correlations of wind speed.

1. Introduction

Wind power is generating an increasing fraction of electricity in many countries and affecting electrical system operation and planning. Long-term wind data are important for predicting these effects. For developers and financers, long-term data reduce uncertainty about the expected revenues of a proposed wind plant. For electrical grid operators and planners, long-term data make it possible to estimate the probabilities of rare events, such as extreme low winds that necessitate conventional power plants as backup. Long-term data are also necessary to assess trends and cycles in wind resource.

Meteorological monitoring stations have collected data for many decades, but those data have several characteristics that make them problematic for wind power analyses [1]. First, meteorological stations measure wind speeds at 8-m or 10-m height, which is far below the 60–100 m hub heights of utility-scale wind turbines. It is possible to extrapolate measured wind speeds to those heights, but such extrapolations are uncertain because meteorological stations do not typically measure variables such as atmospheric stability and surface roughness that are required to calculate the vertical wind profile. Second, meteorological stations are often not located near areas well-suited for wind power development; in the U.S. most stations are located at airports. Third, observations contain errors and gaps in coverage, especially data collected manually before automated stations were deployed [2]. Finally, measurement instruments, station locations, and surrounding land cover sometimes change, which make it difficult to compare measurements from a single site taken in different periods.

Because of these problems with historical data, many wind power researchers have turned to reanalysis data, which interpolate meteorological observations in space and time using numerical weather prediction models. Recent examples include NARR [3], ERA-40 [4], MERRA [5], and the Climate Forecast System Reanalysis (CFSR) we use in this work [6]. Reanalysis data sets are attractive because they span several decades, contain observations for variables, locations, and times not recorded in historic data, and have uniformly-good data quality and no missing observations [1]. Researchers have used reanalysis data for wind resource assessment, long-term trends [7,8], long-term variability [9], geographic smoothing [10–12], and extreme winds [13]. However, the relatively low spatial resolution of reanalysis models smooths local terrain features that enhance wind speed. This means that reanalysis data is likely to somewhat under-predict measured wind speeds at a particular location.

Relatively few of the researchers who use reanalysis wind speeds have validated those data against historical data.

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Researchers who compare reanalysis-predicted wind speeds at 10-m height to historical measurements from meteorological stations find significant uncertainties: RMS error of 2.5–3 m/s for surface-level winds in NARR [3], correlation coefficients of 0.8–0.9 and energy correction factors of 1.06–1.10 for MERRA and CFSR [14], and a correlation coefficient of 0.73 for hourly MERRA data [15]. However, these validations do not capture errors and uncertainties introduced when wind speeds are extrapolated from 10-m to typical wind turbine hub heights using assumed vertical wind speed profiles. A few authors validate reanalysis data using wind speeds measured at heights closer to wind turbine hub height (50–100 m). A comparison of daily average wind speeds from several reanalysis models to tall tower data calculates average R^2 values of 0.73 for CFSR and 0.67 for MERRA [16]. A thorough analysis with offshore wind speed measurements in the UK finds MERRA under-predicts hourly wind speeds by an average of 7% and over-predicts the COV of annual wind speeds by an average of 17%. That study also calculates R^2 values of 64–93% for hourly speeds, 80–97% for daily averages, and 90–99% for monthly averages [17]. Henson finds correlation coefficients of 75–87% for hourly MERRA wind speeds with data from on-shore sites in Massachusetts [9].

In this work we present a model that corrects biases and quantifies the uncertainty in wind energy calculated from reanalysis data. Whereas previous studies estimate uncertainty for individual sites assuming a separate model for each site, the model we present quantifies the uncertainty attributable to between-site differences as well as within-site variability. We apply this model to generate 32 years of quarterly energy generation for individual wind plants, which we analyze to estimate inter-annual variability of wind energy generation and quarterly variability in cash flow to equity holders in a wind plant. We focus on quarterly and annual variations in wind energy because variations on those scales are important to financiers and because the uncertainties in reanalysis-predictions are smaller than at shorter time scales.

2. Methods

We estimate the quarterly energy generated by each of 1002 wind plants in the U.S. Great Plains for the period 1979–2010 using reanalysis wind speed data. We calculate the 80-m height hourly wind speed at each wind plant site by extrapolating data from the CFS reanalysis [18]. We then aggregate the energy for each site by quarter and apply a model we develop to correct for biases and quantify uncertainty in the CFS data. Finally, we simulate 10^3 probable realizations of quarterly energy generation at each site.

2.1. Wind plant locations

We simulate the wind power at the locations of all wind plants from the Eastern Wind Integration and Transmission Study (EWITS) [19] that are in the U.S. Great Plains (north and west of the Mississippi and Ohio rivers). We combine the few wind plants that are less than 5 km apart, which leaves 1002 wind plants. We consider only sites in Great Plains for four reasons. First, most wind power development in the U.S. is taking place in the Great Plains. Second, the terrain is generally flat, so we expect the reanalysis-predicted wind speeds to be more accurate. Third, the area has a good coverage of historical record of meteorological observations, which are assimilated into the reanalysis model. Finally, good empirical validation data were available for the Great Plains in the form of tall-tower wind speed data not assimilated into the reanalysis model.

The empirical data consists of several years of hourly wind speed measurements from tall towers at 78 sites in the Great Plains, measured at heights of 50–120 m. At sites with anemometers at multiple heights, we selected the one closest to 80 m. A table listing the locations, heights, date ranges, and mean wind speeds of the empirical data sets is given in the Supporting Information([38–41]). The sites are divided randomly into two equally-sized subsets: a "training" set used to fit the equations in (2) and a "validation" set used to test the fits. These data were collected by economic development agencies in various states and then checked for quality control and compiled into a single database by the University of North Dakota Energy & Environmental Research Center [20]. We have tried to ensure uniform land cover and geographical properties for all sites by inspecting satellite photographs and excluding sites with trees, structures, or other obstructions within approximately 1 km.

2.2. Extrapolating hub-height wind speed from CFSR data

We estimate hourly wind speed at 80-m height $u(z=80)$ at each location using 1–6 h forecast data from the CFSR [18] and the following formula for a logarithmic vertical wind profile given by Panofsky [21]:

$$u(z) = u_*/\kappa(\log(z/z_0) - \Psi(z/L)) \tag{1}$$

where:

u_* = friction velocity [m/s]
κ = 0.4 (von Kármán constant)
z = hub height [m]
z_0 = surface roughness length [m]
$\Psi(z/L)$ = correction for atmospheric stability, a function of the stability measure z/L
L = Obukhov length [m]

The friction velocity and surface roughness values are taken from the CFS reanalysis data. The surface roughness values vary spatially, depending on land cover, and temporally, depending on season. The Obukhov length is calculated by an expression given in the Supporting Information. The correction for atmospheric stability Ψ is given in (2) for unstable ($z/L < 0$), neutral ($0 \le z/L < 0.5$), and stable ($z/L \ge 0.5$) atmospheric conditions:

$$\Psi(z/L) = \begin{cases} (p_1(z/L)+p_2)\Big/\Big((z/L)^2+q_1(z/L)+q_2\Big) & z/L<0 \\ -5(z/L) & 0\le(z/L)<0.5 \\ -3.76(z/L)^{0.45} & 0.5\le(z/L) \end{cases} \tag{2}$$

where $p_1 = -2.0$, $p_2 = -0.36$, $q_1 = -0.26$, and $q_2 = 2.4$. The expressions we present in (2) for stable and unstable conditions are new in this work because we find the expressions typically given in the literature [22–24] are a poor fit for the CFS reanalysis data.

We determined these novel equations for Ψ in stable and unstable conditions by substituting historical wind speeds from the empirical data described in Section 2.1 for $u(z)$, solving (1) for Ψ, and then fitting empirical curves to Ψ as a function of z/L using robust (least absolute residuals) regression. This robust method is less sensitive to outlier data than are other forms of regression. A more detailed explanation of the fitting of these equations is given in the Supporting Information. The coefficients of these equations are fitted to data from many sites pooled together in order to represent an average site. However, the fitted equations over-compensate for atmospheric stability conditions at some sites and under-compensate at others. We were not able to model this between-site variation as a function of site characteristics, but we attempt to quantify the uncertainty introduced by between-site variation in (4).

When fitting (2), we exclude the small number of data points from hours with $z/L > 10$ (2% of data) or $z/L < -10$ (4% of data) from the curve fitting because variance of the residuals grows rapidly for $|z/L| > 10$.

2.3. Correcting biases and quantifying uncertainty in quarterly energy generation

The hourly hub-height wind speeds extrapolated from reanalysis data using (1) have biases and uncertainties from the extrapolation procedure and from the reanalysis model. We develop a correction and uncertainty model to correct for the biases (a procedure known as Model Output Statistics [25]) and quantify the uncertainties. Our procedure is similar to the linear regression method described by Brower for determining the relationship between wind speeds at different locations [1].

We develop this correction and uncertainty model by comparing the wind power calculated from reanalysis data with (1) to wind power calculated from historical data. First, we interpolate the raw data from the reanalysis model to the locations of the sites in the "validation" subset of the empirical data described in Section 2.1. We use that interpolated raw reanalysis data as inputs to (1) to calculate hub-height wind speeds. Finally, we convert the reanalysis and empirical wind speeds to wind power using the power curve for a generic 2-MW wind turbine (shown in the Supporting Information) [19].

The correction and uncertainty model given in (3) is a hierarchical random-effects model [26] that estimates "actual" quarterly energy $E_{i,j}$ for site i in quarter j as a function of reanalysis energy $R_{i,j}$ for the corresponding site and quarter. The slope β is fixed, the offset α_i for site i is drawn from a normal distribution with mean 0 and standard deviation σ_α (4), and the error term ε for each measurement is drawn from a normal distribution with mean 0 and standard deviation σ_ε (5).

$$E_{i,j} = \alpha_i + \beta R_{i,j} + \varepsilon_{i,j} \tag{3}$$

$$\alpha_i \sim N(0, \sigma_\alpha) \tag{4}$$

$$\varepsilon_{i,j} \sim N(0, \sigma_\varepsilon) \tag{5}$$

We fit the model to the available data using Markov Chain Monte Carlo (MCMC) methods, as implemented in OpenBUGS version 3.2.3 [27]. Fitting the model parameters using MCMC methods yields distributions of probable values for each parameter (β, σ_α, σ_ε), rather than point estimates; summary statistics for the distributions of values of β, σ_α, σ_ε are given in Table 1. Fig. 1 plots the data to which the model is fitted, overlaid with the model using the mean parameter values in Table 1. The inset shows the model for a single site (thin red line) with 1-standard-deviation error bounds (dashed lines).

We apply this model to quarterly wind generation from reanalysis data by first randomly drawing values of the parameters β, σ_α, and σ_ε to simulate 10^3 probable realizations of quarterly energy for each site. Those values of σ_α, and σ_ε drawn for each realization are then used as the parameters for normal distributions from which the offset for each site α_i and the measurement error for each quarterly energy value $\varepsilon_{i,j}$ are drawn. We subsequently refer to the resulting values of quarterly energy as "corrected" reanalysis data.

The estimated model with parameters given in Table 1 indicate that the reanalysis wind speed over-predicts quarterly energy production for turbines with quarterly generation less than 37% capacity factor (~1600 MWh per quarter) and under-predicts for turbines with higher capacity factors, as shown in Fig. 1. The fitted value of the within-site variability parameter $\sigma_\varepsilon = 175$ MWh/quarter and between-site variability parameter $\sigma_\alpha = 435$ MWh/quarter (for a turbine that generates an average of 1950 MWh/quarter) show that between-site variability dominates the uncertainty in energy generation. These results suggest that additional research is needed to determine the source of the between-site variability and find additional inputs to the model to better explain that variability.

To the best of our knowledge, this is first model of the uncertainties and biases in reanalysis-predicted wind speed or energy. Previous work summarized in Section 1 calculated the R^2 values (or the related correlation coefficients) for the relationship between reanalysis and actual wind speeds but not applied those findings to estimating the uncertainty bounds on the reanalysis wind speeds. For comparison with previous work, we fit linear functions (unrelated to the model described in (3)) to quarterly wind energy for each of the 38 sites in the validation subset of the empirical data and find R^2 values in the range −0.36–0.997, with a mean of 0.77.

Table 1
Summary statistics of hierarchical model of quarterly energy for a 2-MW turbine described in (3)–(5). Units are MWh/quarter for a 2-MW turbine.

	Mean	Median	Std. dev.	Pearson corr. Coeffs. For β, σ_α, σ_ε
β	0.80	0.80	0.026	$\begin{bmatrix} 1 & & \\ -0.56 & 1 & \\ 0.17 & -0.094 & 1 \end{bmatrix}$
σ_α	435	429	63	
σ_ε	175	175	5.4	

3. Results

We use the realizations of corrected wind energy developed in Section 2.3 to estimate several measures of long-term wind energy variability.

3.1. Variability of single-site annual energy generation

The energy generated by a single wind plant varies from year to year due to weather and climate. We quantify that variability for each EWITS site using the corrected reanalysis data described in Section 2.3. The coefficient of variation (COV) of annual energy generation is the mean annual energy generation divided by the standard deviation; for individual sites median COV values range from 5.4% to 12%, with a mean value of 7.7%; the median COV values are plotted in Fig. 2. We refer to "median COV" because we calculate 10^3 realizations of COV for each site from the uncertain reanalysis data described in Section 2.3. There is a 90% probability that the COV for a given site is within 4.2% points of the site median.

These values are similar to previous estimates of COV of annual energy: Milligan calculates 10% from historical weather data at one low-wind-speed site in North Dakota [28], Baker calculates 12–13% from historical weather data for 3 sites in the Pacific Northwest [29], and Wan calculates 8%–13% from historical wind power production data at 4 sites in the Great Plains [30]. The COV for individual sites shows a geographic trend that is the inverse of the geographic trend in wind resource [31,32]: sites with better wind resource (average annual wind speed) have lower COV (plotted in the Supporting Information).

This long-term variability of annual energy at an individual site is important to wind plant developers because it sets an upper limit on the allowable debt load for the wind plant. Most plants sell their energy on a fixed-price contract, so revenue variability is proportional to variability in energy generation. The expected revenue in a bad year determines the amount of debt financing a wind plant can obtain. Typically, the debt payments are set to some multiple of the plant's revenue in the 1st percentile ("P99") or 10th percentile

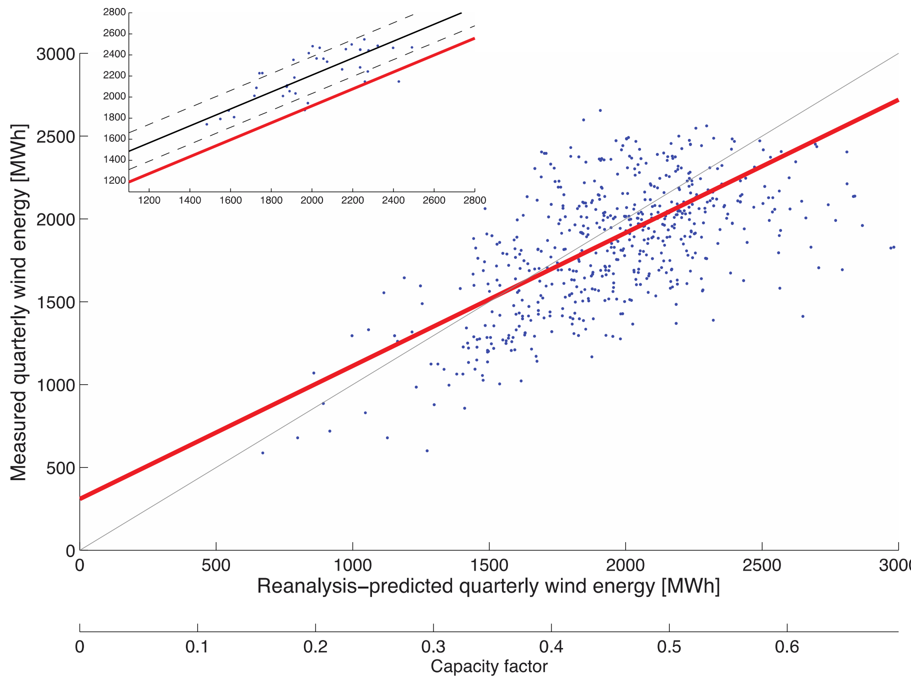

Fig. 1. Comparison of measured energy generation to reanalysis-predicted generation. Each point represents the quarterly generation for a 2-MW turbine in a given site; for comparison, a 2-MW turbine with a 35% capacity factor generates 1500 MWh per quarter. The red line shows the nominal values of the model described by equation (3) and parameters in Table 1. A grey line with a slope of 1 is plotted for comparison. The inset compares data from a single site to its corresponding model: the solid black line shows the site-specific model, which is offset from the nominal model by α_i, and the dashed lines show the error term ε. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

("P90") year [33]. If two plants have identical mean generation but different year-to-year variability in generation, the plant with less variability will be able to take a larger amount of debt and have a higher debt-to-equity ratio. In practice, uncertainties about future revenue will be larger than the results we give here because wind plant developers estimate the distribution of energy generation from much shorter periods of data: 1–2 years, compared to the 32 years we use in our analysis.

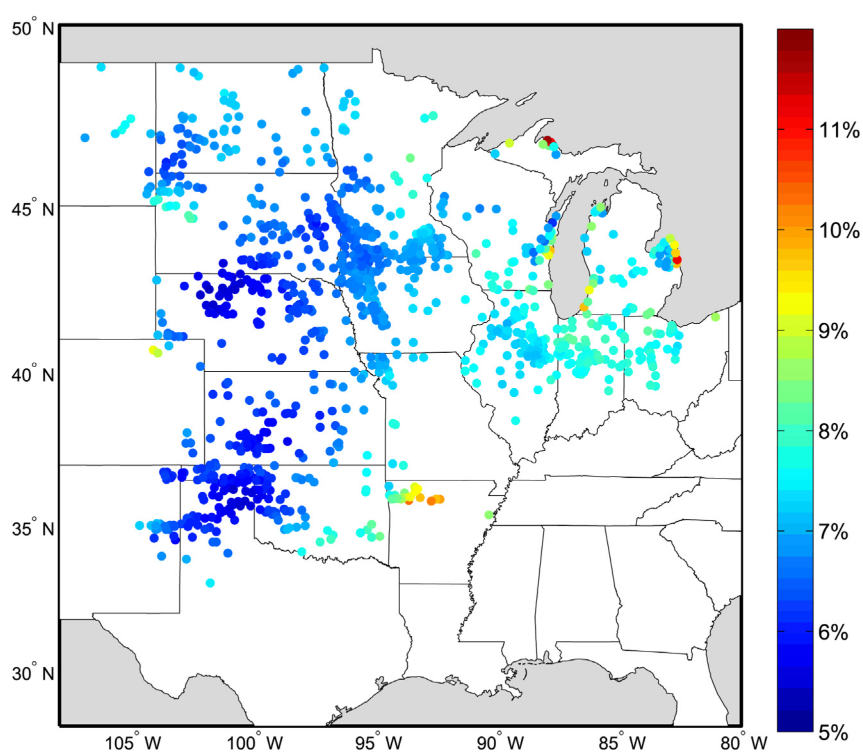

Fig. 2. Median Coefficient of Variation (COV) of annual energy generation for EWITS wind plants in the U.S. Great Plains and the Eastern Interconnect. There is a 90% probability that the COV for a given site is within 4.2% points of the plotted median.

3.2. Variability of aggregate annual energy generation

The inter-annual variability of wind generated in large regions is of interest to power system planners. We calculate the aggregate annual energy generation for all the EWITS sites, using the corrected reanalysis data weighted by capacity. The mean COV of energy for the aggregated sites, 3.0%, is much smaller than the COVs calculated for individual sites, which illustrates the smoothing effects of aggregating many wind plants. Fig. 3 plots a time series of aggregate annual energy (with 1 standard deviation error bars) and Table 2 presents summary statistics.

We also present results from previous studies for comparison with our results. Giebel used reanalysis data to calculate a COV of 6.4% for aggregate annual energy for 83 sites in northern Europe; see Table 2 [10]. Katzenstein used historical data to calculate a COV of 5.4% for 16 sites in the Great Plains [34]; see Table 2 and the red line in Fig. 3. The time series of our results in Fig. 3 is qualitatively similar to Katzenstein's, but our results show less variability (3.0% compared to Katzenstein's 5.4%). To test whether the lower variability of our results is caused by the much larger number of sites we aggregate (1002 compared to 16) or the turbine power curve we use, we use our corrected reanalysis data to calculate the aggregate energy for the 16 sites Katzenstein analyzes with the same power curve. We calculate a COV of 2.9% for those sites. The summary statistics for our analysis of those 16 sites is labeled “This work (compare to Katzenstein)” in Table 2 and a plot of the time series is given in the Supporting Information. For comparison, we also include statistics for aggregate U.S. hydroelectric generation in the last row of Table 2 [35]. These statistics show that aggregate annual hydroelectric is much more variable than aggregate annual wind generation.

The year-to-year variability of aggregate generation is important for the financing of wind plants because these results show that aggregating many wind plants distributed across a large area significantly reduces the variability of energy generation and corresponding revenue. Grid operators already manage the inter-annual variability of hydroelectric generation, which has a COV of 12%, approximately three times as large as the variability we estimate for wind generation. Long-term planning for generation capacity may benefit from understanding the size of this inter-annual variability. However, grid operators typically estimate the contribution of wind power to peak generation capacity based on the correlation between hourly wind power and electricity demand.

3.3. Variability in quarterly cash flow to equity investors

The variability of wind generation affects not only debt financing for a wind plant, as we describe in Section 3.1, but it also equity financing. Variations in cash flow to equity investors are significantly larger than variations in wind generation because the equity investments are leveraged by debt financing. We use the corrected reanalysis data to estimate the COV of quarterly cash flow to an equity investor for single wind plants or portfolios of two wind plants selected to reduce variability.

We create a simple financial model of a wind plant based on typical financing terms in the U.S. in 2013 [36]. The installed capital cost of a wind plant is $2 $\times$ 10^6/MW, a portion of which is financed with debt at 6% interest for 15 years. The debt load is determined as 1.2 times the 10-year average annual 10th percentile revenue (P90), which is calculated from the reanalysis data described in Section 2.3 with a fixed energy price of $25/MWh, operating cost of $24/MWh, and federal production tax credit of $23/MWh. This yields debt financing of approximately 35% of the capital cost, which is significantly lower than the historical averages for wind plants because the capital cost in 2013 was higher than the historical average and the energy price was significantly lower.

Given those financing terms, we calculate the COV of quarterly cash flow for individual wind plants and pairs of wind plants and plot the results in Fig. 4. The median COV for individual sites is 29% with an inter-quartile range from 23 to 39%. Fig. 4 also plots the COV values for various portfolios composed of two wind plants. This shows that aggregating two plants reduces variability of quarterly cash flow, similar to the effects of aggregating many plants we discuss in the previous section. The median COV of randomly-chosen pairs of sites is 25%, a decrease of 4% points from the COV for individual sites. The variability can be reduced further by carefully selecting pairs of sites. The median COV for optimally-chosen pairs (chosen to minimize average correlation of quarterly energy generation) is 20%. However, we find it is possible to achieve COV values nearly as low by selecting pairs of sites from the regions shown in Fig. 5. The median COV values for pairs of sites selected from regions A, B, and C are 18–21%. The Supporting Information gives additional details on how the regions were determined.

To test how much of the variability in our results is random rather than seasonal, we subtract the seasonal means from the quarterly cash flow and calculate a median COV of 22% for the same individual sites (a boxplot of these results is given in the Supporting

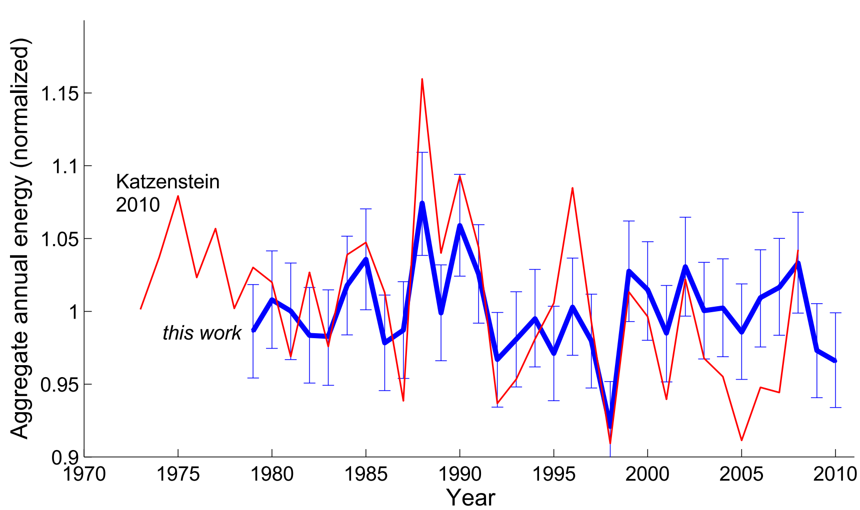

Fig. 3. Annual wind energy estimated for the aggregate of all EWITS wind plants in the U.S. Great Plains (blue) with uncertainty bars showing 1σ confidence intervals. Red line plots aggregate annual wind energy for 16 sites in the Great Plains from Katzenstein [34]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Summary of annual variability of aggregate wind power from this work and two previous studies. Results from this work give ±1σ confidence intervals in parentheses. The last row (labeled "EIA 2012") summarizes annual aggregate hydroelectric generation in the U.S. for comparison.

	Data source	Sites	COV	Max year	Min year	Max year–year change
This work	Reanalysis	1002	3.0% (2.9–3.1)	+7.4% (3.9–11)	−7.9% (4.8–11)	10.6% (10.2–11.1)
This work (compare to Katzenstein)	Reanalysis	16	2.9% (2.6–3.1)	+6.3% (−1.3 + 13.9)	−7.9% (0–13.7)	9.5% (7.9–11.1)
Katzenstein 2010	Historical	16	5.4%	+15%	−9.6%	22%
Giebel 2000	Reanalysis	83	6.4%	+13%	−12%	18%
EIA 2012	**Historical (Hydro)**		**12%**	**+26%**	**−23%**	**21%**

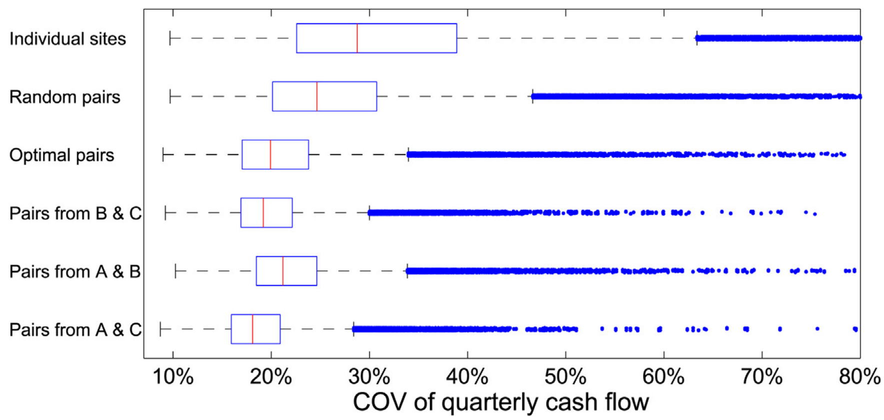

Fig. 4. Coefficient of Variation (COV) of quarterly cash flow to equity investors for individual sites and sites paired according to various criteria. The red lines denote the median, boxes span the 25th and 75th percentile values, the whiskers extend to 1.5 times the inter-quartile range.

Information). This shows that most of the variability is random, rather than seasonal. For comparison, Dunlop estimates a COV of 93% for an individual plant, which is significantly higher than the COV values we calculate [37].

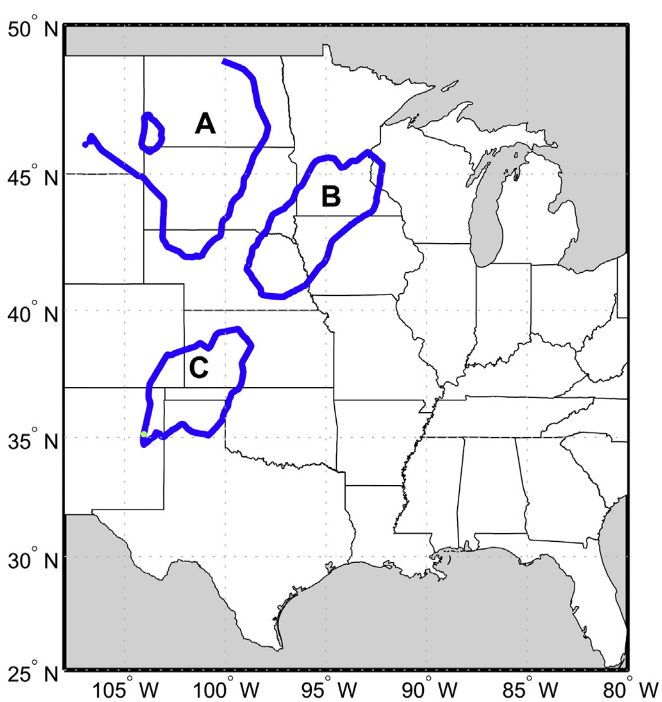

Fig. 5. Regions that have high correlations in quarterly wind energy generation. The correlations between regions are low.

4. Discussion

In this work we develop a model to correct for biases and quantify uncertainties in wind energy calculated from Climate Forecast System Reanalysis (CFSR) data. This model is the first application of model output statistics to reanalysis wind data and the first to systematically quantify the uncertainties of the reanalysis data across many sites. We find the reanalysis data has a positive bias: measured quarterly energy is 80% of the predicted value from CFSR data, plus a constant offset, for matching locations and time periods. More importantly, we find energy predicted from CFSR data has significant uncertainties, dominated by between-site variability.

In spite of the between-site variability in the reanalysis data, we find robust results for measures based on wind energy aggregated over large areas. We estimate the COV of aggregate wind energy from 1002 EWITS wind sites in the Great Plains to be 3.0% ± 0.1%. This inter-annual variability is much smaller than the variability at individual sites (5.4%–12% ± 4.2%), which demonstrates the smoothing effect of aggregating wind plants spread across a large area. We also show robust reductions in the variability of quarterly cash flow to equity investors when pairs of wind plants from certain regions are combined into portfolios.

The significant between-site variability ($\sigma_\alpha = 376$ MWh/quarter for a 2-MW turbine) suggests two possible sources of error. First, the reanalysis data poorly models terrain features because of the low resolution of the reanalysis model relative to the size of features that affect wind power. We compared the reanalysis data from empirical data selected from only flat regions, but it is possible that we did not detect subtle terrain features (e.g. ridges, upwind vegetation) that affect wind energy production. In our future research we will validate these CFSR data in complex terrain, similar to Henson et al. [9], and at offshore sites similar to The Crown Estate [17]. Second, the method we use to extrapolate hourly wind speed to hub height in (2) may introduce uncertainties. Our future work will test whether uncertainties in the uncertainties in the Obukhov length calculated from reanalysis data introduce uncertainties in the extrapolated wind speed. Our ultimate goal is to reduce the uncertainties for hub-height wind speeds so that reanalysis data can accurately model wind power from short time periods (hours) and small areas. This would allow reanalysis data to be used to estimate measures such as the capacity value of wind power, which depends on the coincidence between wind generation and demand for electricity.

To summarize, this work demonstrates a model that corrects biases in the CFSR data and quantifies its uncertainties. We find that CSFR data over-predicts wind plant generation output for wind plants with capacity factors greater than 37% and under-predicts the others and that year-to-year variability of Great Plains wind is likely to be less than half that of aggregate U.S. hydropower.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.renene.2015.05.027

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