

Transforming climate model output to forecasts of wind power production: how much resolution is enough?

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ABSTRACT: Wind power forecasts are useful tools for power load balancing, energy trading and wind farm operations. Long range monthly-to-seasonal forecasting allows the prediction of departures from average weather conditions beyond traditional weather forecast timescales, months in advance. However, it has not yet been demonstrated how these forecasts can be optimally transformed to wind power. The predictable part of a seasonal forecast is for longer monthly averages, not daily averages, but to use monthly averages misses information on variability. To investigate, here a model relating average weather conditions to average wind power output was built, based on the relationship between instantaneous wind speed and power production and incorporating fluctuations in air density due to temperature and wind speed variability. Observed monthly average power output from UK stations was used to validate the model and to investigate the optimal temporal resolution for the data used to drive the model. Multiple simulations of wind power were performed based on reanalysis data, making separate simulations based on monthly, daily and sub-daily averages, using a distribution defined by the mean across the period to incorporate information on variability. Basing the simulation on monthly averages alone is sub-optimal: using daily average winds gives the highest correlation against observations. No improvement over this is gained by using sub-daily averages or including temperature variability. This signifies that to transform seasonal forecasts to wind power a compromise must be made between using the daily averages with debatable skill and the more predictable monthly averages, losing information on day-to-day variability.

KEY WORDS wind energy; seasonal forecasting; wind power; load factor; United Kingdom; reanalysis; downscaling

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1. Introduction

Electricity generation from renewable sources is growing and the total installed capacity of renewable energy globally will reach 3200 GW in 2025 (Frost and Sullivan, 2014). In the United Kingdom wind power is the largest contributor to the renewable energy mix and this share is growing, with a total installed capacity of over 8 GW onshore and 4 GW offshore (RenewableUK, 2014). Records are continuously being broken: during December 2016 wind power supplied 20% of the United Kingdom's weekly energy demand (RenewableUK, 2017). However, despite increases in total stored capacity and headline-grabbing records, intermittency is a problem that will always remain (Albadi and El-Saadany, 2010). On windless days no energy is produced, regardless of total installed capacity. Conversely periods of high wind bring a glut of energy, to be balanced with other sources.

Wind power forecasts can help address this challenge and increase the efficiency of the grid (Pinson, 2013). It is already routine practice to use short term weather forecasts for wind power management (Barthelmie *et al.*, 2008; Foley *et al.*, 2012); however, the development of weather and climate prediction science has enabled the production of skilful forecasts on longer

monthly and seasonal timescales. Where these forecasts have skill they may prove useful in decision-making processes in the wider energy sector; this is an active area of research (e.g. García-Morales and Dubus, 2007; Troccoli, 2010; Lynch *et al.*, 2014; De Felice *et al.*, 2015). Although forecasts are currently under-used by the wind energy industry, recent advances in seasonal forecast skill for wind speed over Europe may provide an impetus for change (Scaife *et al.*, 2014).

Transmission service operators matching supply to demand may be able to make use of wind power forecasts at longer timescales for load balancing, particularly when alternative sources (e.g. coal and nuclear power plants) power up and down on timescales longer than traditional weather forecasts. Scheduling of wind farm maintenance may also be improved by the use of monthly and seasonal forecasts, particularly in the case of offshore turbines where maintenance vessels must be scheduled in advance of work. Wind farm operators can also make use of forecast information through short term financial forecasting, whilst owners, banks and insurance companies can use predictions of generated power to manage risk, increasing the resilience of the industry to shocks.

Compared to traditional weather forecasts which focus on weather conditions for the upcoming few days, monthly and seasonal forecasts generally have the most skill for averages over periods of weeks, months and longer (Troccoli, 2010). Beyond a week, predictions for individual daily averages are perceived to be uninformative due to the fact that predictability on larger

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timescales arises from low frequency oscillations in the climate system (Troccoli, 2010). Given that long range forecasts are most informative for average periods longer than a week (e.g. monthly averages), the question arises: is it possible to forecast the average wind power across a month by using the monthly average alone? Or must one base a long range power forecast on a higher temporal resolution base (e.g. daily or sub-daily averages) in order to make an optimal transformation, even though the predictability of daily variations in long range forecasts is lower? Studies have suggested that assuming a linear relationship between monthly wind speed and power is reasonable (García-Bustamante *et al.*, 2009); however, using monthly average wind loses information about fundamental high frequency variability in weather conditions. Hence, a methodology to transform the skilful time-averaged climate forecast data into useful long range wind power estimates is needed.

The typical spatial resolution of models used for monthly and seasonal weather forecasts is also coarse compared to both that used for shorter range forecasts and the local conditions around most wind turbines. This means that the local conditions (e.g. variability in topography) are often not well represented. Does then the application of complex spatial downscaling lead to improvements in wind power simulation? This is a very relevant question because post-processing methods like downscaling often reduce the skill of forecasts (Frías *et al.*, 2010), suggesting that their use should be kept to a minimum.

Furthermore, air temperature impacts wind power generation: colder air is denser and has more kinetic energy than warmer air at the same speed. Does the inclusion of variability in temperature improve the simulation of wind power?

A methodology is then necessary that takes all these issues into account, striking a compromise between the provision of high frequency, local wind power estimates with debatable skill and value and the provision of averaged, coarse wind power estimates with skilful information that might add value to the decision process. Here, a model that transforms average 10 m wind speed and air temperature to average load factor is created to explore these issues (where load factor is a measure of power independent of turbine model, defined as the power generated by a wind turbine as a percentage of its maximum power). This model is applied to reanalysis data, using monthly, daily and sub-daily (e.g. 6 h) averages as a basis in separate simulations. In each case two simulations are made, with and without the inclusion of temperature variability. Two reanalysis datasets are used: ERA-Interim reanalysis (Dee *et al.*, 2011) and the SeaWind II dataset (hereafter SW2), a spatially downscaled version of ERA-Interim using the Weather Research and Forecasting ARW model (Menendez *et al.*, 2014). Finally, simulated load factor is compared with reported monthly load factor for sites in the UK across the period 2002–2012.

Whilst reanalysis data are not as accurate as wind speed observations from existing wind farm sites, they are used here as a proxy for long range forecast output as they are generated from the same atmosphere–ocean models. They also have the advantage over station data of having global coverage. This allows estimation of the wind energy and power potential in regions where there are not yet wind farms or wind speed measurements.

Note that the current work does not address the question of actual skill of load factor forecasts from monthly and seasonal climate models; research considering power forecast skill on seasonal timescales is in progress. Instead, the focus is on the description and validation of the methodology to estimate the load factor from average meteorological data and an exploration of the compromise in both temporal and spatial resolution of the

data needed for optimal use of the forecasts. It should be noted that a model such as this, essential for transforming seasonal forecasts to load factor predictions, does not currently exist.

The validation of an impact model driven by a seasonal climate forecast can be carried out on three levels (where an impact might be load factor potential, malaria incidence or something else). This follows the definition of a three-tier hierarchical validation approach of end-to-end seasonal climate forecast systems (Morse *et al.*, 2005). The first, tier 1, is the validation of the driving seasonal climate forecast against meteorological observations or reanalysis. Tier 2 evaluates the impact model as a multivariate nonlinear transfer function, by comparing the output of the model driven by meteorological observations or reanalysis to the observations of the impact. The final stage, tier 3, measures the skill of the impact model driven by seasonal climate forecasts against observations of the impact. In this case tier 1 and tier 3 validations are being considered in ongoing work; in the current study tier 2 validation only is the focus.

The following section describes the observations of load factor, the model relating average wind and temperature to load factor and the reanalysis data and methods. Following this, results are presented in Section 3 and a discussion is contained in Section 4.

2. Methodology

2.1. Load factor observations

Load factor is defined as the relationship between the actual and potential power generated by a wind turbine. For instance, a turbine with a maximum power rating of 2 MW operating with an average load factor of 40% across a month will generate power at an average rate of 0.8 MW. Using load factor rather than explicit power is useful as it is independent of the maximum power of a turbine; load factor arising from particular environmental conditions is easily converted to power output of a wind farm by multiplying by turbine rated power for each installed turbine.

Reported monthly load factor for the United Kingdom over 2002–2012 is used here as a reference to validate the load factor model described below. These data are reported from wind farms enrolled in the UK Government's incentive scheme and were originally published by the Renewable Energy Foundation (Renewable Energy Foundation, 2012). An updated version of this dataset is used here; the reader is referred to the appropriate references for a detailed analysis of this useful dataset (Staffell and Green, 2014). Stations with at least 3 months of reporting data are shown in Figure 1; each station covers a subset of the total 11 year period.

2.2. Modelling load factor as a function of average environmental conditions

Here the model used to transform average wind and temperature to average load factor is described. Several factors are taken into account to form the structure of the model:

- the relationship between instantaneous wind speed and power generated by a wind turbine (known as a power curve);
- temporal variability in wind speed;
- the increase of wind speed from surface to turbine height, and
- power losses due to transmission and distribution of electricity.

The ways in which these factors have been incorporated are described in detail in the following sections.

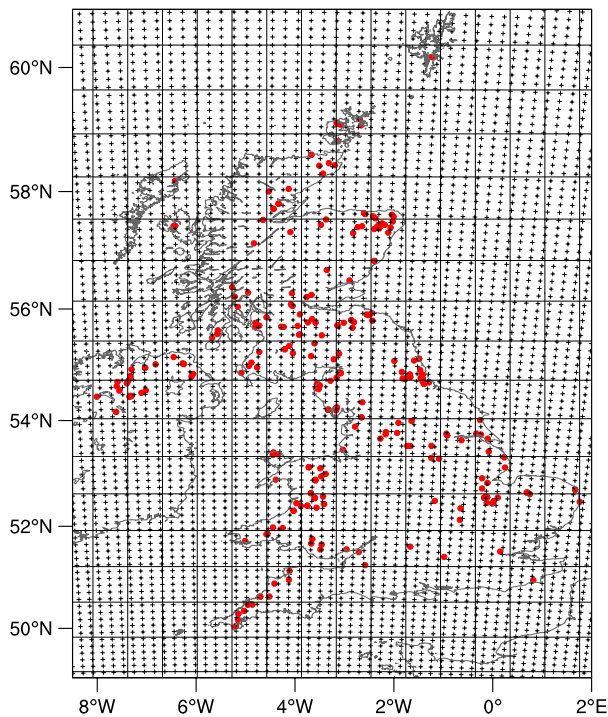


Figure 1. Location of stations with monthly load factor observations as dots. The ERA-Interim grid is overlaid, with the downscaled SeaWind II dataset gridpoints indicated by small black crosses. [Colour figure can be viewed at wileyonlinelibrary.com].

2.2.1. Defining a power curve

The relationship between instantaneous wind speed and generated power by a turbine is nonlinear and described by a power curve (Lydia *et al.*, 2014), the general shape of which is shown by the black curve in Figure 2. At low and high wind speeds no power is generated: below a low wind speed threshold (known as the cut-in speed, around 4 m s^{-1}) the wind is not strong enough for a turbine's blades to spin and above a high speed threshold (known as the cut-out, around 25 m s^{-1}) the blades are prevented from spinning for safety. Above the rated speed (generally 12.5 m s^{-1}), turbine braking occurs, which caps the power generation at the rated power. The rated power is the maximum power of a wind turbine, meaning that between the rated speed and the cut-out speed the turbine operates at its maximum capacity and the load factor is by definition 100%.

The majority of wind turbines have the same power curve shape, described in manufacturers' product specification documents. Power curves are idealized: in practice the instantaneous power will not necessarily follow this relationship as the curves are averages of empirical data, and meso- and micro-scale interference can influence turbine operation (Rosen and Sheinman, 1994). The load factor model described here does not account for such departures from ideal power curve behaviour.

Between cut-in and rated speed, the power generated by a turbine is a function of cubed wind speed and temperature. This arises from a consideration of the kinetic energy generated by a turbine and the mass of air passing through the swept area of the blades. The derivation can be found elsewhere (e.g. Burton *et al.*, 2011), giving the power density P as:

$$P = pAv^3/2RT \quad (1)$$

where p is air pressure (assumed here to be constant at 1000 mb), v is wind speed, A is the surface area of the turbine blades, R is the

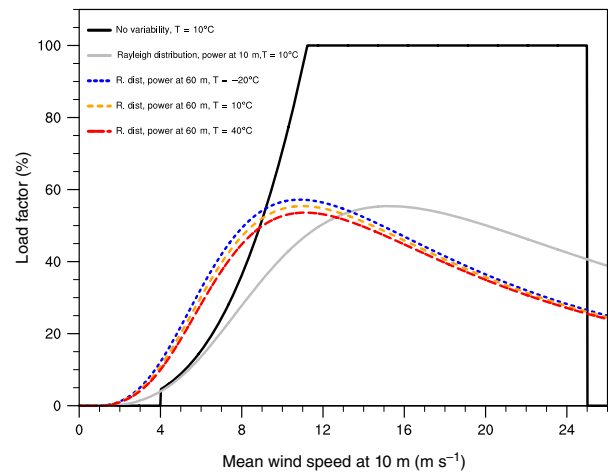


Figure 2. Simulated average load factor as a function of average wind speed, shown for different average temperatures by the dashed curves. The light solid curve indicates simulated load factor if no consideration of hub height is made, and the dark solid curve indicates the load factor corresponding to zero variability in wind (i.e. identical to the theoretical power curve). [Colour figure can be viewed at wileyonlinelibrary.com].

ideal gas constant ($287 \text{ J kg}^{-1} \text{ K}^{-1}$) and T is the air temperature in kelvins. This equation gives the rate of kinetic energy passing through a turbine; however, this is not all extractable, due to theoretical and practical limitations. The Betz law (Betz, 2013) limits the amount of extraction to around 60%, whilst design inefficiencies and practical material limitations reduce this further. The model does not explicitly represent these processes but accounts for them with a scaling factor c :

$$P = cpAv^3/2RT \quad (2)$$

which is set empirically to produce a power curve matching real turbine specifications. Power generated between cut-in and the rated speed in the model is then given by Equation (2). Above the rated speed, power equals the rated power (i.e. load factor is 100%). This gives the curve of Figure 2 (produced with a scaling factor c of 0.19).

The curve is tuned using the centre of the typical turbine operating temperature range of -20 to $40 \text{ }^\circ\text{C}$, i.e. the load factor equals 100% at the rated wind speed for temperatures of $10 \text{ }^\circ\text{C}$. Different average temperatures then give different power curves, examples of which are shown as the dashed curves in Figure 2.

2.2.2. Incorporating a wind speed distribution into the model

Wind speed is not constant and basing a power calculation purely on the average wind speed over a period can lead to errors (Rosen and Sheinman, 1994). To incorporate this variability, the Rayleigh distribution is used (Carta *et al.*, 2009). The Rayleigh distribution naturally arises when the overall magnitude of a vector is related to directional components. It assumes that the magnitudes of zonal and meridional wind speed are uncorrelated, normally distributed, have equal variance and zero mean. Note that this is not necessarily the case for the components of wind speed at all times; however, the Rayleigh distribution has been found in general to be suitable for modelling wind speeds (Pishgar-Komleh *et al.*, 2015). The distribution is given by:

$$F(x; \sigma) = \frac{x}{\sigma} \exp\left(\frac{-x^2}{2\sigma^2}\right) \quad (3)$$

where σ is the scale parameter of the distribution of x , and the mean μ of the distribution is given by:

$$\mu = \sigma\sqrt{\pi/2} \quad (4)$$

To use this distribution to map average wind speed to average power, the average wind speed is first used to calculate a value of σ from Equation (4). This value of σ corresponds to a specific Rayleigh distribution, which is then multiplied by a power curve (corresponding to a specific average temperature) to produce a load factor distribution function. This function represents the distribution of load factor across a period with a specific average speed and temperature, with wind speed variability described by a Rayleigh distribution. The average of this distribution corresponds to the average load factor expected from a period with specified conditions. By repeating this process across a range of wind speeds, a distribution can be generated which relates any average wind speed to an average load factor, giving the curves described in Figure 2. Note that if a constant wind speed is assumed, the load factor simply follows the general turbine power curve. Using this distribution means that, although the underlying data may be averaged across a period, the model incorporates information on the underlying variability across that period.

Other distributions are available; some work has suggested that a Weibull distribution may be preferable for modelling wind speeds in certain situations (Carta *et al.*, 2009). However, the Weibull distribution cannot be applied generally as it trades accuracy for generality and depends on the estimation of an extra parameter. Further development of the model may consider alternative distributions fitted to the specific wind regime under study (e.g. lognormal, inverse Gaussian; a full catalogue is given by Carta *et al.*, 2009). However, it may prove difficult to estimate an extra parameter in a seasonal climate forecasting context due to the relatively small sample size of hindcast verification years. For a baseline validation of the model here the Rayleigh distribution is preferred.

2.2.3. Consideration of height and losses

Generally the wind speed from a weather or climate model is available at a constant level of 10 m above the surface, or at the height corresponding to fixed pressure levels. It is difficult to interpolate pressure levels directly to hub height, as the physical height of the levels changes over time. Although others have followed more complex methods involving model output on several levels (Staffell and Green, 2014), the required levels are often not available from climate forecast systems. Therefore a simpler relationship between 10 m wind and wind at hub height is used here; using the wind profile power law (Burton *et al.*, 2011) wind at 10 m is transformed to 60 m (the average UK hub height, Staffell and Green, 2014). This is described by:

$$\frac{u}{u_r} = \left(\frac{z}{z_r}\right)^\alpha \quad (5)$$

where u and z are speed and height (the subscript r indicates values at a reference level) and α is an empirically derived co-efficient related to atmospheric stability, which varies depending on weather conditions. Here it is set to 0.143, corresponding to neutral stability over land (Burton *et al.*, 2011). Previous work has shown that the choice of α has an impact on hourly power simulation, although an average value of α can accurately represent long term generation (Kubik *et al.*, 2013).

Table 1. List of simulations carried out. In each case, the listed variable(s) are transformed to monthly load factor for each station using Figure 2 and taking the nearest reanalysis gridpoint to each station.

80 km ERA-Interim	15 km SeaWind II dataset
Monthly 10 m wind	Monthly 10 m wind
Daily 10 m wind	Daily 10 m wind
Daily 10 m wind and 2 m air temperature	Daily 10 m wind and 2 m air temperature
Six-hourly 10 m wind	Hourly 10 m wind
Six-hourly 10 m wind and 2 m air temperature	Hourly 10 m wind air temperature

Using a value of $\alpha = 0.143$ and mapping between 10 and 60 m gives the relationship:

$$u_{60m} = 1.29u_{10m} \quad (6)$$

This transformation of wind speed to account for height differences is made before calculating the distributions for wind speed and load factor described in Section 2.2.2. The difference between curves calculated using 10 and 60 m winds is shown by the dashed and light solid curves in Figure 2. Note that any variation of temperature with height is ignored: a dry adiabatic lapse rate of $9.8^\circ\text{C km}^{-1}$ suggests a negligible temperature change of $<1^\circ\text{C}$ between ground and hub height; the difference in temperature with height for saturated air would be lower still.

One final factor included in the model is the power losses arising from the transmission and distribution of electricity. Following previous work (Staffell and Green, 2014), a performance ratio of 0.725 is used to scale the load factor and account for these losses.

2.3. Simulating monthly load factor using reanalysis

By using the model described in Section 2.2, average 10 m wind and air temperature can be transformed to average load factor. This is carried out for reanalysis data at different temporal and spatial scales in the simulations described in Table 1. In each case data at a different temporal resolution are first transformed to load factor at that same temporal resolution and then averaged across each month for each station. This is then compared with the load factor observations described in Section 2.1.

The reanalysis dataset used is ERA-Interim (Dee *et al.*, 2011), a global atmospheric reanalysis produced at the European Centre for Medium-range Weather Forecasts (ECMWF). This product uses a large and diverse set of observations combined with the ECMWF atmospheric model to produce a gridded spatially and temporally complete dataset. The load factor simulations here based on ERA-Interim use monthly, daily and 6 h 10 m wind. In each case the load factor model is used to calculate the average load factor for each base period and from these the monthly load factor is calculated. For each of the daily and 6 h simulations two simulations are made, one in which the corresponding variations in 2 m temperature are taken into account, and one in which a constant temperature of 10°C is assumed. Creating simulations with and without the inclusion of temperature variability enables an assessment of the added value of information on temperature variability.

The spatial resolution of ERA-Interim is roughly 80 km in the horizontal (indicated in Figure 1). For each station the simulated value of load factor in the nearest grid box is taken to represent the load factor for that station. More sophisticated statistical methods are possible to move from coarse model resolution to

station values (e.g. weighted interpolation between gridpoints or methods based on neural networks informed by the underlying observed data). However, these methods rely on station data records, which for many locations are not available. No attempt was made to optimize load factor simulation using the station data available in this instance, in order to understand the optimal method of transforming gridpoint data to wind power forecasts in situations where station data are not available.

To investigate the impact of increased spatial resolution of the underlying wind and temperature data, the SW2 dataset was used. This dataset is produced by using ERA-Interim boundary conditions to drive a high resolution weather model (WRF-ARW, Menendez *et al.*, 2014). The spatial resolution of SW2 is approximately 15 km, and allows better representation of smaller scale topographic features and atmospheric processes, potentially giving more realistic values for the wind than the lower resolution driving the dataset at each station. However, although it is an improvement over 80 km, not all topographic features and processes are represented at 15 km. The SW2 grid is shown in Figure 1 by small crosses and, as with the ERA-Interim data, the load factor for each station is taken as the nearest gridpoint. SW2 is available at hourly resolution, which is used in the sub-daily simulation instead of the 6 h averages used for ERA-Interim data; a Rayleigh distribution is assumed over each hour. Note also that whilst ERA-Interim overlaps the entire load factor observation period 2002–2012, SW2 is limited to 2002–2010.

2.4. Comparing simulated and observed load factor

Simulated monthly load factor is compared to observations by calculating the bias and the Pearson's correlation across all months in the time series. Bias is calculated by subtracting average load factor from simulated load factor (to avoid confusion: the units of the bias are per cent as it is a difference between two percentages rather than a ratio relative to one of them). For the correlation, the 12 month seasonal cycle of both the observation and simulation data is calculated for each dataset separately and subtracted, in order to calculate the skill of predicting load factor variations around this relatively well defined cycle. Significance values for correlations at the 95% level are based on the number of months of observations for each station and are calculated using a *t* test (Wilks, 2011).

A baseline simulation is used as a benchmark for assessment of the added value of the load factor model. The baseline is calculated by using untransformed monthly 10 m ERA-Interim winds as a predictor of load factor, calculating the correlation of the wind directly with load factor observations. This can be interpreted as the least sophisticated method of estimating monthly load factor, using wind information only at the lowest temporal resolution and making no transformation. The significance of correlation differences against the baseline simulation is calculated by using the Fisher *r*-to-*z* transformation (Wilks, 2011).

3. Results

Results for ERA-Interim are shown in Figure 3 for simulations based on monthly mean wind and daily wind (it should be re-emphasized here that although the underlying data comprise averages across the respective period, variability is included through the use of a Rayleigh distribution, described in Section 2.3). Average observed load factor is shown in the top left plot. Below this, the average simulated load factor is shown as a difference from the observed, for simulations based on monthly mean wind and daily mean wind. The general spatial

pattern of simulated load factor is consistent with observations, with the largest simulated and observed values near the coast in northern Scotland, Wales and Cornwall (not shown). However, overall the simulations underestimate the load factor. The highest discrepancy is for Northern Ireland and Wales, where simulated load factor is too low by 10–15%. Areas in the southeast have the lowest bias, with simulations only around 5% lower than the observations.

Where monthly wind speed is transformed directly to monthly load factor a large bias is present: this method produces values of load factor lower than 10% on average. This is below the observed values of around 15–35%, resulting in a negative load factor bias of up to 30%. By using daily and sub-daily data this bias is greatly reduced, bringing the simulated load factor to around 15–20% on average. There is no difference in the bias when 6 h averages are used, nor is there any improvement when temperature variations are incorporated into the calculation (not shown).

The correlation of a baseline simulation with observations (with seasonal cycle removed from simulations and observations) is shown in the top right panel of Figure 3. The baseline simulation used here is where 10 m ERA-Interim winds correlated directly with load factor observations (without being transformed to load factor themselves). Differences from this baseline are shown below this, for load factor simulations based on monthly and daily winds. Baseline correlations are significant at the 95% level and range between 0.4 and 0.7, with the highest correlations seen inland and the lowest in coastal areas, particularly in northern Scotland, the east coast of England and in the southwest.

Using monthly mean wind transformed to load factor does not improve from the baseline, and in many cases reduces the correlation (although generally the difference is not significant at the 95% level). The simulation based on daily mean winds, however, does give significant improvement to the baseline correlation: most correlations are 0.1–0.2 higher than the baseline, ranging mostly between 0.6 and 0.9. This indicates that the cumulative power generated across a month is dependent on the day-to-day variability in wind speed and fluctuations do not average out over time due to the nonlinear power curve. For a small number of inland stations, using daily data improves correlations significantly from the baseline; these stations are mostly inland where correlations are already high. The largest changes arise in coastal areas, where correlations are improved by around 0.3–0.4. The station with the largest overall improvement is in the Shetland Islands, where the correlation co-efficient improves from around 0.3 using the baseline method to 0.7. Results for 6 h wind are no different to those for daily wind, and incorporating temperature into the calculation does not impact the results (not shown).

Figure 4 shows the results when the SW2 dataset is used. Broadly the same conclusions can be drawn about these simulations as those based on ERA-Interim: a poor performance when the load factor is based on monthly wind and an improvement in correlation from the baseline when daily mean winds are used, which is not bettered by using sub-daily (in this case, hourly) reanalysis or by incorporating temperature fluctuations. Note that in Figure 4 the same baseline is used as in Figure 3, i.e. the correlation between monthly ERA-Interim winds and load factor observations.

There are three main differences between the two figures. First, the mean biases are very slightly reduced for SW2 and the hourly data reduce this further (although this is a small change). Second, a simulated load factor based on SW2 monthly means reduces the correlation from the baseline by a more significant amount than a load factor based on monthly ERA-Interim winds. Finally, the

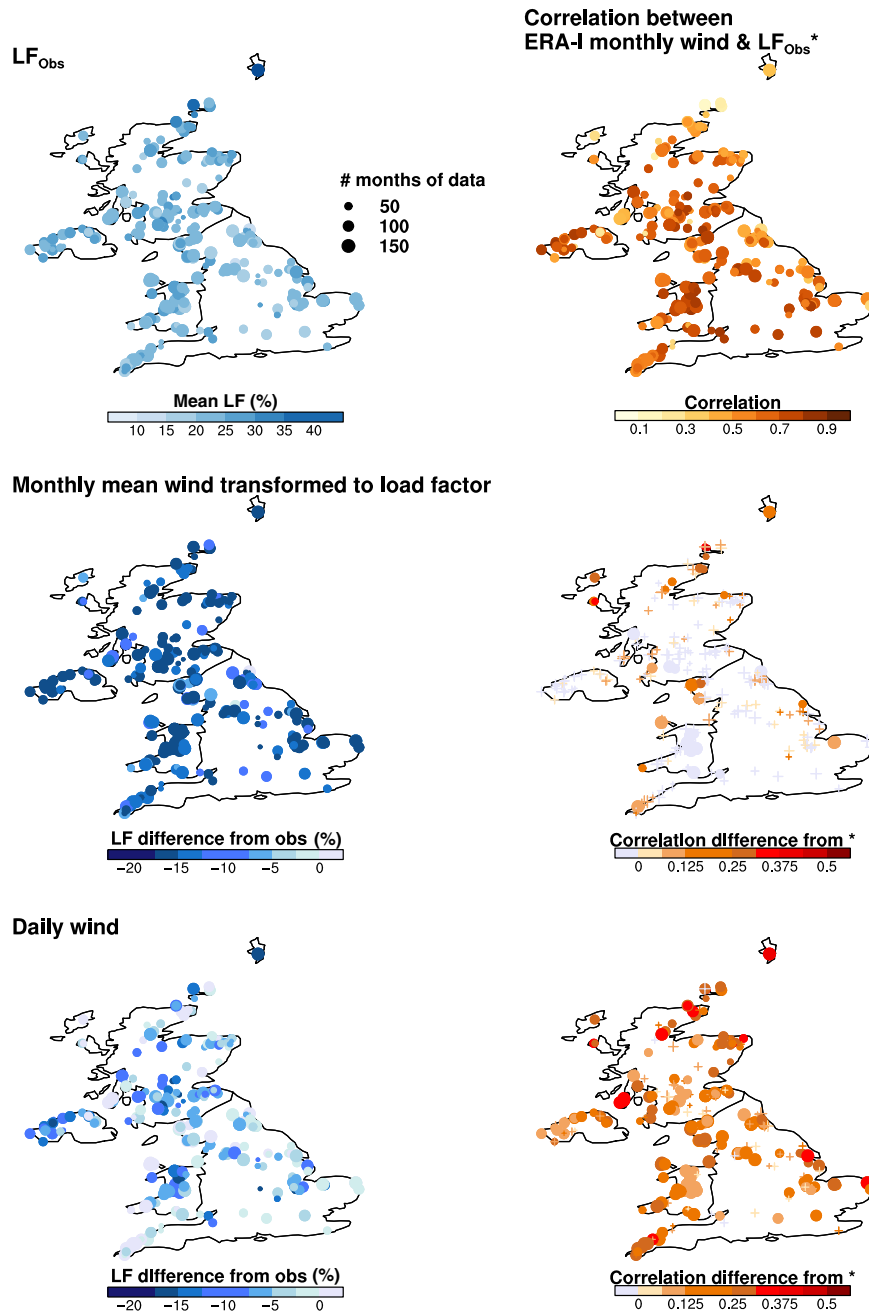


Figure 3. Results for ERA-Interim across all months with observations in the period 2002–2012. The top row shows the mean load factor (LF) for each station from observations and the baseline correlation (monthly 10 m ERA-Interim wind vs load factor observations). Below this is shown the bias in load factor and difference of correlation from baseline for the monthly 10 m wind and daily 10 m wind simulations (all other simulations show little difference from the daily wind simulations and so are omitted for clarity). The number of observations for each station is indicated by the size of the circles, and in correlation plots the points below 95% significance are shown as crosses. [Colour figure can be viewed at wileyonlinelibrary.com].

SW2 daily wind correlations have more spatial variability than those of ERA-Interim. In some regions there is more improvement over the baseline, which is the case near the coast, particularly in Cornwall, Wales and north Scotland. However, there are also reductions from the baseline correlation; some stations show a higher correlation of observed load factor against monthly ERA-Interim wind than they do against simulated load factor transformed from downscaled daily winds (although generally these correlation differences are not significant).

The results for all experiments are summarized as a distribution across all stations in Figures 5 and 6. These show how both the bias and the correlation of load factor are improved using daily

wind data instead of monthly average data alone, indicating that for reasonable estimates of load factor higher temporal resolution than monthly average wind speed is necessary. At the same time, all methods result in an average bias, indicating that some bias correction in an operational forecast setting is necessary. Although the median of the bias for the sub-daily averages is slightly higher than daily averages for ERA-Interim in general the distribution is unchanged and there is no improvement in the correlations when using sub-daily data. It is also clear that the impact of incorporating temperature variations is very small. Differences between ERA-Interim and SW2 results are small in terms of bias although Figure 6 reveals that the SW2-based

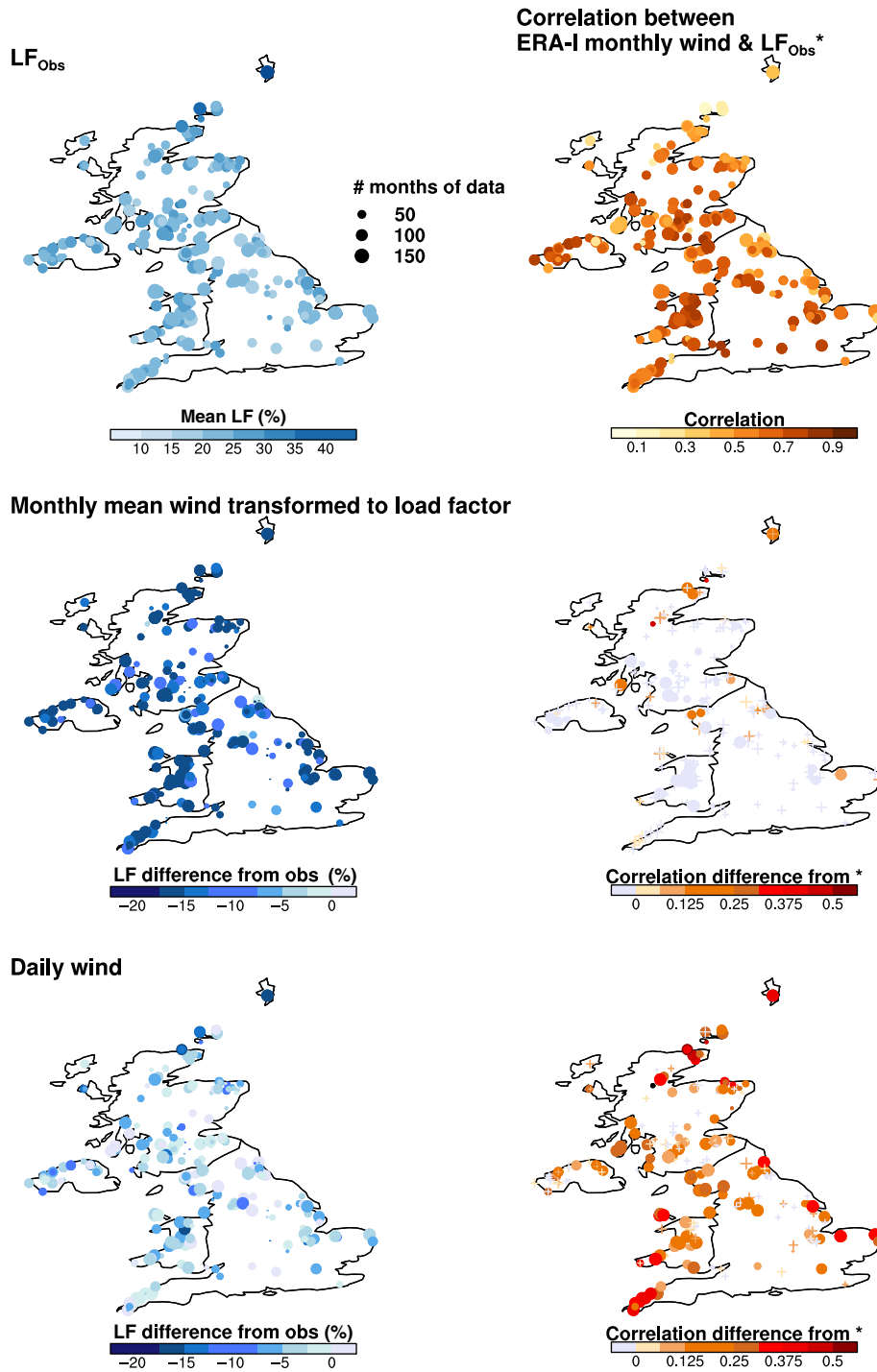


Figure 4. As Figure 3 for the downscaled SeaWind II dataset reanalysis. [Colour figure can be viewed at wileyonlinelibrary.com].

load factor correlations are slightly shifted toward more positive values compared to ERA-Interim; for load factor simulation based on daily wind some stations show negative correlation to ERA-Interim whilst all correlations for SW2 are positive.

4. Discussion and conclusions

The results show that the optimal simulation of load factor is gained by using the model to transform daily wind speed to load factor. This gives a significant improvement over the baseline of using monthly wind as a proxy for load factor (the

median correlation across stations is 0.77 when using daily data compared to the median of the baseline of 0.60). There is clearly significant day-to-day variability in wind speed, and this result demonstrates that these fluctuations do not average out in the long term: it is not the case that a month of low wind speed variability will output the same power as a month of high variability when it is transformed by the nonlinear power curve, even if the monthly average speed is identical.

Using the methodology described in this study to transform mean monthly wind to load factor does not improve over simply using the mean monthly wind as a predictor of load factor. Therefore, in a situation where only monthly climate model

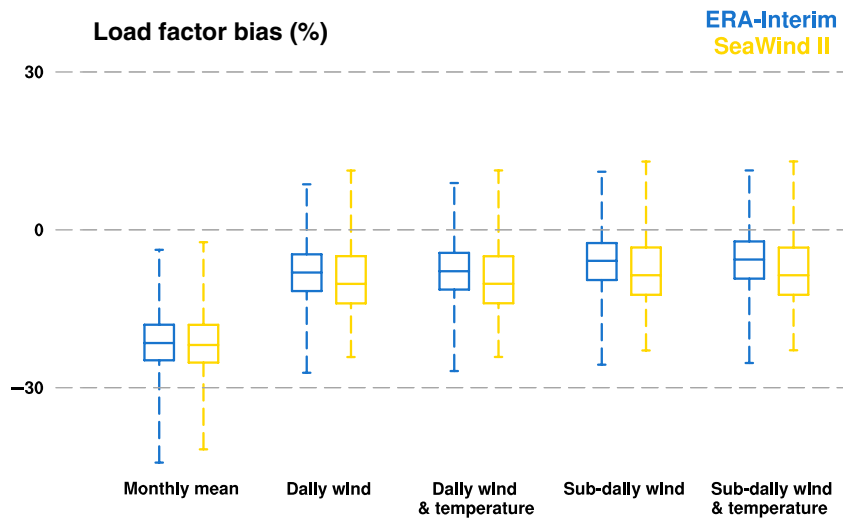


Figure 5. Distribution of the average bias for all stations, for each method of load factor described in Table 1. Sub-daily refers to 6 h data for ERA-Interim and hourly data from SeaWind II dataset. The extent of the whiskers indicates the range of the bias across all stations, whilst the box indicates the interquartile range (25th–75th percentile) and the central horizontal line indicates the median bias of all stations. [Colour figure can be viewed at wileyonlinelibrary.com].

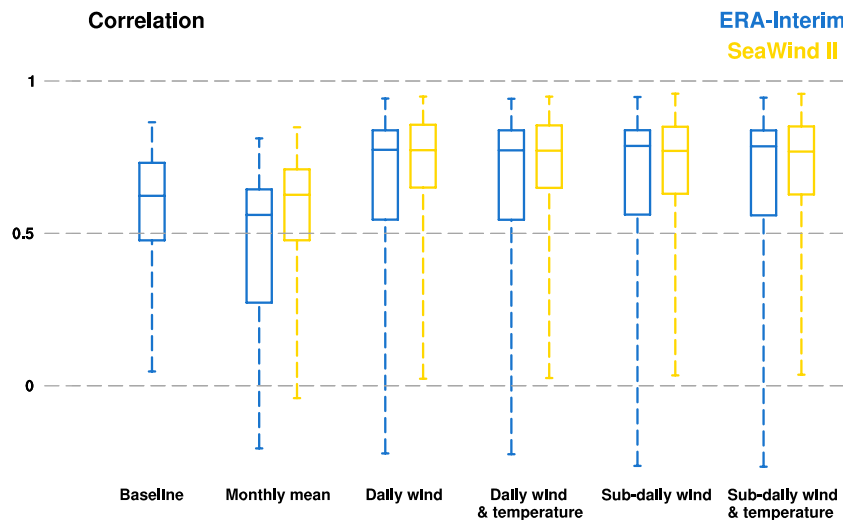


Figure 6. As Figure 5 for correlation against the observational data. Also shown is the distribution of baseline correlations for all stations, which for each station is the correlation of monthly ERA-Interim 10 m wind at the nearest gridpoint against the observed load factor for that station. [Colour figure can be viewed at wileyonlinelibrary.com].

output is available (or the forecast sub-monthly variability has no skill), the optimal forecast would be a simple transformation of monthly average 10 m winds into load factor.

There is no significant improvement in correlations observed by basing the simulation on sub-daily averages, nor is there any improvement by incorporating temperature-based air density variations into the simulation. The fact that sub-daily averages do not give improved predictions does not mean that using actual observed minute-to-minute variations would not lead to a better simulation of load factor. However, monthly and seasonal forecast models generally provide 6 h values at best and it is unlikely that these would be more skilful than a monthly mean estimate.

Dynamically downscaling data to higher spatial resolution can add value to driving reanalysis data by more clearly representing complex variations in topography and processes (e.g. Gula and Peltier, 2012). Improvements are seen here for simulated load

factor based on the downscaled SW2 data, particularly for stations near the coast, suggesting that the winds taken from this dataset are more accurate than those from the lower resolution ERA-Interim. However, the downscaled data do not give a uniform improvement; for some stations the correlations with observations are lower for the downscaled data. There are also known biases in the driving reanalysis winds: in general these are too low, at least for the SW2 data (Menendez *et al.*, 2014). It is likely that using winds from the reanalysis that are too weak is a primary reason for the negative load factor bias. Several simple bias corrections were attempted before calculating load factor, but these did not improve results.

The method of interpolation of gridded data to individual stations used here is relatively crude: the nearest gridpoint to each station is taken. More sophisticated methods of interpolation are possible. In an operational context the ideal situation would be to use observed daily wind time series from a station to

downscale large scale data statistically to individual stations. Since there is high spatial variability in wind speeds, this is likely to give optimal wind and load factor simulation. Relatively large biases in load factor are seen in the current study; inclusion of local effects and model tuning may reduce these. However, the results indicate that in a forecasting setting some bias correction post-processing may be necessary to calibrate forecast output. Statistical downscaling was not attempted in the current study due to the absence of individual daily station data. Besides, as mentioned in Section 1, downscaling, like most post-processing methods, introduces the risk of reducing the already low skill of climate forecasts.

The model described here is a starting point. Development may proceed in several directions: improving the hub height transformation with a more complex atmospheric stability-based relationship, and incorporating stochastic departures from the power curve from turbulent effects, shown to be important for power production (Hedevang, 2014). Alternative distributions may be explored; the Rayleigh distribution was chosen for its suitability and the need for only one parameter. It may be found that other distributions are more suitable for specific regions and wind regimes, although this requires work to estimate the optimal parameters, which may take a different value for different locations even within the United Kingdom, let alone for other regions of the world. Tuning to perform well for the United Kingdom has not been attempted and would be desirable in an operational forecasting sense. However, the model without tuning is a baseline against which improvements or alternatives might be measured.

It has been shown that daily data are as good a base for simulating monthly averages as sub-daily average data are. However, the question of the lowest temporal resolution necessary to give significant improvement over a basic transform of monthly average wind speed is open. To pose the question another way: is the correlation improvement over the baseline seen here for calculations based on daily average data maintained when the calculation is based upon 2 day average winds, 5 day averages or 10 day averages? At what temporal resolution does the correlation approach the baseline?

This is an important idea to understand if monthly-to-seasonal forecasts are to be used to make load factor predictions. Because of the nature of seasonal forecasts, with predictability coming from low frequency variations in climatic processes, it is the case that monthly (and possibly weekly) means have more skill than daily averages. If it turns out to be the case that simulated monthly load factor is just as good when based on weekly as it is when based on daily data, it may be optimal to transform monthly-to-seasonal forecasts to a load factor forecast based on the more skilful weekly means rather than daily averages. Alternatively if no forecast skill is found for weekly or daily variability then it may be more sensible to base a forecast on monthly winds alone, despite the fact that using monthly averages loses information about daily variability: the improvement shown here from using model output of daily average data instead of monthly averages will only translate to a forecasting scenario if there is some predictable information in the daily variability. Considerations such as these may have the side effect of helping to reduce data traffic and storage, a major issue with the new high resolution seasonal forecast systems that are being developed.

The interaction of monthly-to-seasonal forecasting research with the wind energy industry is an emerging research area. It is not clear yet to what extent these long range forecasts will ultimately find use in this field; however, they have already proved useful in other industries. A key development in the

future is to use seasonal hindcast data to examine the long term forecast accuracy of seasonal wind power forecasts and work is currently under way to examine this as part of the SPECS and EUPORIAS projects. As the forecasts themselves continue to improve, this research, dialogue and collaboration will aid users hoping to exploit these products for the benefit of the industry and society.

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