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Evaluating the accuracy of CFSR reanalysis hourly wind speed forecasts for the UK, using in situ measurements and geographical information

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A R T I C L E I N F O

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A B S T R A C T

Climate data can be used in simulations to estimate the output of wind turbines in locations where meteorological observations are not available. We perform the most comprehensive evaluation of the NCEP CFSR reanalysis model hourly wind speed hindcasts to date, and the first for the UK, by correlating the data against 264 onshore and 12 offshore synoptic weather stations, over a period of 30 years. The correlation of CFSR data to in situ measurements is similar to alternative approaches used in other studies both onshore and offshore. We investigate the impact of the topography, land use and mean wind speed on the onshore locations for the first time. The analysis of these spatial factors shows that CFSR represents the variety of terrain over UK well, and that the worst correlated sites are those at the highest elevations.

1. Introduction

Medium-term European Union (EU) energy policy requires 20% of primary energy to be supplied by renewables and a 20% reduction in greenhouse gas emissions from 1990 levels by 2020 (an agreement colloquially known as EU 202020). The renewable target is not evenly split between member states; the UK's target is to supply 15% of energy demand from renewable resources by 2020, which represents a substantial increase on the 4% actual contribution of renewables in 2012 [1]. Currently, renewable electricity is the largest contributor to these targets; capacity grew by 38% to 19.5 GW between July 2012 and June 2013. Wind capacity increased onshore by 1.6 GW–7 GW and offshore by 41%–3.5 GW in the same period [2]. Fig. 1 illustrates the growth of wind capacity, onshore and offshore and summarises a number of medium term forecasts on wind capacity. The spread of values, steadily increasing in magnitude, demonstrates that beyond the next several years there is a great deal of uncertainty about the extent to which wind will contribute to the UK energy mix. The onshore forecasts appear low compared to the previous installed capacity, because some of the forecasts were made before this capacity was installed, which further illustrates the difficulty of predicting future capacity. According to these scenarios, the largest predicted combined capacity by 2020 may be more than 50 GW and the smallest less than 20 GW.

One of the key challenges when introducing large wind capacities is to cope with varying intermittent generation. As wind speeds vary across the UK and are different onshore and offshore, the level of intermittency for the electricity system depends on the location of wind farms. Wind speed is influenced by factors that change over small spatial resolutions such as terrain, elevation and buildings, as well as air density and other weather influences [7]. These changes can result in local measured differences of up to an order of magnitude [8]. The same factors influence changes in wind speed over all temporal resolutions from seconds (e.g. gusts due to building driven wind tunnels) to decades (e.g. changes in weather and climate), driving intermittent generation. The varied terrain in the UK means that there is considerable spatial diversity in this intermittency.

Historically, wind capacity in the UK has been small, particularly when compared to feasible future scenarios (Fig. 1). Data from operational wind farms in the UK is only available over a short time period, which may not include low frequency climate events such as extended periods of high or low wind. It is also unlikely that the wind speeds experienced by existing capacity are as diverse as those that will be experienced by future wind farm fleets, particularly with the addition of offshore capacity. Consequently, it is

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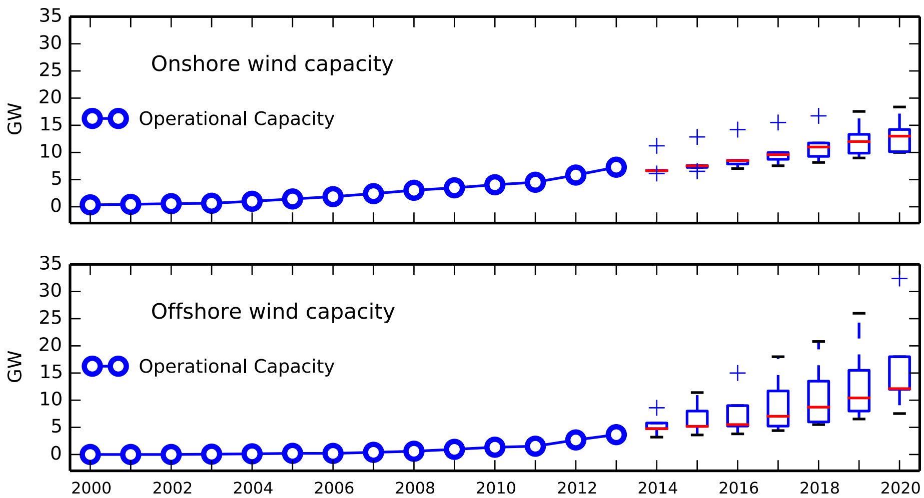

Fig. 1. Installed and projected wind capacity, derived from data on installed capacity from DECC [3] and forecasts from DECC. [4], National Grid [5], Renewables Advisory Board and Douglas Westwood [6]. The boxplots represent the forecasts, the central line is the median; and the edges of the box are the 75th and 25th percentile. The whiskers are the most extreme points, the gap between the dash and the whiskers is due to the fixed length of the dash, the pluses are outliers.

difficult to extrapolate current generation trends to future deployments, especially as there is little data available on generation at a disaggregated level. An alternative approach is to estimate generation using wind speed data from either weather station observations or from weather or climate models, for both regional planning and at the scale of an individual wind farm or turbine.

1.1. Estimating potential wind generation through simulation

1.1.1. Onshore, using weather station data

Some studies estimate the spatiotemporal variation of wind generation across large onshore areas by interpolating historical measurements from synoptic weather stations. Weather stations measure wind speed at a height of 10 m and several statistical methods have been developed to estimate wind speed at the turbine height, which is typically assumed to be 80 m [see Ref. [9]]. Electricity generation from a turbine can then be estimated from these data using a power curve provided by turbine manufacturers (e.g. Fig. 2). In the UK, this method has been used to investigate the impacts of intermittency [10–12], and to explore scenarios of national output [13,14] using synoptic MIDAS[1] data [15]. MIDAS wind speed observations are provided as hourly mean values at the most temporally disaggregated level. This represents a compromise compared to using measured turbine output; these mean values have been shown to vary between ± 30 to 40% when compared to minutely values, meaning that some of the intermittency is smoothed [8].

The UK network of synoptic weather stations is spatially diverse and, onshore, appears to be spatially comprehensive (Fig. 3). Attempts to assess the wind resource across the UK, [e.g [10]], have assumed that the wind harnessed by farms would be represented by a subset of these stations; however, station networks are generally biased towards populated areas, where wind farms cannot be built, and towards low lying areas that experience lower wind speeds [16]. Moreover, the land uses at many weather stations are unsuitable for the location of turbines, for example urban areas or wetlands. It is also possible that the locations which *are* suitable for wind farm development are not used for other reasons, such as planning restrictions or low wind speeds. There is no existing research that explores the impact of synoptic station location with respect to either wind turbine simulation or evaluation of other wind datasets.

Alongside these spatial issues, MIDAS, in common with all weather observation datasets, has gaps and duplications. Data are also provided at multiple temporal resolutions, with repeated time steps and apparently erroneous values. These discrepancies must be filtered in order to obtain a continuous dataset.

1.1.2. Onshore, using reanalysis data

Some researchers have looked for alternative data sources to overcome these disadvantages. One option is climate reanalysis, which provides a global time series for a range of climate variables on a gridded basis at a number of different altitudes. All of the latest generation of climate reanalyses utilise a core of conventional data, including wind speed, temperature, moisture and air pressure, as well as other data such as precipitation. Data sources change owing to new technologies being introduced; current platforms include, but are not limited to, radiosonde, satellite, buoy, aircraft and ship reports [17]. Data are run through a global circulation model (GCM)

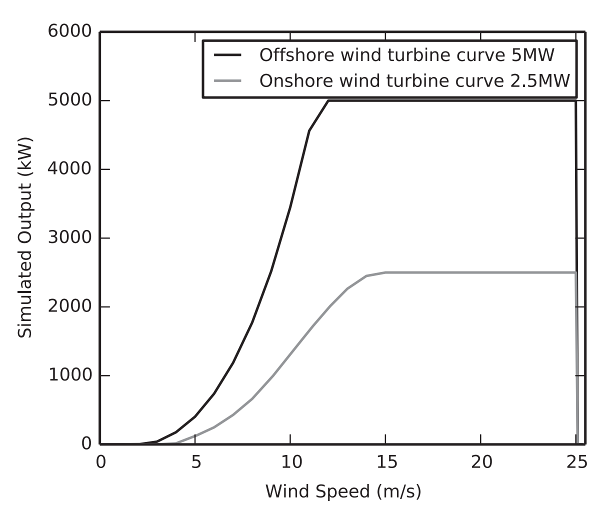

Fig. 2. Wind turbine curves used for simulation; above 25 m/s there is no generation as turbines are designed to cut-out to avoid damage from excessive vibration.

[1] MIDAS is the UK Met Office Integrated Data Archive System.

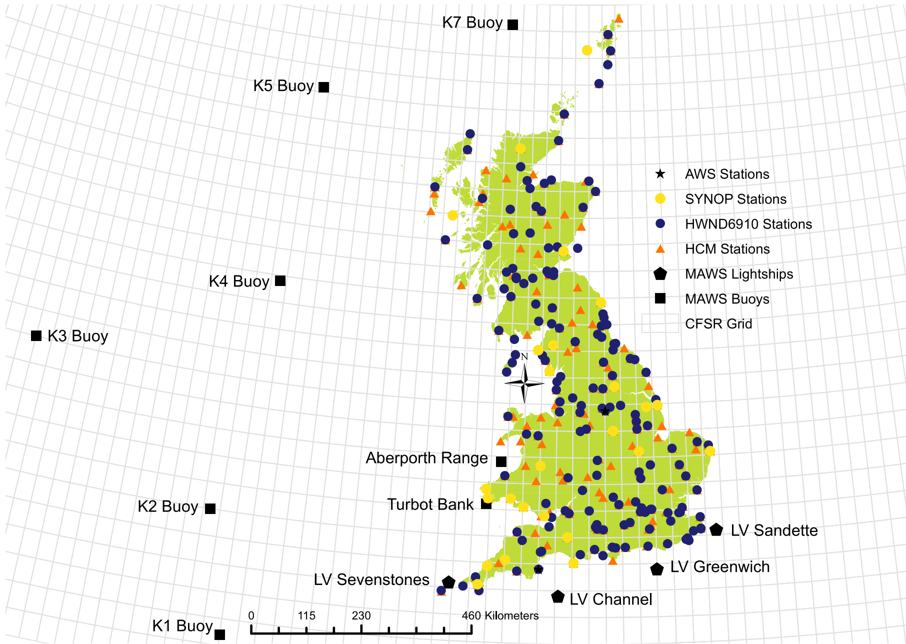

Fig. 3. Locations of MIDAS stations with respect to CFSR Grid.

in hindsight. The convention is to produce an analysis of this model every 6 h. Two climate reanalysis products are available that provide forecasts from these 6-hourly analyses at an hourly resolution (the same as station data); NASA – MERRA (Modern Era Retrospective Analysis for Research and Applications) [18] and NCEP – CFSR (National Centre for Climate Prediction Climate Forecast System Reanalysis) [19]. CFSR and MERRA are based on the same set of observations and use similar models to extrapolate these data over space and time, to the same temporal scope. CFSR is provided at a marginally finer spatial resolution ($0.5° \times 0.5°$ vs. $0.5°$ vs. $0.66°$). Despite this, Decker, et al. [20] found that, globally, MERRA provides more accurate hourly wind speed data than CFSR in a comparison in situ measurements using flux tower observations.

The hourly resolution of MERRA and CFSR allow these datasets to capture extremes, such as storm peaks, which other reanalyses may miss; e.g. NCEP FNL (Final), ECMWF ERA-Interim (European Centre for Medium Range Weather Forecasts – European Reanalysis) and NCEP-NCAR (National Centre for Atmospheric Research) which all provide data at 6 hourly intervals [21]. These datasets are also provided at a coarser spatial resolution: 1°, 0.7° and 2.5° respectively. Variability at a smaller temporal resolution (e.g. wind gusts) will not be captured by any dataset that provides hourly values; this requires either downscaling or use of other data from MIDAS (such as daily maximum gust speed, analysis of which has been carried out by Hewston and Dorling [22]). Reanalysis GCM's operate at a temporal resolution of around 20 min, but results are always aggregated over longer periods.

Recent studies simulating UK wind turbine output from reanalysis data use only MERRA data [23,24] but neither study justifies this model choice over CFSR. The NCEP-NCAR reanalysis model was used to characterise the onshore wind resource, and for wind turbine simulation in northern Europe [25] and the USA [26]. Another alternative method is to downscale reanalysis data, which reduces the spatial resolution of the gridded data and takes into account influences on wind speed at the local scale. This can be done using spatial statistical methods such as interpolation from nearby data [e.g. [23]]. Alternatively, it can be done using mesoscale modelling which integrates topographic data into more complex models, using reanalysis or analysis data to provide boundary data [e.g. [27]]. Both of these methods have provided very accurate results, as described below. The drawback of downscaling, particularly mesoscale modelling, is that it is extremely computationally intensive and therefore the resulting data often covers a shorter period of time than raw reanalysis data; this can counteract one of the benefits of using of reanalysis wind speeds.

1.1.3. *Estimating offshore wind generation potential*

There are very few stations that record UK offshore wind speed (Fig. 3) and no previous studies have simulated offshore UK turbine output using raw reanalysis data. However, Hawkins, et al. [27] have simulated offshore UK output using mesoscale modelling, with the NCEP FNL model providing boundary data to the Weather Research and Forecasting (WRF) model.

1.2. *Review of the use of reanalyses for wind turbine simulation*

Reanalysis models can be used to estimate wind speed at any onshore or offshore UK location as they produce data for the entire planet. These simulations can be performed across a large spatial area without the drawbacks of irregular and discontinuous data that are encountered when using synoptic weather station data. However, several problems remain. First, the wind speed is homogeneous across the whole of a grid square, which onshore may incorporate variable terrain that can alter wind speed. Second, data, as with MIDAS, are provided at 10 m above the surface (offshore buoy data at 6 m) and therefore reflect the state of the climate at the Earth's surface and are subject to the influences surrounding the station (e.g. topography), which may not be evident at turbine height. MERRA is the exception, where wind speed data is also provided at 50 m.

Several studies have assessed the skill of different reanalysis and mesoscale models at estimating the wind speed in different countries, those considering onshore areas are summarised in Table 1 and those considering offshore areas are summarised in Table 2. Notably, none of the studies examining onshore areas have considered the importance of topography and land use. Studies

Table 1
Summary of studies evaluating the accuracy of reanalysis data, onshore. Blanks indicate repeats or that the metric is not used.

		Author	Spatial		Temporal		Data	Reference	Correlated to	Correlation		RMSE	Bias (m/s)
			Scope	Resolution (degrees)	Scope	Resolution				Pr	R^2		
Onshore	Wind Speed	Liléo and Petrik [31]	Sweden	0.5	Length of mast data (1-30 years)	Hourly	NCEP–CFSR	Saha et al. [19]	25 meteorological and telecommunication masts	0.79–0.87 (mean 0.83)			
				0.6			NASA–MERRA	Rienecker et al. [18]		0.75–0.89 (mean 0.84)			
				2.5		6 h	NCEP–NCAR	Kanamitsu et al. [52]		0.64–0.83 (mean 0.73)			
		Hawkins et al. [27]	UK	0.1	10 years	6 h	NCEP – FNL + WRF	Skamarock et al. [42]	220 MIDAS stations		0.96	0.44 m/s	0.02
		Kiss et al. [41]	Hungary	0.75	2.5 years	6 h	ECMWF ERA-interim	Simmons et al. [43]	2 grid points to 2 towers	0.73–0.77			
		Staffell and Green [24]	UK	Site	20 years	Hourly	Downscaled MERRA		157 MIDAS stations				5.5 ± 1.6
		Shravan Kumar and Anandan [34]	India	2.5	1 year	6 h	NCEP–NCAR		NARL Doppler Sodar	0.56–0.78			
		Bao and Zhang [30]	Tibet	Site	4 months	6 h	NCEP–CFSR		Radiosondes at 11 stations	U = 0.93, V = 0.86			~1
							NCEP–NCAR			U = 0.9, V = 0.83			
							ERA–interim			U = 0.93, V = 0.89			
							ERA 40	Uppala et al. [40]		U = 0.93, V = 0.88			
		Lledó et al. [32]	Europe	2.5	Unknown	Daily	NCEP–NCAR		37 "Tall Towers"		0.64		
				0.5			NCEP–CFSR				0.74		
				0.75			ERA –interim				0.73		
				0.6			NASA–MERRA				0.66		
		Carvalho et al [29]	Portugal	0.083	1 year	Hourly	NCAR(R2) + WRF		13 stations	0.69		2.49	0.49
							ERA – interim + WRF			0.79		2.1	0.34
							CFSR + WRF			0.78		2.19	0.47
							MERRA + WRF			0.76		2.26	0.49
							NCEP – FNL + WRF			0.77		2.17	0.31
							NCEP – GFS + WRF			0.78		2.13	0.3
		Liléo et al. [33]	Norway, Denmark, Sweden	0.75	1–8 years	6 h	ERA–interim		18 stations and 24 masts at turbine sites	Median 0.8			
				0.5		Hourly	CFSR			Median 0.8			
				0.6		Hourly	MERRA			Median 0.85			
				0.1		Hourly	ERA interim + WRF			Median 0.83			
				0.1		Hourly	FNL + WRF			Median 0.83			
	Simulated	Kubik et al. [23]	Northern Ireland	0.1	1 year	Hourly	MERRA		Measured generation data	0.91		12%	
				Site			MIDAS	UKMO [15]		0.88		14%	
		Staffell and Green [24]	UK	Site	10 years	Monthly	Downscaled MERRA		Renewable Obligation Certificates		0.84		

Table 2
Summary of studies evaluating the accuracy of reanalysis data, offshore.

	Author	Spatial		Temporal		Data	Reference Correlated to	Correlation		RMSE	Bias (m/s)
		Scope	Resolution (degrees)	Scope	Resolution			Pr	R^2		
Offshore Wind Speed	Hawkins et al. [27]	UK	0.1	10 years	6 h	NCEP – FNL + WRF	Buoys, lightships, platforms		0.89	1.33 m/s	−0.02
	Menendez et al. [39]	Spain	15km	20 years	Daily	ECMWF ERA-interim + WRF	Buoys	0.7–0.9			0–1
	Winterfeldt et al. [35]	North Sea	2.5	<10 years	1 h	NCEP–NCAR	Buoys, lightships, platforms			2.7 m/s	
	Staffell and Green [24]	UK	Site	20 years	Hourly	Downscaled MERRA	Buoys, lightships, platforms				5.5 ± 1.6
	Carvalho et al. [28]	Iberian Peninsula	0.083	10 Months	Hourly	NCAR(R2) + WRF	5 Buoys	0.76		2.43	0.34
						ERA – interim + WRF		0.88		1.85	0.48
						CFSR + WRF		0.87		1.94	0.6
						MERRA + WRF		0.86		2.01	0.59
						NCEP – FNL + WRF		0.87		1.89	0.53
						NCEP – GFS + WRF		0.88		1.89	0.56
	Carvalho et al. [38]	Iberian Peninsula	2.5	1 year	6 h	NCEP–NCAR (R2)	5 Buoys		0.64	3.43	0.87
			0.75		6 h	ERA–interim			0.78	2.45	0.58
			0.5		Hourly	CFSR			0.87	1.85	0.16
			0.6		Hourly	MERRA			0.87	1.93	0.52
			1		6 h	NCEP–FNL			0.85	2.3	0.98
			0.5		6 h	NCEP–GFS			0.87	1.89	0.22
	Stopa and Cheung [36]	Peru	0.5	1979–2009	Hourly	CFSR	1 Buoy	0.81		1.37	6.14%
		Hawaii					4 Buoys	0.86		1.37	−3.90%
		Gulf of Mexico					5 Buoys	0.87		1.52	0.42%
		NW Atlantic					5 Buoys	0.89		1.73	4.23%
		Alaska					5 Buoys	0.91		1.7	3.90%
		NE Pacific					5 Buoys	0.91		1.5	2.38%
	Chawla et al. [37]	Atlantic/Gulf of Mexico	0.5	1979–2009	Hourly	CFSR	12 Buoys		0.84	1.74	-0.03
		Pacific/Hawaii					10 Buoys		0.87	1.49	−0.21
Sim	Hawkins et al. [27]	UK	0.1	10 Years	Monthly	NCEP – FNL + WRF	Renewable Obligation Certificates		0.94	1.33	0.05

which evaluate the accuracy of wind generation estimates covering GB using reanalysis or reanalysis driven simulations are also summarised in the tables. Where the spatial resolution of the study is referred to as site, wind speed data has been interpolated to the in situ location, otherwise the resolution refers to the grid square, with the nearest grid point value used for comparison. There are a number of studies which evaluate the accuracy of mesoscale modelling output using reanalysis data for boundary conditions outside of the UK. Since this type of dataset and the geographical scope are not the focus of this study, only those studies which consider those results alongside raw reanalysis data are included in the review, with the exception of Carvalho et al. [28] and Carvalho et al. [29] who conduct a comparative analysis of WRF outputs driven by different reanalyses and analyses.

A limited number of metrics are used to evaluate the correlation between both wind speed and simulated output time series in these studies. Root Means Square Error (RMSE) and a correlation coefficient (either Pearson's R or R^2) are the most commonly used; bias is also used, predominantly in offshore studies. The results found by Decker et al. [20] are not included in the table as a ranking system is used in the place of statistics; this means that the findings cannot be compared to the rest of the studies. Correlation metrics for simulated data cannot be directly compared to those for wind speed values as simulation is subject to a number of uncertainties that affect correlation, including error introduced through height correction, scaling factors and the simulation method itself.

1.2.1. Onshore

Table 1 demonstrates that raw reanalysis wind speed data is reasonably close to onshore in situ measurements, with Pearson's R between 0.56 and 0.89. Bao and Zhang [30] describe larger correlation coefficients; this may be a result of considering the U and V components of wind separately. However, the difference may also be due to topography, as the research was carried out on the Tibetan plateau, or because of the in situ measurements as radiosondes are used (multiple pressure levels are examined but only those closest to the ground (100 hPa) are described in the table). Liléo and Petrik [31] have demonstrated that the finer spatial resolution models, CFSR and MERRA, provide more accurate data than the coarser resolution NCEP – NCAR model for Sweden, although the different temporal resolutions mean that the results are not directly comparable. Bao and Zhang harmonise their analysis to 6 h for all datasets and find that the finer spatial resolution datasets perform marginally better. Lledó et al. [32] find that CFSR and ERA – interim perform better than the lower resolution NCAR, but MERRA only performs marginally better. Liléo et al. [33] are the only authors evaluating multiple datasets to find that the correlation between CFSR and hourly synoptic weather station measurements is worse than MERRA, as Decker et al. [20] found when comparing them against flux tower observations. Even in extremely mountainous terrain in India, good correlations between the NCEP – NCAR reanalysis models and in situ measurements have been observed [34].

Evaluation of the output of mesoscale models has been performed onshore by several authors. Hawkins et al. [27] show that using NCEP FNL to provide boundary conditions for WRF produces a very good correlation with UK in situ measurements ($R^2 = 0.96$) and a low RMSE (0.44 m/s), when compared against a long time series of data from a large number of onshore stations. Liléo et al. [33] demonstrate similarly accurate results from mesoscale data; however these are only marginally more accurate than those found when using raw CFSR or ERA – interim data in the same locations and are worse than raw MERRA data. Carvalho et al. [29] show that the correlation coefficients for mesoscale models are similar in magnitude to those found for raw reanalysis data. Interestingly the range of metrics used show that using an older, coarser resolution reanalysis dataset (ERA-interim and the FNL and GFS analyses) results in the most accurate of the mesoscale models. Using CFSR data as an input produces marginally superior results compared to using MERRA.

With respect to the use of this data for the estimation of wind generation, Kubik, et al. [23] bilinearly interpolate MERRA data to MIDAS station sites in Northern Ireland to the nearest 0.1°. They then simulate total installed capacity using both in situ and reanalysis data, at a given capacity factor, assuming that this capacity is evenly distributed across these sites, and using the simulation method described above. While the comparison with measured generation data demonstrates that both datasets result in a good correlation, downscaled reanalysis data is marginally more accurate (Table 1). Interestingly the analysis performed by Staffell and Green [24] shows that downscaled data achieves a similar correlation, although R^2 is used rather than R and the evaluation data is considerably more temporally aggregated.

1.2.2. Offshore

Offshore wind speed, especially in areas that are not close to land, is not subject to many of the spatial factors that influence changes in wind speed onshore; as a result is likely to be more homogenous over larger areas. This means that it is potentially easier to produce accurate offshore wind data using a reanalysis. The results described in Winterfeldt et al. [35] support this assertion as they find a low RMSE for offshore wind, despite using a reanalysis provided at a coarse spatial resolution (~200 km^2) and having to apply temporal downscaling (6 h −1 h).

Carvalho et al. [28] find that raw reanalysis data provided at all spatial resolutions finer than NCAR achieve a similar and superior correlation, and the finer temporal resolution datasets perform well, despite the greater complexity of wind speed at the 1 h resolution. This pattern is echoed in the other metrics used (RMSE and Bias), where CFSR provides the best results.

Stopa and Cheung [36] find that CFSR performs well over a very large geographical scope and long time series; however the buoys providing in situ measurement are very sparse. The RMSE of CFSR is slightly lower than found in the Iberian Peninsula in most locations [28]. Chawla et al. [37] find a similar result to Stopa and Cheung [36] in a subset of the same locations; R^2 values of CFSR in these locations are similar to the results found by Carvalho et al. [38], demonstrating the consistency of performance of CFSR across the Atlantic and Pacific oceans.

Table 2 demonstrates that spatial downscaling reduces error; this is best illustrated in the comparison of results from Carvalho et al. [28] and Carvalho et al. [38], where the same locations are used for mesoscale and raw reanalysis data respectively. There is a reduction in RMSE and Bias in almost every case for the mesoscale data. Unfortunately comparison of correlation between these papers is difficult owing to the use of different coefficients. However comparing the results from Refs. [38–36] shows that mesoscale modelling does not significantly improve the correlation between CFSR derived data and offshore in situ measurements. The results described by Menendez et al. [39] and Hawkins et al. [27], are similar to other mesoscale models and the raw reanalysis data from Stopa and Cheung [36] and Chawla et al. [37]. This review of the literature suggests that mesoscale modelling does not necessarily represent an improvement on raw reanalysis data and that CFSR performs at least as well as MERRA both onshore and offshore.

When the downscaled data created by Hawkins et al. [27] were used for simulation, a very high correlation was found to both onshore and offshore turbine output; however, as with Staffell and Green [24], this was aggregated to monthly load factors where a lot of detail is lost.

1.3. Contribution of this paper

The scope and resolution of the CFSR reanalysis model, combined with its ease of use compared to observed data that requires quality checking and contains gaps, makes it a viable alternative to both in situ and downscaled data for estimating the generation potential of wind capacities, provided that the wind speed data is of reasonable accuracy. While CFSR wind speeds have been compared with observations at a number of locations, the potential benefits of this data source have not been examined for the UK, also existing studies have not used an extensive network of stations. This paper addresses this gap by evaluating the skill of the CFSR model for UK forecasts using high-resolution observations from 264 onshore and 12 offshore locations.

UK onshore weather stations locations represent a range of topographic conditions and land uses and experience different wind conditions. This means that a single average value for a grid cell that may contain a large variety of these conditions may not represent some weather stations within the cell well. This study explores the impact of these spatial factors on the skill of the CFSR model for the first time.

2. Methodology

2.1. Reanalysis data

CFSR reanalysis data are provided on a Gaussian grid defined by NCEP, (designated T382 the resolution in approximately 38 km^2), longitudes are evenly spaced, but latitudes are not. We used the wgrib2 software, developed by NCEP, to interpolate the meteorological data to a 0.5°°×°0.5° decimal grid for comparison with other datasets. The data cover the period from 1980 to 2010 and the spatial scope includes the UK sovereign waters shown in Fig. 4.

2.2. In situ wind speed measurements

We obtained hourly wind speed measurements from the Mean Hourly Wind, UK Hourly Weather and Global Marine Observations databases of the British Atmospheric Data Centre (BADC). The BADC maintains and distributes atmospheric data produced by Natural Environment Research Council (NERC) projects to UK researchers. Owing to the size of the dataset, it was necessary to automate quality checking. First, we filtered the data to exclude those sites and time series outside of the spatial and temporal boundaries. We then removed points that had not been quality checked by the UKMO from the remaining time series. We also removed identical repeat values from points at which two different values are provided for the same time period. We removed values above 35 m/s as outliers; most of these values were considerably higher (up to several hundred m/s) and isolated. Since 25 m/s is currently the upper threshold for power generation, wind speeds above this threshold are largely irrelevant for simulation (Fig. 2). However, as higher values may illustrate correlation trends, we selected 35 m/s as the cut-off for this study. Following processing, the time series for most locations are discontinuous. Long data gaps were considered to be an indicator of poor quality data collection; therefore, we removed time series containing gaps of one week or more from the analysis. We did not alter the offshore wind speed data for buoys from 6 m above sea level because of the potential errors in the method necessary to bring them in line with the CFSR dataset (10 m). Although Winterfeldt et al. [35] do correct offshore

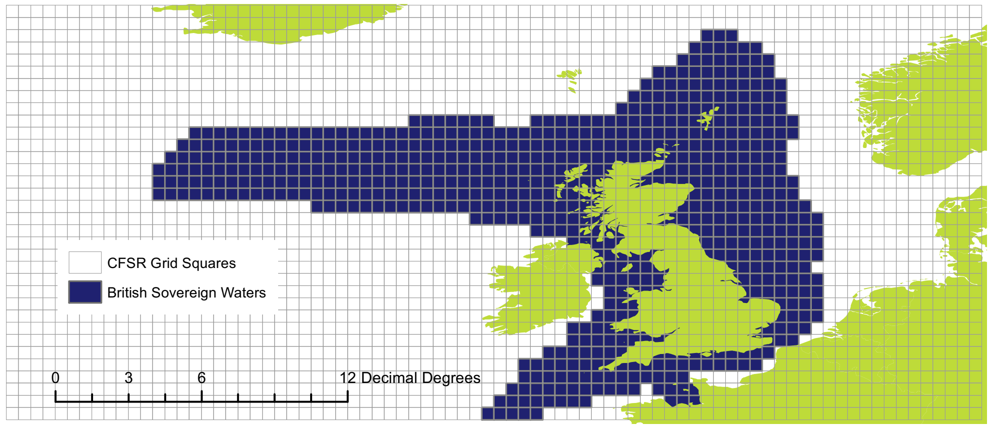

Fig. 4. Spatial boundaries of CFSR data. This covers UK sovereign waters so that all potential offshore capacities may be explored in future modelling work.

wind speed for height, several authors have demonstrated that the bias is very small – less than 0.5 m/s [44–47]. Finally, we matched the cleaned data spatially to the appropriate CFSR grid square and temporally using timestamps.

The filtering resulted in 355 onshore time series, compromising data from the AWS, SYNOP, HCM and HWND6910 messages originating from stations that contribute to the MIDAS database. Some stations provide time series for multiple messages. Only a single instance has been used for each location. Therefore there are 264 unique onshore MIDAS station locations used in this study. There are 209 CFSR grid squares covering the Great Britain land mass, of which 98 have two or more stations within them, 45 have only one station and 71 have no stations. Offshore, 12 suitable time series have been extracted. Onshore and offshore stations are shown in Fig. 3, which includes the relative distribution of message types. These MIDAS stations provide almost 36 million onshore and more than 1 million offshore hourly data points to compare against CFSR reanalysis data. Fig. 5 shows that the majority of stations provide high quality data for over 95% of the time. There are, however, a small number of stations where there are more data points missing due to lack of observations or removal following the methods described above.

2.3. Onshore spatial factors

In order to investigate the influences of onshore factors on wind speed, we characterised the MIDAS station points in terms of height

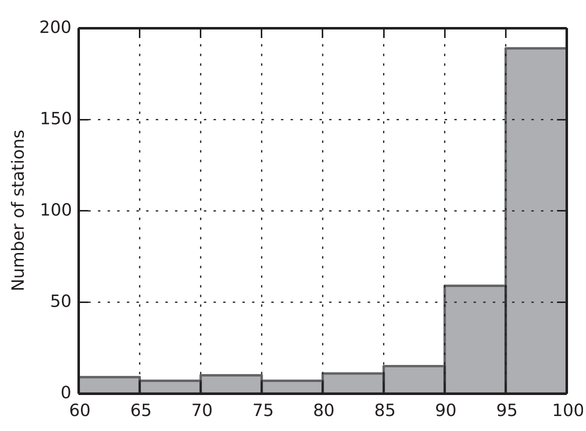

Fig. 5. Completeness of MIDAS wind speed time series used to compare against CFSR.

above sea-level at the station base using the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) [48] and according to land use using the CORINE land cover map [49]. Analysis of this land use data has revealed that the projection is not correctly defined, which leads to a slight mis-location of the MIDAS stations (<10 m). Therefore subsequent analysis uses an aggregated land use classification, which is provided within the CORINE dataset, to assign a land use to each MIDAS location as accurately as possible. This land use is used to analyse whether the effects of surface characteristics such as roughness are accounted for by CFSR. We also used a buffer analysis to classify onshore stations within 5 km of a simplified shoreline as coastal, with all other sites defined as non-coastal. Therefore, 46% of the stations are defined as coastal and 54% as non-coastal.

2.4. Statistical methods

Due to large amount of spatially disaggregated data it was necessary to use statistical methods to summarise the relationship between the matched time series over the study area. We compared the matched MIDAS and CFSR timeseries and used density plots to visually represent correlation, and, subsequently, to evaluate percentage error. Following the precedent set by previous studies, we used Pearson's correlation coefficient (Pr) to measure the strength of the relationship. In order to measure the magnitude of average error across the data and according to the methods identified in the literature review, we used root means squared error RMSE $= \sqrt{\frac{\sum_{t=1}^{n}(CFSR_t - MIDAS_t)^2}{n}}$. This is expressed in m/s to allow analysis of its effect on turbine power curves. Finally, to determine the direction of this error (−ve, +ve) we measured the bias of the CFSR data, where Bias $= Mean\,(CFSR_t - MIDAS_t)$.

3. Results and discussion

Fig. 6 demonstrates how the correlation between CFSR and the in situ wind data varies across the MIDAS stations. The large number of onshore sites necessitates aggregation to a histogram, whereas the relatively few offshore sites allow individual points to be plotted. The majority of onshore sites have a similar range of correlations as offshore; however, there are a number of sites that are less well correlated. The results show that mean onshore Pr = 0.81 and mean offshore Pr = 0.85. These results are in line with the studies evaluating raw reanalysis data described in Tables 1 and 2. In comparison to onshore raw reanalysis dataset the correlation is very similar to that found by Refs. [31,33] and an improvement on

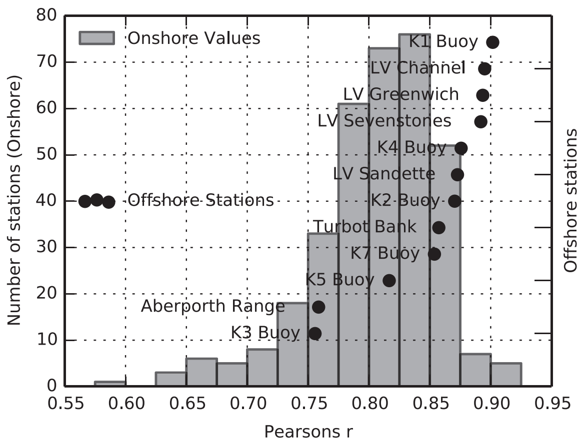

Fig. 6. Distribution of Pearson's correlation between MIDAS and CFSR time series. Offshore sites are named to allow comparison to Fig. 3.

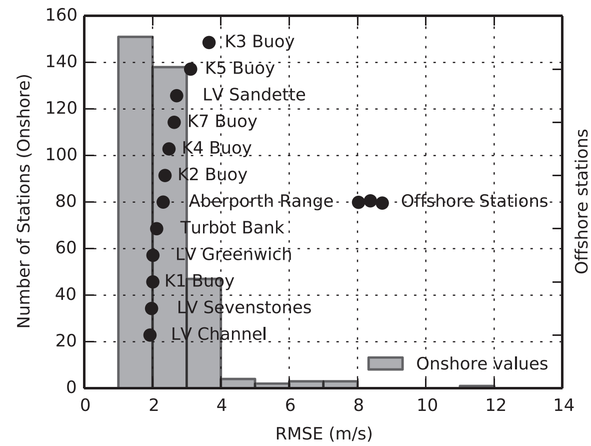

Fig. 8. RMSE of MIDAS and CFSR time series.

the coarser datasets examined in Refs. [41,34]. The correlation is not as good as that found by Bao and Zhang [30], although, as described above, their analysis is conducted in a different way. Onshore, the mean correlation is slightly better than mesoscale analysis in Portugal [29] and slightly worse than in Scandinavia [33]. The best correlated sites approach the correlation found in the UK downscaled study [27], although the majority have much lower correlation coefficients. Offshore, the correlation is in line with the analysis of raw reanalysis in Refs. [36,37], although slightly lower than some locations. Mesoscale modelling using CFSR and other reanalysis data show only slightly improved correlation coefficients than found here [39,28,27]. These results demonstrate that downscaling may not be necessary, particularly offshore, where wind speed is not influenced by the land mass, although mesoscale modelling of wind over the UK has achieved better correlation than found here.

Fig. 7(a) shows the relationship between CFSR and MIDAS at a single site with a Pr similar to the onshore mean (0.81). The plot shows that there are a large number of values that correlate well. There is, however, noise at all wind speeds, particularly below 10 m/s. Fig. 7(b) shows the site with the highest correlation coefficient (0.91). This site experiences less error at low wind speeds than Fig. 6(a) and has a higher density of values around the ideal correlation. The line of missing values between 17 and 17.5 m/s is consistent across all sites and is a result of the conversion of MIDAS data, which are provided to the nearest knot, to harmonise with CFSR which is provided in m/s Fig. 6(c) and (d) demonstrates that poor correlation may be due to wind speed being either under or over estimated by CFSR. Both sites exhibit problems with MIDAS error at the lowest wind speeds.

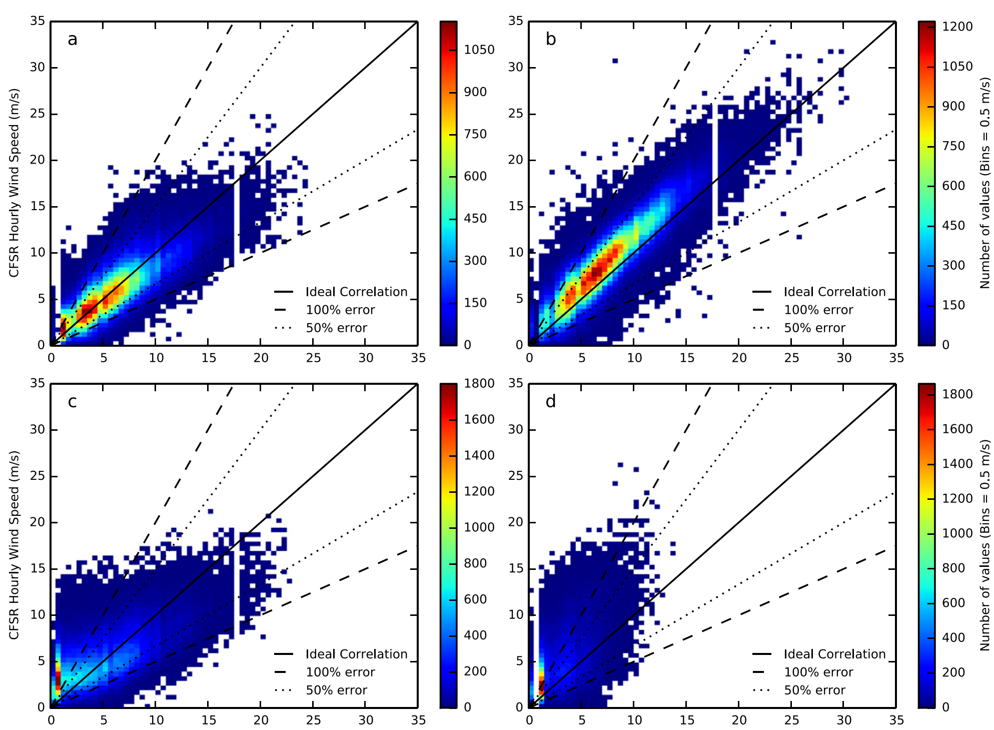

Fig. 7. Correlation between MIDAS and CSFR time series. A – Illustrative typical correlation, b – The MIDAS site to which CFSR most closely correlates, and examples of sites where MIDAS and CFSR correlate poorly, due to either high (c) or low (d) wind speeds.

Fig. 8 shows that RMSE is similar onshore and offshore. As with Pr there are more outliers onshore, but in this case only with larger errors. Unfortunately, none of the studies evaluating raw onshore reanalyses use RMSE as a metric. The onshore error found here (mean 2.35 m/s) is much larger than the 0.44 m/s found by Hawkins et al. [27], but in line with that found by Carvalho et al. [29], it may be that the mesoscale modelling works better for the UK, or that results are affected by using a longer time series as Hawkins et al. did. The mean RMSE in this study is higher for offshore sites, as found in Hawkins et al. [27], although the difference is smaller (2.44 m/s compared to 1.33 m/s). The mean offshore error is smaller than the 2.77 m/s found by Winterfeldt et al. [35], although this was found using an older, coarser resolution, dataset. The offshore RMSE found by studies in other areas of the world varies; the value found here is higher than found using raw CFSR reanalysis data in the Iberian Peninsula [38], the oceans surrounding North America [36,37], and most of the mesoscale models [28]. However CFSR performs better than NCAR and ERA interim data from Ref. [38], and similarly to mesoscale model data driven by NCAR [28].

In order to ascertain the extent to which these results are influenced by wind speed, particularly the RMSE values, Fig. 9 compares both Pr and RMSE to the mean wind speed of the MIDAS time series. Pr appears to be independent of wind speed and the correlation between mean wind speed and RMSE is also unclear. Fig. 9 does, however, highlight that the sites with the highest RMSE (>9 m/s) are those with a mean wind speed that is greater than experienced by most of the sites across the UK (8 of 276). There are not enough offshore sites to discern a relationship between wind speed and either Pr or RMSE.

Bias may be a more useful measure than Pr or RMSE for ascertaining how the two datasets interact over time as it gives an indication of which dataset is producing higher or lower wind speeds. Fig. 10 shows how the bias is evenly distributed in the positive and negative directions for both onshore and offshore sites. Offshore sites show less extreme biases, which could be due to the homogeneity of the wind resource in terms of mean wind speed or could reflect that the offshore wind speeds are not as high as at the windiest onshore sites. The figure shows that the largest magnitude RMSE is created where CFSR underestimates the wind speed. These are the same eight sites identified in the analysis of Fig. 9, reasserting that CFSR does not represent the sites that experience the highest mean wind speeds well. The mean bias is greater offshore (0.56 m/s) than onshore (0.35 m/s). Onshore, the bias is lower than the interpolated raw reanalysis data used by Staffell and Green [24] and the mesoscale data driven by CFSR in Carvalho et al. [29], but not the better performing reanalysis models. The bias is larger than that found by

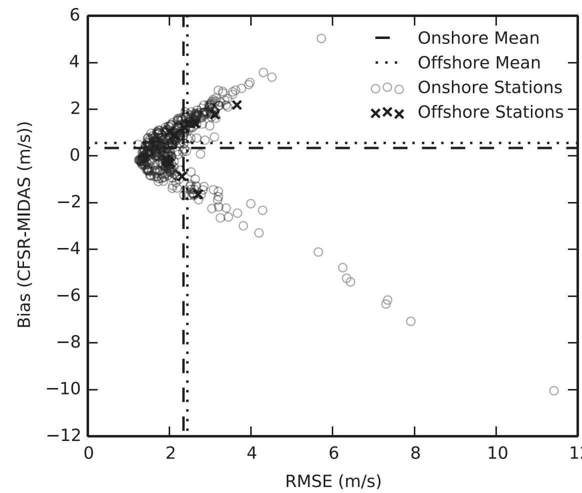

Fig. 10. Bias of CFSR vs. MIDAS as a function of RMSE.

Hawkins et al. [27] both onshore and offshore. Offshore, the bias is similar to that seen in the mesoscale modelling in Ref. [28]; interestingly Ref. [38] find a much lower bias with raw CFSR data, but other reanalysis data exhibit a similar or higher bias to that found here.

The comparison of results to those in published studies has shown that CFSR is as accurate as any other raw reanalysis dataset for the UK, challenging the finding by Ref. [20] that MERRA hourly wind speeds are more accurate than CFSR. In some respects, raw CFSR data is also very close to the results obtained when using downscaled data, although accuracy appears to vary dependent on location. Offshore CFSR data can even be closer to in situ measurements as wind speeds are homogeneous and the topographic data utilised by mesoscale modelling offer little benefit due to the lack of terrain. Downscaling does improve the correlation between similar reanalyses and in situ measurements onshore in the UK, but elsewhere results are variable and very often worse. As highlighted by Kubik et al. [23], mesoscale modelling is computationally intensive so that long term datasets are difficult to produce; the review of evaluations suggest that this effort does not always return a more accurate dataset.

3.1. Spatial factors affecting CFSR accuracy

Analysis has shown that the largest RMSE and bias between the MIDAS and CFSR time series is driven by high mean wind speeds. If this were the only factor driving correlation, it would be expected

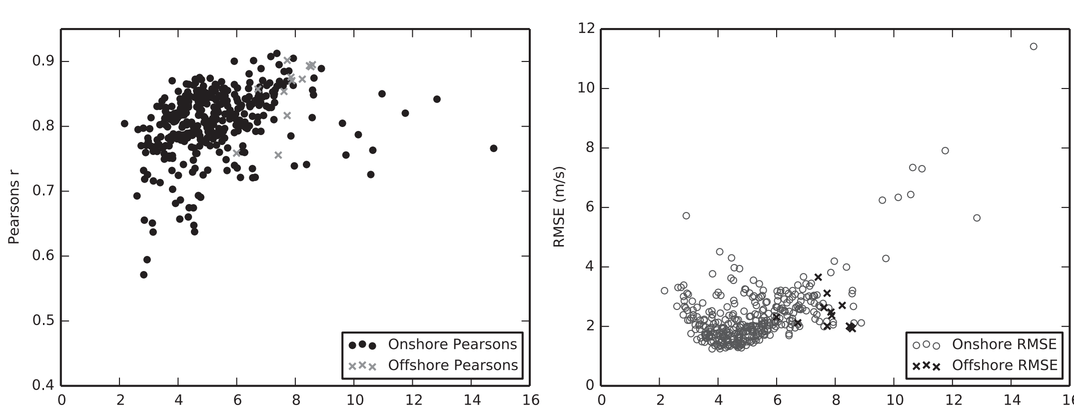

Fig. 9. Pearson's R (left) and RMSE (right) of MIDAS and CFSR time series in relation to the mean wind speed of the MIDAS time series.

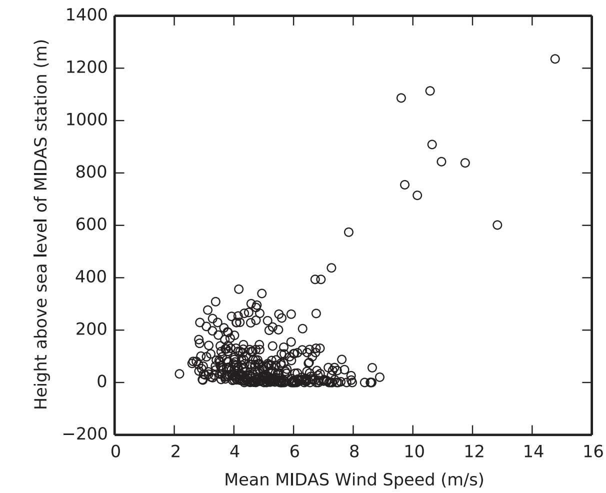

Fig. 11. Relationship between mean wind speed and height of MIDAS station.

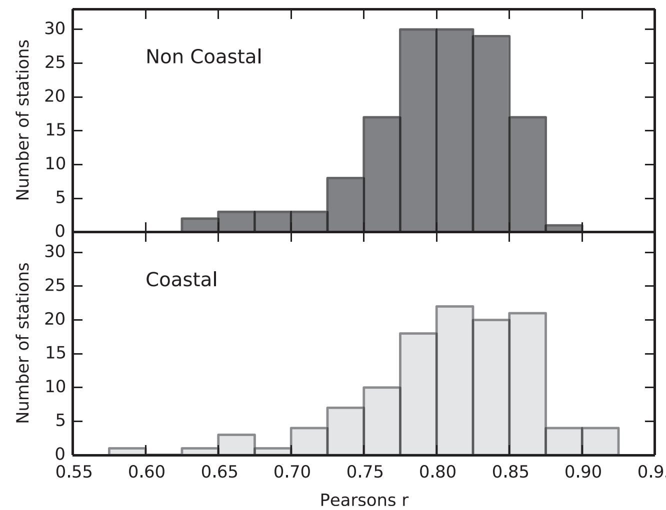

Fig. 13. Distribution of Pearson's correlation between MIDAS and CFSR with onshore sites classified as coastal and non-coastal.

that, as mean wind speed increased, so would bias and RMSE, and that Pr would decrease. However, as Fig. 9 shows, this is not the case. This suggests that there may be other influencing factors. Figs. 10–13 show the results of the investigation of the spatial factors that affect correlation, comparing potential drivers of divergence between MIDAS and CFSR to Pr and RMSE (bias has not been plotted as RMSE can be considered to be a proxy for the magnitude of bias as shown in Fig. 10).

3.1.1. Elevation and mean wind speed

Fig. 11 shows that the sites identified in Fig. 8 as having high wind speeds and larger errors are those at a high altitude (above 600 m elevation), where wind speeds increase above a threshold that CFSR finds hard to represent. This could be problematic for the use of CFSR as a wind turbine simulation tool, as these sites potentially provide the ideal wind resource for power generation. However, the low number of meteorological stations reflects the isolated nature of these sites; they are all on the peaks of the UK's highest hills (e.g. Cairngorm Mountain and Great Dun Fell) and are therefore extremely unlikely to have wind turbines near them, not only due to inaccessibility but also as these are within zones with restricted planning rules such as national parks. This reinforces the assertion made in the introduction that many MIDAS sites are in areas unsuitable for wind turbine simulation. Removal of these stations from the analysis does not have a significant effect on Pr as the correlations between MIDAS and CFSR at these points are close to the mean. However it does slightly alter the RMSE; the mean reduces from 2.35 m/s to 2.2 m/s and the bias reduces from 0.34 m/s to 0.32 m/s. The impact of removal is very small as there are so few stations at this elevation. As the UK is not very mountainous and the high elevation sites are not viable as turbine locations, these can effectively be ignored when considering the suitability of CFSR as a wind speed dataset for simulation. This may not be the case in other countries and the data should be tested against wind speed measurements at high elevations where turbines can be erected.

3.1.2. Land use

Wind speed close to the surface can change locally on account of the presence of buildings or a change in the surface roughness that

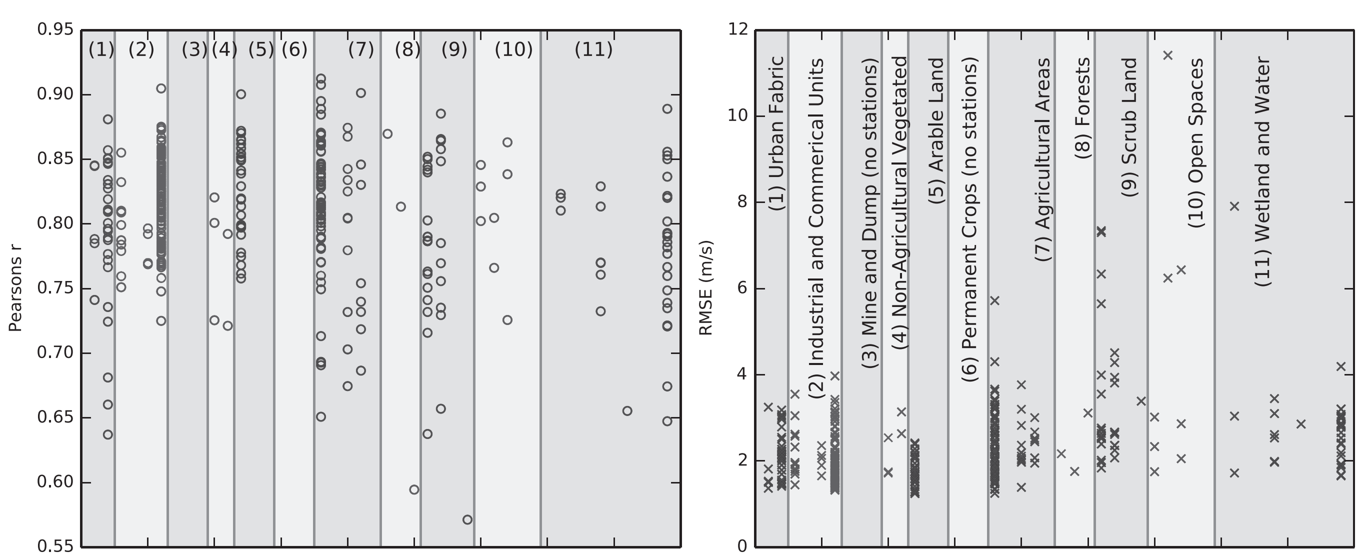

Fig. 12. Relationship between land use at MIDAS station location and correlation between MIDAS and CFSR time series. The land use classification shown from CORINE is aggregated as described in Section 2.3. This results in separate columns of data within the land use bands which represent less aggregated land use classifications.

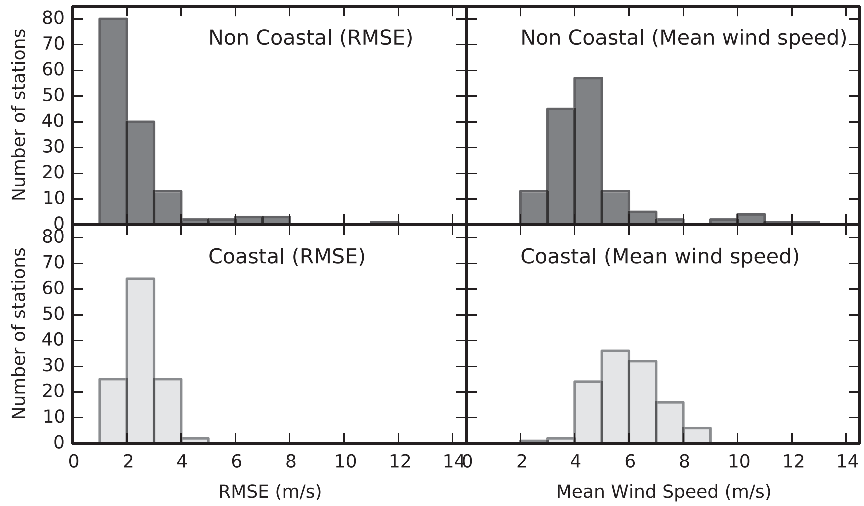

Fig. 14. Coastal sites have a slightly increased RMSE, this is predominantly down to the distribution of wind speed.

causes turbulence. Fig. 12 examines whether land use at a station location drives a divergence from CFSR wind speeds. The figure shows that within each land use band there is a range of Pr and RMSE. Those land uses with the poorest correlation also contain correlations higher than the mean and vice versa. This means that it is not possible to identify any specific land use that is not well represented by CFSR. It is possible that an analysis of individual grid squares with multiple stations may show more. However, although there are many such grid squares over the UK, most of these only contain two stations and it is difficult to discern patterns from so little data. Sites on arable land are the best represented by CFSR with the smallest range of RMSE at the lowest magnitude. This may be because arable land can be homogenous over large areas and represent the majority of a grid square, or that this land use is close to the mean conditions over much of the UK. Interestingly, sites located on urban fabric show low error, despite the complex nature of this type of land use; this suggests that wind conditions could vary significantly from those across a grid square. With the exception of London, UK urban conurbations are not large enough to cover a whole grid square; therefore, CSFR data must represent other land uses at the same time as urban fabric. This suggests that CSFR is very successful at representing wind speeds over a range of land uses and surface roughnesses.

Those land uses with extreme RMSE values represent the sites with the highest altitude. These are located on scrub land and open spaces, with one site found in wetland or water. Given that these land uses also contain low RMSE values, it is likely that the land use is not a driving factor of CFSR error at these locations.

3.1.3. *Proximity to coast*

Coastal areas generally experience higher wind speeds than inland areas [50]. Provided that these areas are not subject to development restrictions, this makes them advantageous for wind turbines. CFSR data representing these areas not only covers the coastal land but also sea and inland areas. This means one value must represent a large variety of surface conditions, which may result in poor correlation with sites in a particular location. Coastal areas have also been identified as being a modelling challenge, due to topography, changes in roughness and variable thermal gradients [28,51]. Fig. 13 shows how correlation varies between coastal and non-coastal sites to test how CFSR deals with this challenge. It does not appear that there is any significant difference between those sites that are near the coast and those that are inland when looking at Pr. However, Fig. 14 shows that RMSE is slightly higher for coastal sites; this pattern is reflected in the mean wind speed plot, suggesting that the larger error is caused by different wind conditions. However the RMSE and mean wind speeds are lower than for those sites which are at high elevations and poorly represented by CFSR.

4. Conclusion

This paper has shown that CFSR wind speed estimates are well correlated to both onshore and offshore in situ measurements. Through characterising onshore stations with respect to elevation, land use, mean wind speed and proximity to the coast, we have shown that CFSR wind speeds are less accurate at high elevation locations where mean wind speeds are higher than in the rest of the UK. Yet CFSR is as accurate as any other raw reanalysis dataset that has been evaluated to date. CFSR data is comparable to downscaled data for onshore and offshore locations, although UK conditions may be better represented by mesoscale modelling. Comparative analysis of the methods for the UK would be beneficial. CFSR represents the impact of surface roughness variations on wind speed effectively across a range of complex terrain. In view of the high estimating skill and the advantages of spatial homogeneity and of spatiotemporal scope and scale, we conclude that CFSR may not only provide an alternative to in situ measurements for the UK but also compete with downscaled data which is much more difficult to produce.

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