# Estimation of Weibull parameters for wind energy analysis across the UK

Shu, Zhenru; Jesson, Mike

*DOI:*
10.1063/5.0038001

# Estimation of Weibull parameters for wind energy analysis across the UK

Z. R. Shu*, Mike Jesson

Department of Civil Engineering, University of Birmingham, Edgbaston, Birmingham, UK

*Corresponding author: z.shu@bham.ac.uk*

**Abstract**

Harvesting wind energy resources is a major part of UK strategy to diversify the power supply portfolio and mitigate environment degradation. Based on wind speed data for the period 1981-2018, collected at 38 surface observation stations, this study presents a comprehensive assessment of wind speed characteristics by means of statistical analysis using the Weibull distribution function. The estimated Weibull parameters are used to evaluate wind power density at both station and regional level, and important, turbine-specific wind energy assessment parameters. It is shown that, the Weibull distribution function provides satisfactory modelling of the probability distribution of daily mean wind speeds, with the correlation coefficient generally exceeding 0.9. Site-to-site variability in wind power density and other essential parameters is apparent. The Weibull scale parameter lies in the range between 4.96 m/s to 12.06 m/s, and the shape parameter ranges from 1.63-2.97. The estimated wind power density ranges from 125 W/m$^2$ to 1407 W/m$^2$. Statistically significant long-term trends in annual mean wind speed are identified for only 15 of the 38 stations and 3 of the 11 geographical regions. Seasonal variability of Weibull parameters and wind power density is confirmed and discussed.

**Keywords:** Wind speed, wind energy, statistical analysis, Weibull distribution, Weibull parameters, United Kingdom

## 1 Introduction

Harvesting renewable energy resource represents one of a range of strategies to reduce carbon dioxide emission and decelerate environment degradation. Reportedly, the accumulated installation of renewable energy was sufficient to provide an estimate of 27.3% of global electricity generation at the end of 2019 [1]. Notable among the increase in the use of renewable energy technologies is the rapid increase in the use of wind energy, with worldwide installation of new wind power generation exceeding 60 GW in 2019, a 19% increase compared to 2018, leading to a total installation capacity of approximately 650 GW [2]. In particular, the wind power resources in the UK are significant on a national scale [3][4], and wind power development in the UK has met a rapid growth, with the cumulative total installation capacity increased from 5.2GW in 2010 to 23.9GW in 2019 [5][6]. Despite increasing interest in offshore wind power generation, onshore wind power still plays a dominant role in the UK wind power market, accounting for 57.7% of the total installation capacity and 12% of total electricity demand in 2019 [6] .

While the benefits of harnessing wind energy are evident, the implementation may be subject to a number of practical difficulties and uncertainties, one of which is the intermittent and unsteady nature of wind. The theoretical energy carrying by wind ($P$) is linked to the third power of wind speed, as shown in Eq.(1), where $\rho$ is the air density, $A$ represents the area swept out by the rotor blades perpendicular to the prevailing direction of the wind and $v$ is the wind speed [7]. Hence, accurate understanding of wind speed characteristics is imperative in different aspects of wind energy development, ranging from identification of desirable sites to prediction of the economic viability of wind farm to structural design of wind turbines.

$$P = \frac{1}{2} A \rho v^3 \tag{1}$$

However, precise prediction of wind is not an easy task since wind, like many other meteorological parameters [8], often exhibits significant variability over a range of scales, both spatially and temporally [9][10]. In the view of wind power development, the variation of wind speed at a given location is generally characterized by a probability distribution [11] which indicates the likelihood that a given wind speed will occur. Most commonly used for wind energy assessments is the two-parameter Weibull distribution, which has been shown to accurately capture the skewness of the wind speed distribution, $f(v)$, than other statistical functions [11] and has been used in a number of studies (e.g. [12]-[20]). The Weibull distribution function, as given in Eq.(2), generally contains a scale parameter, $c$, in units of wind speed, which determines the abscissa scale of the wind speed distribution, and a dimensionless shape parameter, $k$, which reflects the width of the distribution:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \qquad (v > 0; k, c > 0) \tag{2}$$

In the UK, estimation of Weibull parameters for wind energy analysis has been carried out previously by Earl et al., [21] and Früh [22]. Based on 2-year surface wind observation at 72 stations, Früh [22] concluded that the shape parameter ranges from 1.43 to 2.23, and the scale parameter at 10m height ranges from 4.76m/s to 8.71 m/s. Given the assertion of Gross et al. [24] show that at least 7 years of wind speed data is required due to year-to-year variability (this variability has been estimated as about 4% [25]) the 2-year period seems short, but a similar range of shape parameter is also reported by Earl et al. [21] from a much longer (31-year) data set. Earl et al. also noted that the Weibull shape parameter depends strongly on both the strength of mean wind and the topographic effect of the site.

It is important to note that the wind characteristics in the UK depend heavily on the climate of the northeast Atlantic region, which not only exhibits substantial decadal variability in storminess, but also reveals considerable inter- and intra-annual variability in extreme wind speeds [21]. As mentioned earlier, Watson et al. [25] found an annual variability of 4%, and also showed a long-term slight decrease in wind speed across the UK in all regions expect the southeast, which experienced a slight increase. However, it is not clearly stated which of these trends is statistically significant, and the variation over the whole network of stations examined was shown not to be. Earl et al. [21] also reported pronounced local variability in UK hourly mean wind speeds within the period from 1980-2010, over which 15 of the 40 observation sites used displayed a statistically significant decrease (95% confidence level) on inter-annual basis, whereas 8 indicated an increase, of which two were statistically significant. Hewston and Dorling [26] focused on the long-term variability in daily maximum gust speed (DMGS) measured at 43 surface stations over a 26-yr period spanning from 1980-2005. It was shown that the DMGS values generally exhibit a statistically significant decrease within the considered period, declining 5% across the observation network, while the extreme DMGS values (i.e., the 98th percentile of DMGS, which refers to the 190 days in the 1980-2005 record with the highest observed gust speeds) show a statistically significant decrease of 8%.

In such context, the main goal of this study is to provide an updated assessment of long-term and seasonal wind speed variation over the UK at local, regional and national level, including changes in Weibull distributions and implications for wind power generation. Data from 1981 to 2018 from 38 surface observation stations across the UK is analysed. The remaining contents in this paper are organized as follows: Section 2 details the data used and its processing. Section 3 introduces the determination of various parameters involved in this study. Results from statistical analysis are documented and discussed in Section 4, and the main conclusions and summary are given in Section 5.

## 2 Application of the Weibull Distribution Function

Statistical analysis of wind speed and wind energy using the Weibull distribution requires the calculation of the scale and shape parameters. A number of different methods have been proposed and evaluated with the aim of determining the best practice (e.g. [19], [20],[27]-[33]) but with no clear consensus. To illustrate, Chang [28] compared six common numerical methods in estimating Weibull parameters for wind energy applications, which showed that the maximum likelihood method is most suitable in accordance to double checks of potential energy and cumulative distribution function. Ahmed [30] and Mohammadi et al [20] reported that the traditional empirical method, i.e., the mean-standard deviation method, is sometimes more efficient regarding the determination of parameters in Weibull distribution function. Moreover, Mohammadi and Mostafaeipour [19] and Mohammadi et al [20] concluded that the power density method tends to be more preferable for describing wind speed distribution and predicting wind power potential due to its higher statistical accuracy. In this study, four of the most common methods were applied to the data(the empirical method of Justus (EMJ) [34], is based on the mean and standard deviation of wind speed ($V$ and $\sigma_v$ respectively; $v$ is used herein for instantaneous wind speeds). The Weibull scale and shape parameters are calculated using:

$$k = \left(\frac{\sigma_v}{V}\right)^{-1.086} \quad (1 \le k \le 10) \tag{3}$$

$$c = \frac{V}{\Gamma\,(1 + 1/k)} \tag{4}$$

where $\Gamma$ is the gamma function.

Once the shape parameter, $k$, is estimated based on Eq. (3), an alternative, empirical method was also proposed by Lysen [35] to determine the corresponding scale parameter, $c$, as follows:

$$c = V\left(0.568 + \frac{0.433}{k}\right)^{-\frac{1}{k}} \tag{5}$$

The maximum likelihood method (MLM) is a mathematical likelihood function of the wind speed data in time series format [20] in which the Weibull scale and shape parameters are derived based on extensive numerical iterations [27][28][32]:

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} \ln(v_i)}{n}\right]^{-1} \tag{6}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{1/k} \tag{7}$$

in which $v_i$ is the wind speed data measured at the time interval $i$, and $n$ is the number of non-zero data.

The power density method (PDM), originally proposed by Akdag and Dinler [36], calculates the shape parameter using:

$$E_{pf} = \frac{\overline{v^3}}{\mathrm{V}^3} \tag{8}$$

$$k = 1 + \frac{3.69}{(E_{pf})^2} \tag{9}$$

where $\overline{v^3}$ is the mean of the cubed wind speed. The scale parameter in PDM is estimated in a the same manner as in the EMJ, as shown in (4).

Once these Weibull parameters are determined, they can be applied to estimate a number of parameters that are important to wind power assessment. Each model of wind turbine has several characteristic wind speeds: the cut-in wind speed, $v_c$, the cut-off wind speed, $v_f$, and the rated wind speed, $v_r$. Below $v_c$ or above $v_f$ the turbine will not operate, while energy production is maximal at $v_r$. The probability that a turbine will be in operation can therefore be calculated based on the cumulative Weibull distribution function [37]:

$$P(v_c < v < v_f) = exp\left[-\left(\frac{v_c}{c}\right)^k\right] - exp\left[-\left(\frac{v_f}{c}\right)^k\right] \tag{10}$$

Moreover, as discussed by Sasi and Basu [38], the estimated Weibull parameters can as well be utilized to compute the capacity factor (*CF*) of a wind turbine:

$$CF = \frac{\exp\left[-\left({}^{v_c}/_{c}\right)^k\right] - \exp\left[-\left({}^{v_r}/_{c}\right)^k\right]}{\left({}^{v_r}/_{c}\right)^k - \left({}^{v_c}/_{c}\right)^k} - \exp\left[-\left({}^{v_f}/_{c}\right)^k\right] \tag{11}$$

This represents the ratio of predicted actual energy output to the maximum possible (i.e. if the wind speed is constantly at $v_r$) over a year of operation. The Weibull distribution also allows quantification of two useful characteristic wind speeds. The first is the most probable wind speed ($v_{mp}$) and second the wind speed carrying maximum energy ($v_{max.E}$). The latter is closely tied to the rated wind speed of the turbine being assessed, $v_r$, with the turbine operating most efficiently if $v_r \cong v_{max,E}$. These speeds are given by [28][39]:

$$v_{mp} = c\left(1 - \frac{1}{k}\right)^{1/k} \tag{12}$$

$$v_{max.E} = c\left(1 + \frac{2}{k}\right)^{1/k} \tag{13}$$

For engineers and specialists involved in wind energy industry, the wind power density (*WPD*) is an important parameter that reflects how energetic the winds are at the location of interest. In the light of several previous studies [12][13][28], the WPD can be determined using the Weibull parameters:

$$WPD = \frac{P}{A} = \int_0^\infty \frac{1}{2}\,\rho\, v^3 f(v)dv = \frac{1}{2}\,\rho\, c^3\, \Gamma\left(1 + \frac{3}{k}\right) \tag{14}$$

where $\rho$ is the density of ambient air (often adopted as 1.225 kg/m$^3$).

## 3 Data collection and processing

### *3.1 Data collection and quality control*

Hourly mean wind speed and wind direction data have been extracted from the Met Office Integrated Data Archive System (MIDAS), via the British Atmospheric Data Centre (BADC). Explicitly, "hourly mean" is herein used to signify the mean of data recorded over an entire hour, rather than a once-an-hour recording of a 10-minute mean speed as used in some contexts. Data covering the period 1981-2018 is used, taken from 38 observation stations spread across the country (see Figure 1 and Table 1) were used. All of the observation sites meet the UK Met Office (UKMO) site exposure requirements, which are reasonably representative of an open exposure condition. Wind speed data is recorded by a cup anemometer mounted at a height of 10m above the local ground, with wind direction measured by a traditional wind vane at the same height [41]. All the records archived in MIDAS have an attribute version number which may take a value of 0 and 1 only. Essentially, a record with a version number of 1 represents the best available value of the data at the time in the sense that they have been properly corrected in accordance to a rigorous quality control [41]. On this account, a non-zero criterion, similar to that performed by Watson et al [25], is applied during the data extraction process in this study, which aims to minimize the risk of irregular or erroneous values in the dataset.

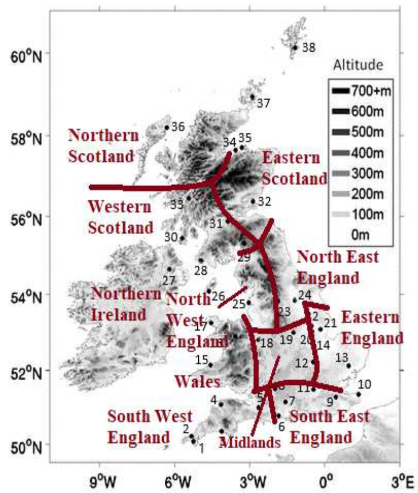


**Figure 1 Surface observation network involved in this study, modified based on Earl et al., [21]. Marked regions are in accordance with the Met. Office classification for UK regional climate [40].**

Previous statistical analyses of wind energy have been carried out using wind data at various temporal resolution: 10-min, hourly and daily. In the current study, the recorded hourly wind speeds are averaged over each day to provide the corresponding daily mean values. It has been shown that, when performing long-term estimate of the full-load duration and the electricity generation, the results based on daily and hourly wind data are overall equivalent, with the correlation coefficient of the regression fit exceeding 0.95 [42] The use of daily observation of mean wind speed for wind energy analysis can also be found in several previous studies [16][43]-[45]. A further discussion on the use of daily wind data will be given hereinafter in Section 4.

In addition, UK is one of the countries that most frequently affected by the extratropical cyclones, which are associated predominantly with areas of low atmospheric pressure over the North Atlantic. These cyclonic windstorms are the major contributor in terms of the high wind speed records in long-term time series, and sometimes may generate extreme wind speeds that result in wind turbines being shut down [4]. Differentiation of different types of windstorm is often considered crucial for extreme wind speed analysis [46]-[49]. However, given the nature of the present study and the relatively lower likelihood of the occurrence of the extreme wind speeds [4], no additional attempt has been made to separate out different windstorms. In order to distinguish between local effects (e.g. changes in local surface roughness) and larger scale changes in the wind climate, the 38 stations have been divided into regions (see Figure 1 and Table 1).

**Table 1 Surface observation network involved in this study, modified based on Earl et al.,[21].**

| Region | Station Number | Station Name | Altitude $(m)$ | Gradient of Linear Fit $(ms^{-1}/year)$ | Fit p-Value | Significant at 95% level? |
|---|---|---|---|---|---|---|
| Northern Scotland | 36 | Stornaway Airport | 15 | 0.026 | 0.001 | Y |
| | 37 | Kirkwall | 26 | -0.015 | 0.008 | Y |
| | 38 | Lerwick | 82 | 0.008 | 0.352 | N |
| | | Regional Mean | | 0.006 | 0.297 | N |
| Eastern Scotland | 31 | Salsburgh | 277 | -0.033 | 0.000 | Y |
| | 32 | Leuchars | 10 | -0.004 | 0.860 | N |
| | 34 | Kinloss | 5 | -0.001 | 0.960 | N |
| | 35 | Lossiemouth | 6 | 0.006 | 0.521 | N |
| | | Regional Mean | | -0.008 | 0.081 | N |
| Western Scotland | 28 | West Freugh | 11 | -0.001 | 0.521 | N |
| | 29 | Eskdalemuir | 242 | -0.006 | 0.339 | N |
| | 30 | Machrihanish | 10 | -0.001 | 0.841 | N |
| | 33 | Dunstaffnage | 3 | -0.020 | 0.000 | Y |
| | | Regional Mean | | -0.007 | 0.179 | N |
| Northern Ireland | 27 | Aldergrove | 68 | -0.021 | 0.000 | Y |
| | | Regional Mean | | -0.021 | 0.000 | Y |
| North-West England | 25 | Blackpool Squires Gate | 10 | 0.001 | 0.870 | N |
| | 26 | Ronaldsway | 16 | -0.007 | 0.320 | N |
| | | Regional Mean | | -0.003 | 0.734 | N |
| North-East England | 23 | Bingley | 262 | -0.034 | 0.000 | Y |
| | 24 | Church Fenton | 8 | 0.028 | 0.000 | Y |
| | | Regional Mean | | -0.003 | 0.538 | N |
| Midlands | 12 | Bedford | 85 | -0.009 | 0.020 | Y |
| | 14 | Wittering | 73 | 0.005 | 0.128 | N |
| | 18 | Shawbury | 72 | 0.008 | 0.068 | N |
| | 19 | Nottingham Watnall | 117 | -0.015 | 0.000 | Y |
| | | Regional Mean | | -0.003 | 0.489 | N |
| Eastern England | 13 | Wattisham | 89 | -0.010 | 0.007 | Y |
| | 20 | Cranwell | 62 | 0.009 | 0.061 | N |
| | 21 | Coningsby | 6 | 0.001 | 0.880 | N |
| | 22 | Waddington | 68 | 0.004 | 0.513 | N |
| | | Regional Mean | | 0.001 | 0.772 | N |
| | 6 | Hurn | 10 | 0.002 | 0.589 | N |

| | | | | | | |
|---|---|---|---|---|---|---|
| South-East England | 7 | Middle Wallop | 90 | -0.006 | 0.043 | Y |
| | 8 | Lyneham | 145 | -0.006 | 0.242 | N |
| | 9 | East Malling | 33 | 0.038 | 0.010 | Y |
| | 10 | Manston | 44 | 0.008 | 0.308 | N |
| | 11 | Heathrow | 25 | 0.034 | 0.000 | Y |
| | Regional Mean | | | 0.012 | 0.002 | Y |
| | | | | | | |
| South-West England | 1 | Culdrose | 78 | -0.006 | 0.782 | N |
| | 2 | Camborne | 87 | -0.024 | 0.000 | Y |
| | 3 | Plymouth Mountbatten | 50 | -0.007 | 0.213 | N |
| | 4 | Chivenor | 6 | -0.002 | 0.660 | N |
| | 5 | Yeovilton | 20 | -0.003 | 0.489 | N |
| | Regional Mean | | | -0.008 | 0.078 | N |
| Wales | 15 | Aberporth | 115 | -0.008 | 0.159 | N |
| | 16 | Bala | 163 | -0.032 | 0.000 | Y |
| | 17 | Valley | 10 | 0.006 | 0.258 | N |
| | Regional Mean | | | -0.011 | 0.037 | Y |

To further highlight the necessity of this study, long-term variability of mean annual wind speed across different UK regions is examined based on extended wind speed data from 1981 to 2018, as shown in Figure 2. Region-to region variability is apparent. To illustrate, the annual mean wind speed recorded at Midlands, North West England and Eastern England remains relatively unchanged; the values at South East England exhibits a pronounced upward trend, whereas those at Northern Ireland, Western Scotland and Wales tend to reveal an opposite trend in which the annual mean wind speed is shown to decrease. Earl et al [21] and Hewston and Dorling [26] both reported that there is no distinguishable geographic pattern to the distribution of stations exhibiting statistically decrease (or increase) changes. The difference in the long-term variability of wind speed at different stations could provide important implication for the strategical optimization of the integration of wind power into UK electricity network, e.g. with increasing integration of wind power at regions where wind speed shows a long-term increase.

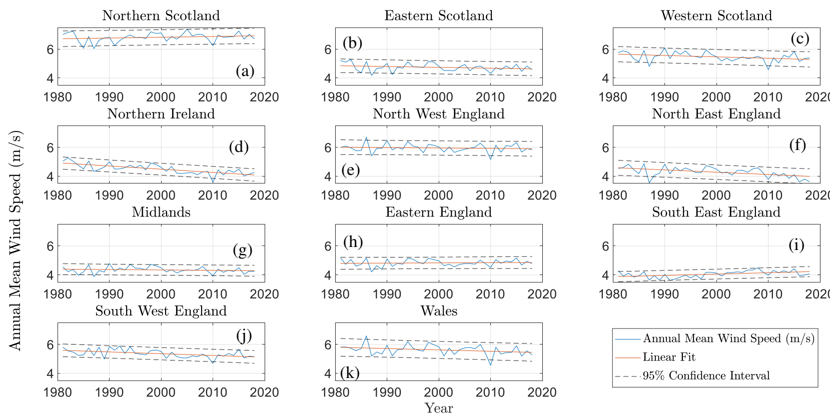


**Figure 2 The variation of annual mean wind speed between 1981-2018 across different UK regions. The p-value and slope for linear regression fit are also demonstrated.**

### *3.2 Extrapolation of wind speed data*

It is recognised that the wind within the atmospheric boundary layer is mainly modulated by the underlying surface roughness and the atmospheric stability, and the consequent vertical profile of wind speed typically follows a monotonic-type increase with height. For accurate estimation of wind energy, it is therefore necessary to correct the wind speed to compensate for the height of modern wind turbines. Note that a variety of wind speed profile models have been established to describe the height-dependence of wind speed [14], among which the simple power-law model is more often used as a handy tool to conduct vertical wind speed extrapolation in wind energy community [50]:

$$v = v_R * \left(\frac{z}{z_R}\right)^{\alpha} \tag{15}$$

where $v$ is the daily wind speed estimated at the prospective hub height of a wind turbine, $z$ (i.e. rotor`s height above ground level), $v_R$ is the reference wind speed measured at the reference height $z_R$ (e.g. 10m above the ground), and $\alpha$ is the power law coefficient. It is to be noted that the power law coefficient does not remain constant for all locations and may vary as a function of numerous factors, such as the nature of terrain, wind speed and atmospheric stratification condition [51]-[56]. For instance, Touma [56] found that the power law coefficient typically increases in magnitude when the atmosphere becomes more stable, and decreases when atmospheric unstability strengthens. Gualtieri [55] and Rehman and Al-Abbadi [52] showed that the power law coefficient is subjected to distinct diurnal and seasonal variability. By contrast, Rehman and Al-Abbadi [53] addressed that no regular seasonal trend exists in the power law coefficient, whereas the diurnal variation is apparent, with larger values observed during night-time and early morning and lower values midday. It should be noted that this study examined wind field characteristics in Saudi Arabia, where themal effects are likely to be extreme. The common value of power law coefficient lies in the range of 0.1-0.4, with the most frequent adopted value of 0.143 (1/7) for wind power analysis [51]. Accordingly, in this study the MIDAS wind data measured at the standard level of 10m above the ground are converted to a wind turbine hub height of 100 m using the $1/7^{th}$ power law when applied directly to wind turbine function. All the graphic representations of analysis results given in this study were produced using MATLAB, unless otherwise specified.

## 4 Results and Discussion

### *4.1 Current UK Wind Climate*

The prevailing wind direction over the wind direction is broadly south-west (see Figure 1), due to the location of the UK at a latitude where the wind climate is dominated by the eastward passage of large weather systems [57]. The mean wind direction ranges from 181° to 212° over the network. The large-scale topographical effects noted by, for example, Lapworth and McGregor [58] are evident with the highland over Wales, Northern England and Scotland having a distinct effect on the mean direction. Topographic effects at a relative localised scale are also important - for example, Station 29 is located in a northeast-to-southwest orientated valley, which results in a wind rose plot with a clearly defined prevailing wind direction while in south and central England (e.g. Station 7,10,12) there is a much wider spread.

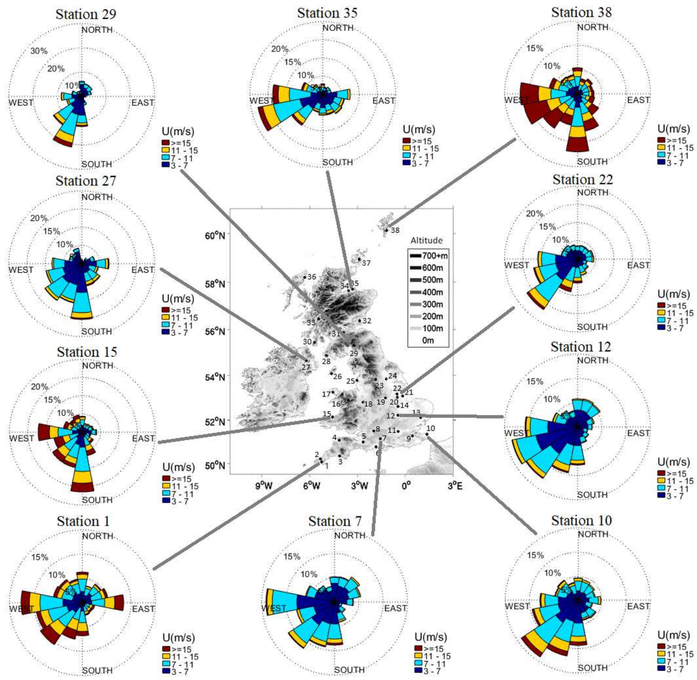


**Figure 3 Wind rose plots at selected locations.**

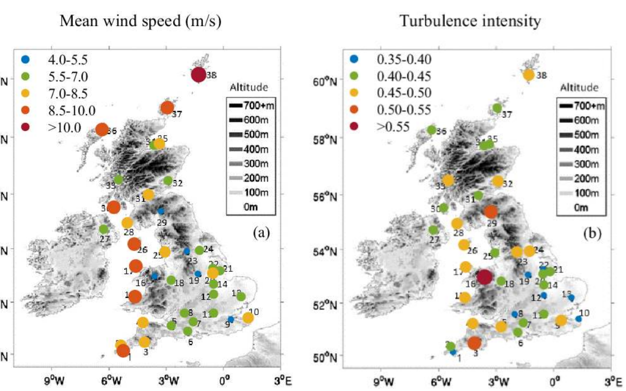


**Figure 4 Distribution of mean wind speed and turbulence intensity. Coloured version is available online**

Site-to-site variability of mean wind speed (Figure 4a) and turbulence intensity (Figure 4b) is also apparent due to the effect of geographic diversity. Clearly, the western coastal regions and Orkney and Shetland islands are generally the windiest regions, whereas the wind speeds associated with inland and eastern regions are much smaller in magnitude. The estimated hub height wind speed ranges between 4.44 m/s at Bala (Station 16) to 10.69 m/s at Lerwick (Station 38). Note that extreme low wind speeds (i.e, < 5.5m/s) are found mostly at the observation sites (e.g. Station 16, 19, 23 and 29) where the topographic-induced sheltering is likely. In general, the wind speed map generated in this study demonstrates a good agreement with those reported in previous studies [21][26][59], in which it has been well documented that the spatial variability of wind speed in the UK is mainly modulated by two factors, i.e, the exposure to fetch over the Atlantic Ocean and Irish Sea and the relative location to the storm track. Typically, the higher and farther north an observation site is, the stronger the wind due to reduced friction and closer proximity to the higher storm track density region to the south and east of Iceland [59]. As for the distribution of turbulence intensity (see Figure 4b), the largest value occurs at Bala, which may be attributed to the surround mountainous terrain both shielding the site causing extreme roughness levels; conversely, central and eastern England, where the terrain is relatively open and flat, produce lower turbulence intensities.

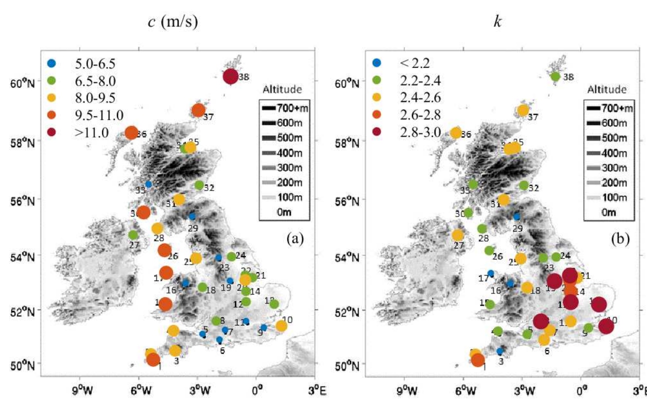


**Figure 5 Distribution of Weibull scale parameter (c) and shape parameter (k). Coloured version is available online**

The considerable site-to-site variability in mean wind speed and turbulence intensity leads to variation in the corresponding Weibull parameters (Figure 5). From a practical point of view, the value of scale parameter reflects how windy an observation site is, and the shape parameter indicates how peaked the distribution of wind speed is. As can be seen from Figure 5a, the distribution of scale parameter is more or less consistent with that of mean wind speed, where the observation sites located in the western coasts and Scotland possess larger values. In contrast, the scale parameters obtained at southern part of England are generally the smallest. The spread of scale parameter in this study lies in the range from 4.96 m/s at Station 16 to 12.06 m/s at Station 38. The shape parameter, on the other hand, is also subject to distinct spatial variation (Figure 5b), with larger shape parameters occurring in the southeast and central England where the turbulence intensity is lower, indicating a smaller temporal variation in wind speed which is reflected in the narrower spike in the probability density function.. Overall, the spatial distribution of shape parameter is in line with that summarized by Earl et al [21]. Numerically, the shape parameter derived in this study ranges from 1.63 to 2.97, which appears to be larger than those given in previous studies [21] [22], but this may be due to the vertical extrapolation of wind speed to a larger hub height.

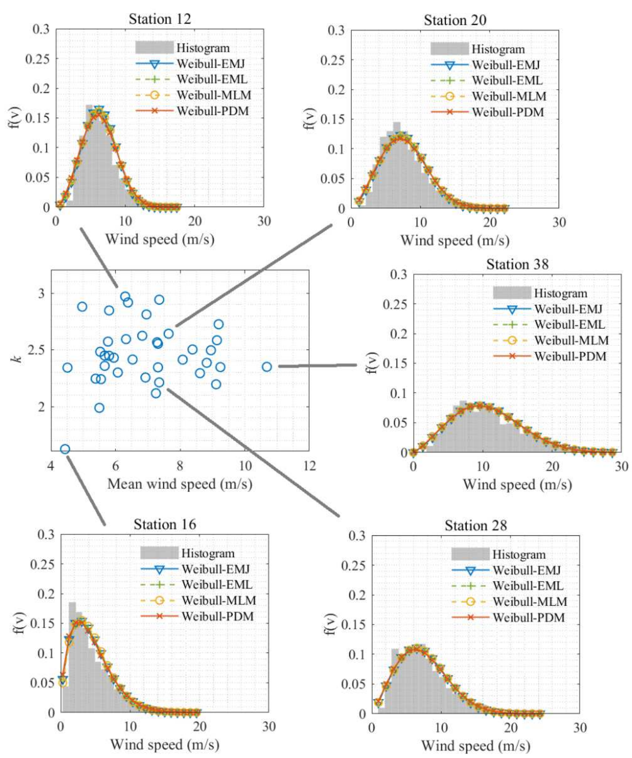


**Figure 6 Comparison of wind data histogram with different Weibull distribution fits**

Earl et al. [21] found that the Weibull shape parameter, calculated using hourly mean wind speed data, showed a slight positive correlation (not statistically significant) with mean wind speed. Such a correlation is not evident in the current study (Figure 6), nor is any significant difference between the Weibull estimation methods. To examine the goodness of Weibull distribution fit to the histogram of measured wind speed, the coefficient of correlation ($R^2$) is obtained:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}\left(f_m(v_i) - f_p(v_i)\right)^2}{\sum_{i=1}^{n}\left(f_m(v_i) - \overline{f_m}\right)^2}\right] \tag{16}$$

where $f_m$ is the probability determined from the wind speed histogram for wind speed $v_i$, $f_p$ is the probability predicted by the Weibull distribution function for $v_i$, and $i$ indexes the $n$ wind speed intervals used to construct the histogram. The correlation coefficient across the observation network varies between 0.90 and 0.96, with 9 of the 38 sites having a value exceeding 0.95 and 36 above 0.90. Further, the goodness of fit was found to be an inverse function of shape parameter (not shown), i.e. the larger the shape parameter, the lower $R^2$ value. Furthermore, it is noteworthy that the Weibull distribution fit based on the power density method (PDM) generally possess the largest correlation coefficient compared to the other methods, implying that the PDM is more preferable in terms of approximating the distribution of wind speeds in this study. For the remainder of this paper only PDM is presented, and may be considered representative of all.

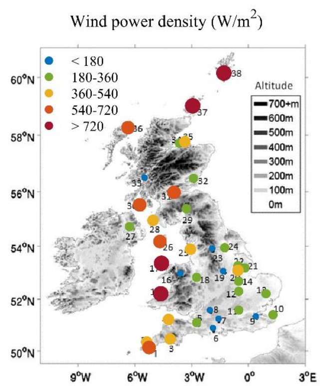


**Figure 7 Distribution of wind power density across the observation network. Coloured version is available online**

Once the scale and shape parameters are determined, the wind power density at different sites across the network can be evaluated. It should be noted that this calculation does not take into account the operating limits of the particular turbine installed, and therefore represents the potential available wind energy rather than what a turbine can extract. The network average of wind power density is about 458 W/m$^2$, with the largest value (1407 W/m$^2$) obtained at Lerwick (Station 38) and the lowest value (125 W/m$^2$) obtained at Nottingham Watnall (Station 19). In terms of the regions defined in Figure 1, variation is seen in the mean wind power density over each region, Northern Scotland has the highest mean value at 1010 W/m$^2$, followed by North West England (677 W/m$^2$), Wales (590 W/m$^2$) and Western Scotland (544 W/m$^2$). North East

England and South East England have the lowest regional wind power densities, with mean values of 198 W/m$^2$ and 221 W/m$^2$ respectively.

Likewise, Figure 8a and Figure 8b demonstrate respectively the distribution of the most probable wind speed $(V_{mp})$ and the wind speed carrying maximum energy $(V_{max.E})$ based on the corresponding Weibull parameters. The estimated $V_{mp}$ lies in the range between 2.75 m/s and 9.52 m/s, with a network average of 6.30 m/s. As shown in Figure 8a, larger $V_{mp}$ are associated predominantly with sites in the western coast of England, Wales and Scotland, as well as in the southeast part of England. The distribution of $V_{max.E}$ is follows a similar northwest-to-southeast pattern, the magnitude of which ranges from 6.63 m/s to 15.67 m/s.

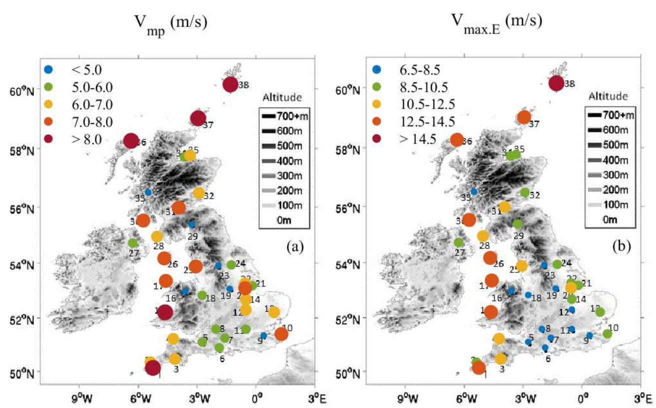


**Figure 8 Distribution of $V_{mp}$ and $V_{max.E}$ across the observation network. Coloured version is available online**

### 4.2 *Current UK Wind Climate – Case Study*

In order to demonstrate the real-world impact of these wind characteristics, the Weibull parameters are applied to determine the capacity factor and operation probability of two commercial wind turbines, namely the Siemens SWT-2.3-93 and Vestas V80-2.0 (specifications are shown in Table 2). The selected wind turbines have similar hub heights and cut-off wind speeds, but the Siemens has lower cut-in and rated wind speeds. The distribution pattern of the estimated capacity factor is similar for both turbines (Figure 9 and Figure 10), in and generally matches the WPD distribution (Figure 7). The operation probability is generally largest in the coastal western and northern regions and the south-east coast of England, though the latter is an area of low

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capacity factory. including South East and South West England, Wales and Scotland. Notwithstanding the similarities in the spatial pattern, considerable difference can still be found in the magnitude of capacity factor and operation probability depending on different wind turbines. For example, the spread of capacity factor associated with Siemens SWT-2.3-93 ranges from 7% to 56% with a network average value of 25.7%, whereas the values associated with Vestas V80-2.0 lies between 4% to 46% with a network average of 18.3%. Likewise, the operation probability for Siemens SWT-2.3-93 varies between 57% and 95%, and those for Vestas V80-2.0 ranges from 49% to 93%. This clearly shows that at a given location, wind turbines with different design properties may result in different performance for the same wind characteristics.

**Table 2 Specifications of the wind turbines considered in this study.**

| Manufacturer | Siemens | Vestas |
|---|---|---|
| Model | SWT-2.3-93[60] | V80-2.0 [61] |
| Hub height (m) | 101 | 100 |
| Cut-in wind speed (m/s) | 3.5 | 4 |
| Rated wind speed (m/s) | 13 | 15 |
| Cut-off wind speed (m/s) | 25 | 25 |

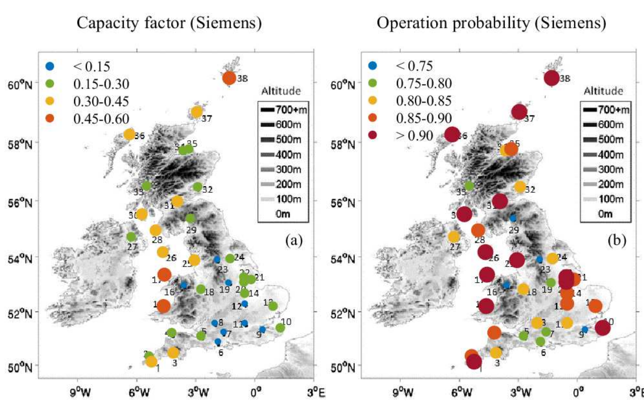



**Figure 9 Distribution of estimated capacity factor and operation probability of Siemens SWT-2.3-93 wind turbine. Coloured version is available online**

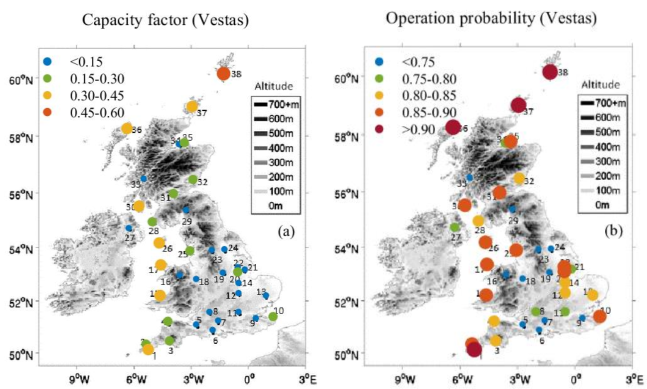



**Figure 10 Distribution of estimated capacity factor and operation probability of Vestas V80-2.0 wind turbine. Coloured version is available online**

### *4.3 Long-term Trends*

As stated in Section 1, previous studies (e.g. [21] [25]) have indicated variation in both regional and individual station wind speeds between 1980 and 2010. Extending this to 2018, 15 of the 38 stations show statistically significant (at the 95% level), determined using the Mann-Kendall test implemented in [62] changes over the period. However, the variation is only significant in 3 of the 11 regions: Northern Ireland, South-East England and Wales. Northern Ireland only contains a single station and therefore local variations in ground roughness (vegetation growth, construction) cannot be discounted. In South-East England, where Watson et al. [25] saw a small increase, three of the six stations in South-East England have significant variations. Two of these are positive, with the negative change being approximately a factor of 6 smaller, giving a regional change of 0.012 $ms^{-1}/year$, though this equates to an increase in mean wind speed of only approximately $0.5ms^{-1}$. In Wales, only the change at Bala is statistically significant, with the remaining two stations not (Figure 11).

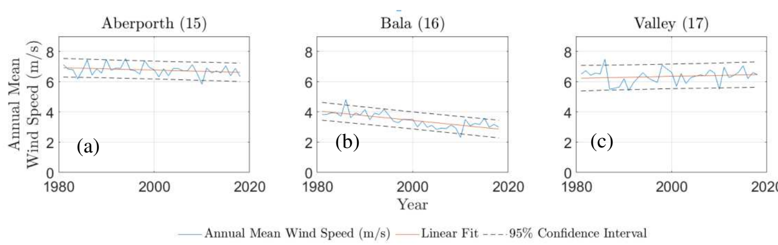



**Figure 11 Annual mean wind speeds at the Wales regional stations**

Following the assertion of Gross et al. [24] that 7 years' data is required for an accurate assessment of site wind characteristics, the Weibull shape and scale parameters have been calculated for each year from 1987-2018 using the seven year' data up to and including the year in question (Figure 12 and Figure 13).

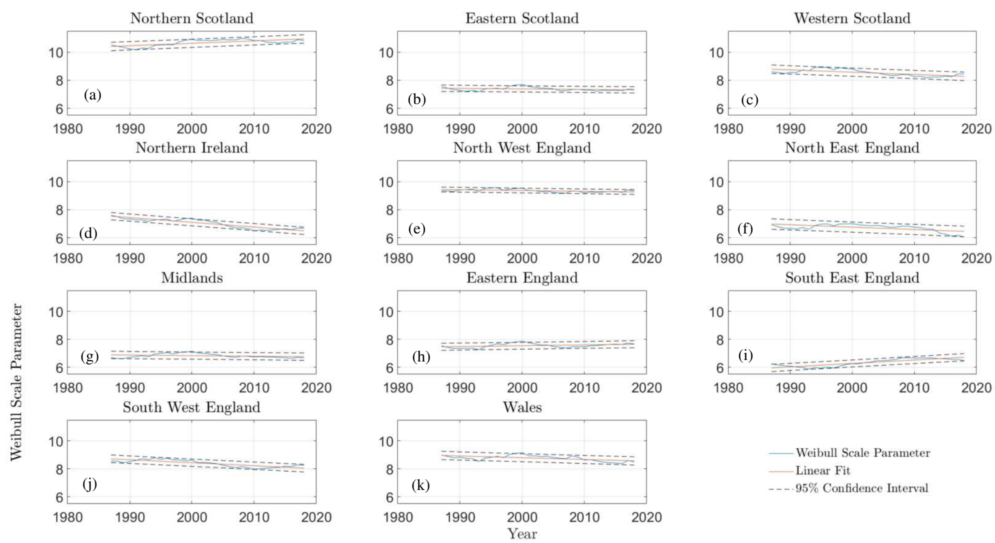



**Figure 12 Seven-year Weibull scale parameter by region**

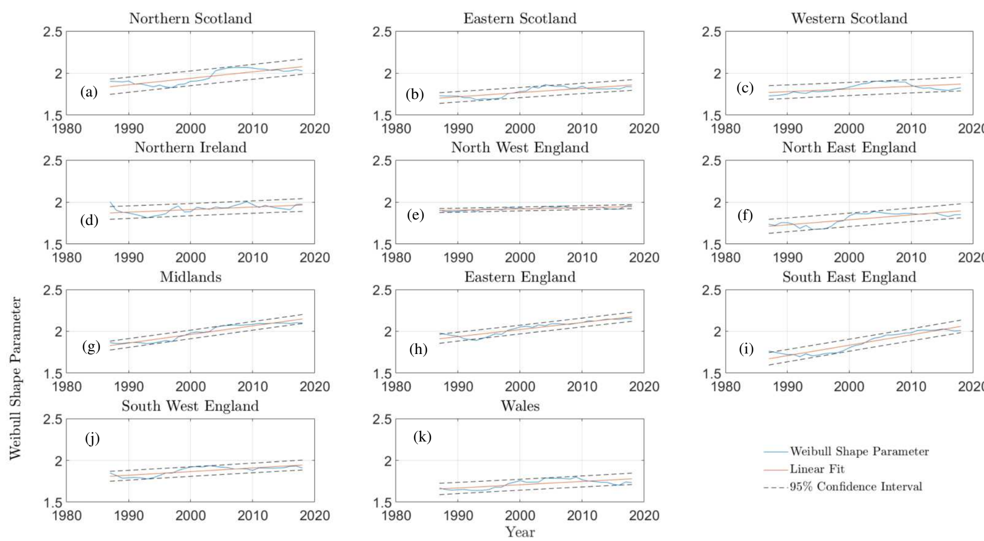



**Figure 13 Seven-year Weibull shape parameter by region**

**Table 3 Trends in the seven-year Weibull parameters**

| Region | Scale Parameter ($ms^{-1}$) | | | Shape Parameter | | | Wind Power Density | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Gradient of Linear Fit ($ms^{-1}$ $/year$)** | **Fit p-Value** | **Significant at 95% level?** | **Gradient of Linear Fit ($ms^{-1}$ $/year$)** | **Fit p-Value** | **Significant at 95% level?** | **Gradient of Linear Fit ($ms^{-1}$ $/year$)** | **Fit p-Value** | **Significant at 95% level?** | **Mean WPD ($Wm^{-2}$)** | **Annual Change [1] (%)** |
| Northern Scotland | 0.017 | 0.001 | Y | 0.008 | 0.000 | Y | 0.912 | 0.783 | N | 1003 | 0.10 |
| Eastern Scotland | -0.004 | 0.089 | N | 0.005 | 0.000 | Y | -1.976 | 0.000 | Y | 376 | -0.50 |
| Western Scotland | -0.016 | 0.000 | Y | 0.003 | 0.000 | Y | -4.510 | 0.000 | Y | 565 | -0.80 |
| Northern Ireland | -0.034 | 0.000 | Y | 0.003 | 0.001 | Y | -4.774 | 0.000 | Y | 298 | -1.60 |
| North West England | -0.006 | 0.008 | Y | 0.002 | 0.000 | Y | -1.861 | 0.001 | Y | 693 | -0.30 |
| North East England | -0.017 | 0.001 | Y | 0.006 | 0.002 | Y | -3.223 | 0.000 | Y | 281 | -1.10 |
| Midlands | -0.004 | 0.062 | N | 0.010 | 0.000 | Y | -1.896 | 0.000 | Y | 262 | -0.70 |
| Eastern England | 0.006 | 0.017 | Y | 0.008 | 0.000 | Y | -0.651 | 0.277 | N | 345 | -0.20 |
| South East England | 0.025 | 0.000 | Y | 0.013 | 0.000 | Y | 0.795 | 0.001 | Y | 226 | 0.40 |

[1] Ratio of mean annual change (gradient) to mean WPD

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| South West England | -0.022 | 0.000 | Y | 0.004 | 0.000 | Y | -5.485 | 0.000 | Y | 518 | -1.10 |
| Wales | -0.013 | 0.001 | Y | 0.004 | 0.002 | Y | -4.701 | 0.000 | Y | 658 | -0.70 |

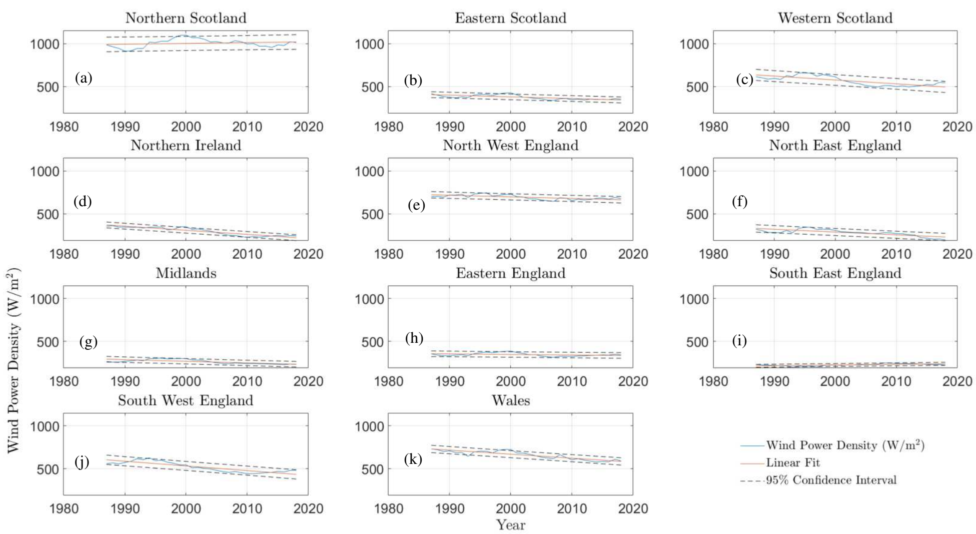



**Figure 14 Seven-year wind power density by region**

The link between the scale parameter and the mean wind speed is clear from comparison of the gradients (Table 3 and Table 1), with the sign of the gradient of each being the same for each region. At the 95% level, more of the regions have a significant change in the scale parameter than in the mean wind speed. This is due to the dependence of the estimation of the Weibull parameters on both the scale parameter and the shape parameter – the latter is seen to follow a significant, increasing trend for all regions (Table 3 and Figure 13).

The implications of these changes for wind power production can be seen from the WPD and the variation of its seven-year value with time (Table 3 and Figure 14). In Northern Scotland, where WPD is the greatest (~ 1 W/m$^2$), there is no significant trend. All other regions apart from Eastern England and South-East England have statistically significant decreases – the trend in Eastern England is insignificant, and South-East England has a mean rise of 0.4% per year though from a low mean value of 226 W/m$^2$. In the case of South-West England and Wales, which have relatively high WPD and therefore show good potential for wind energy investment, these decreases (1.2% and 0.7% respectively) are arguably important in the long term.

### *4.4 Long-term Trends – Case Study*

Examination of the long-term trends for the seven-year capacity factor and operational probability of the example turbines (Siemens SWT-2.3-93 and Vestas V80-2.0 reveals the same regional trends for each turbine, as would be expected. Capacity factor is decreasing for all regions with statistically significant trends for both turbines, with the exception of Northern Scotland where an increase of 0.1% per year is seen. This amounts to 1% per decade. Northern Ireland, North-East England and South-East England have seen mean decadal decreases of 3%, 2% and 2% respectively. Operational probability is increasing in all regions with statistically significant trends apart from Northern Ireland. As discussed previously Northern Ireland is represented by a single station and it seems likely that local effects are having an influence on this station. The other stations have an annual increase of 0.1%, with the exception of South-East England where the increase is 0.3% (Siemens) and 0.4% (Vestas). The relatively large increase seen in this region is likely due to the low wind speeds in the area, with the trend for increasing wind speed (Table 1) having a larger impact in bringing the wind speed above the cut-in speed than in other regions.

**Table 4 Trends in the seven-year Capacity Factor and Operational Probability for two example wind turbines**

| Region | Capacity Factor | | | | | | Operational Probability | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Siemens | | | Vestas | | | Siemens | | | Vestas | | |
| | Gradient of Linear Fit ($\%/year$) | Signif. at 95% level? | Mean (%) | Gradient of Linear Fit ($\%/year$) | Signif. at 95% level? | Mean (%) | Gradient of Linear Fit ($\%/year$) | Signif. at 95% level? | Mean (%) | Gradient of Linear Fit ($\%/year$) | Signif. at 95% level? | Mean (%) |
| Northern Scotland | 0.1 | Y | 48 | 0.1 | Y | 40 | 0.1 | Y | 89 | 0.1 | Y | 86 |
| Eastern Scotland | -0.1 | Y | 28 | -0.1 | Y | 21 | 0.1 | N | 77 | 0.1 | N | 71 |
| Western Scotland | -0.1 | Y | 36 | -0.1 | Y | 28 | 0.0 | N | 82 | 0.0 | N | 78 |
| Northern Ireland | -0.3 | Y | 24 | -0.2 | Y | 18 | -0.1 | Y | 77 | -0.2 | Y | 71 |
| North West England | 0.0 | Y | 41 | 0.0 | Y | 32 | 0.0 | N | 86 | 0.0 | N | 82 |
| North East England | -0.2 | Y | 23 | -0.2 | Y | 17 | 0.0 | N | 73 | 0.0 | N | 67 |
| Midlands | -0.1 | Y | 22 | -0.1 | Y | 16 | 0.1 | Y | 77 | 0.1 | Y | 71 |
| Eastern England | 0.0 | N | 27 | -0.1 | Y | 20 | 0.1 | Y | 81 | 0.1 | Y | 76 |
| South East England | 0.0 | Y | 20 | 0.0 | N | 14 | 0.3 | Y | 72 | 0.4 | Y | 65 |
| South West England | -0.2 | Y | 35 | -0.2 | Y | 27 | 0.0 | N | 82 | 0.0 | N | 78 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wales | -0.1 | Y | 38 | -0.1 | Y | 30 | 0.0 | N | 81 | 0.0 | N | 77 |

### *4.5 Seasonal Variation*

In addition to the spatial distribution of mean wind characteristics, the seasonal wind characteristics are also of essential importance in the interest of predicting the variation of wind power generation within an annual cycle, which may have implications to strategize the operation and management of the electricity network. Sinden [4][63] addressed that the electricity demand in the UK is subjected to pronounced seasonal variation, in which winter is often the season requiring most electricity power output due to heating and lighting purposes, whereas electricity demand is at its lowest in summer. In 2019, approximately 79.70 TWh of electricity is consumed in spring, 69.35 TWh in summer, 67.51 TWh in autumn and 78.71 TWh in winter [64]. In parallel, seasonal variability of wind speed across the UK is also obvious, which is mainly driven by the depressions in the mid-latitudes of the northern hemisphere. The depressions are likely to be more vigorous in winter than that in summer and, consequently, the storminess in winter tends to be more severe [65][66].Correspondingly, as can be seen in Figure 15, the seasonal variation of Weibull distribution fit is clearly distinguishable, where the wind speed distribution during the summer months of June, July and August tends to be more peaked with smaller scale parameter (i.e, abscissa of the distribution peak), whereas those during the winter months of December, January and February appears to be much wider with lower peaks. Figure 16 reveals that the wind power density during winter is typically higher than those during summer. Quantitatively, the majority of the observation sites (36 out of 38) possess twice as much wind power density during winter than that during summer, and 14 out of the 38 stations possess triple the wind power density during winter than that during summer. The network average wind power density is estimated to be 392 W/m$^2$ in spring, 210 W/m$^2$ in summer 347 W/m$^2$ in autumn and 639 W/m$^2$ in winter. At regional scale, the degree of seasonal variability also appears to be somewhat different. The most significant seasonal variability in wind power density is observed at Wales, with a coefficient of variation of 55%, followed successively by Northern Scotland (53%), Western Scotland (51%), and North West England (51%). In contrast, the seasonal variability is at its lowest in South East England with a coefficient of variation of 35%. Based on the results and existing statistics, the seasonal contribution of wind power to electricity demand can be estimated to be respectively 12% in spring, 7% in summer, 10% in autumn and 18% in winter. The results here further support the conclusion by Sinden

[4] that there exists a positive relationship between the wind power output and the electricity demand in the UK, i.e., the availability of wind power during times of peak electricity demand is higher than that at times of low electricity demand. Overall, the broad similarities in the seasonal pattern of wind power and electricity demand is encouraging.

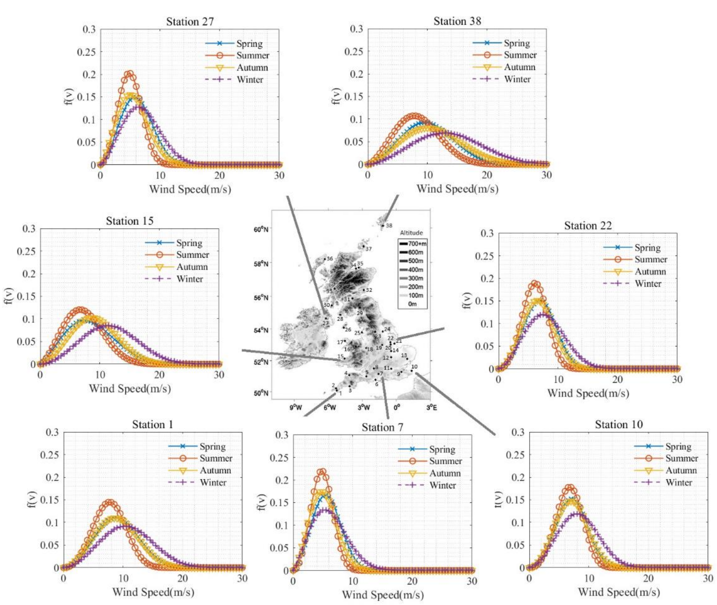
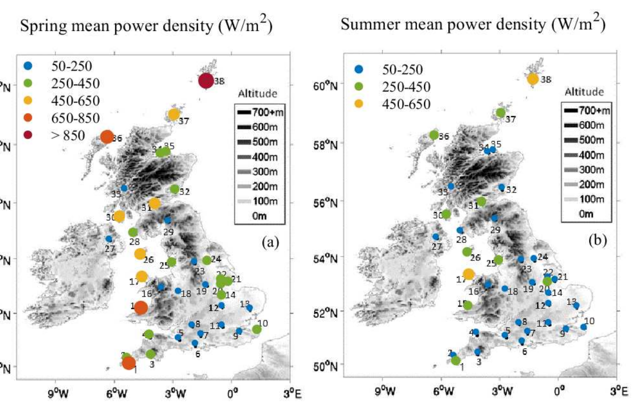



**Figure 15 Weibull distribution of seasonal wind speed at selected stations**



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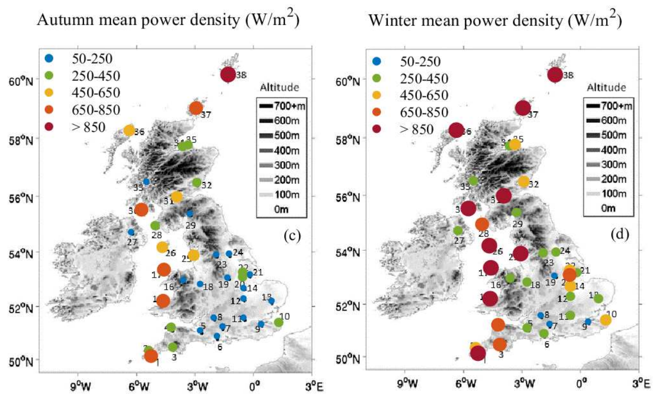


**Figure 16 Distribution of seasonal mean power density. Coloured version is available online**

## 5 Conclusions and Summary

Given its abundant availability and environment-friendly nature, wind energy has been developing at an remarkable pace over the past few decades, and is anticipated to grow rapidly in the interest of diversifying the power supply portfolio and mitigating climate change and environment degradation. To inform this development, this study presents a updated overview of wind speed and wind energy characteristics across the UK based on statistical analysis of long-term (1981-2018) surface wind observations at 38 stations, extending previous studies and bringing our understanding of trends up to date. This analysis has been conducted at both station and regional level, based on the regions defined by the UK Meteorological Office. The important conclusions drawn from this work are:

1) Statistically significant, long-term changes in annual mean wind speed are seen at 15 of the 38 stations. However, there is no region which shows a consistent increasing or decreasing trend across all its stations, with the exception of Northern Ireland which includes a single station.

2) The lack of consistent trends over all stations in a region implies the importance of local topographical effects.

3) South-East England has a statistically significant increase in annual mean wind speed, but this amounts to less than $0.5ms^{-1}$ over the entire period.

4) The probability distributions are modelled well using a Weibull distribution. The scale parameter follows trends which are similar to those of the annual mean wind speed, though with a greater proportion of statistical significance; the trends in the shape parameter are significant for all regions.

5) Application of the Weibull parameters to determine capacity factor and operational probability for two representative wind turbines (Siemens SWT-2.3-93 and Vestas V80-2.0) shows a small (typically ~1% per decade) decrease in capacity factor for all regions with a significant trend. Conversely, the operational probability is generally increasing but again by the same small magnitude with the exception of the South-East where an increase of about 4% per decade is seen, with the caveat that this region has low wind power density.

6) In addition to the considerable variability in space, the estimated wind power density across the network is also subject to clear seasonality, with wind power density during winter months at least twice that during summer months.

**CRediT Authorship Contribution Statement**

**Zhenru Shu** : Conceptualization, Formal analysis, Writing - original draft, Methodology; **Mike Jesson**: Formal analysis, Writing - review & editing

**Competing Interests**

The authors declare no competing interest.

**Data Availability Statement**

The data that support the findings of this study are available from British Atmospheric Data Centre (BADC) and UK Met Office (UKMO). Restrictions may apply to the availability of these data, which were used under license for this study.

**Acknowledgements**

The authors would like to thank the British Atmospheric Data Centre (BADC) and UK Met Office (UKMO) for providing access to the MIDAS data. A special thanks is also due to Professor Mark Sterling at University of Birmingham for reviewing and commenting on the original draft of this paper. We also would like to thank the anonymous reviewers for their constructive comments. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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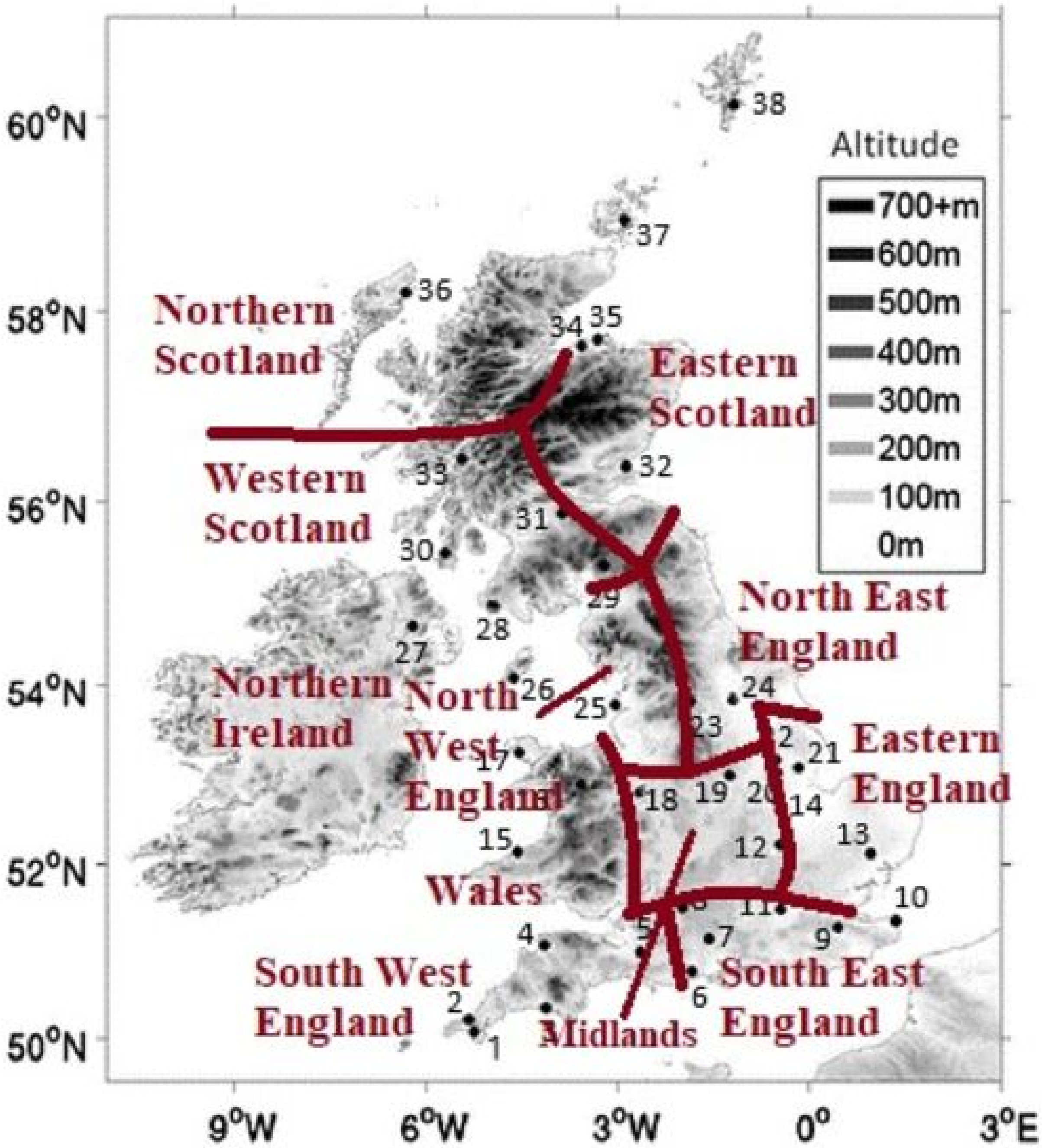
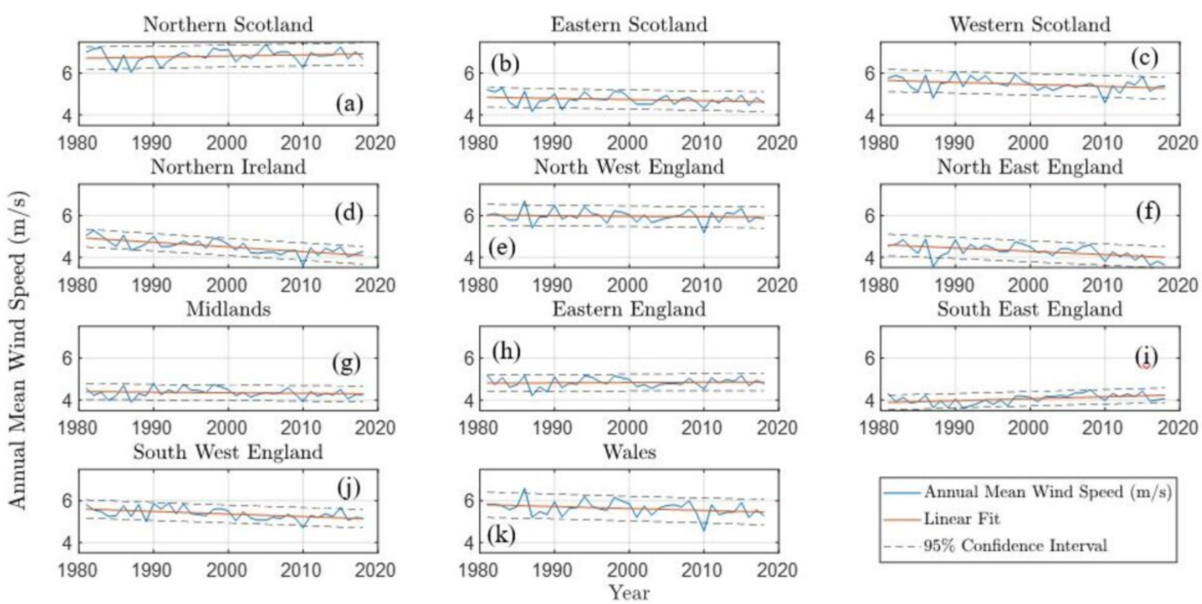
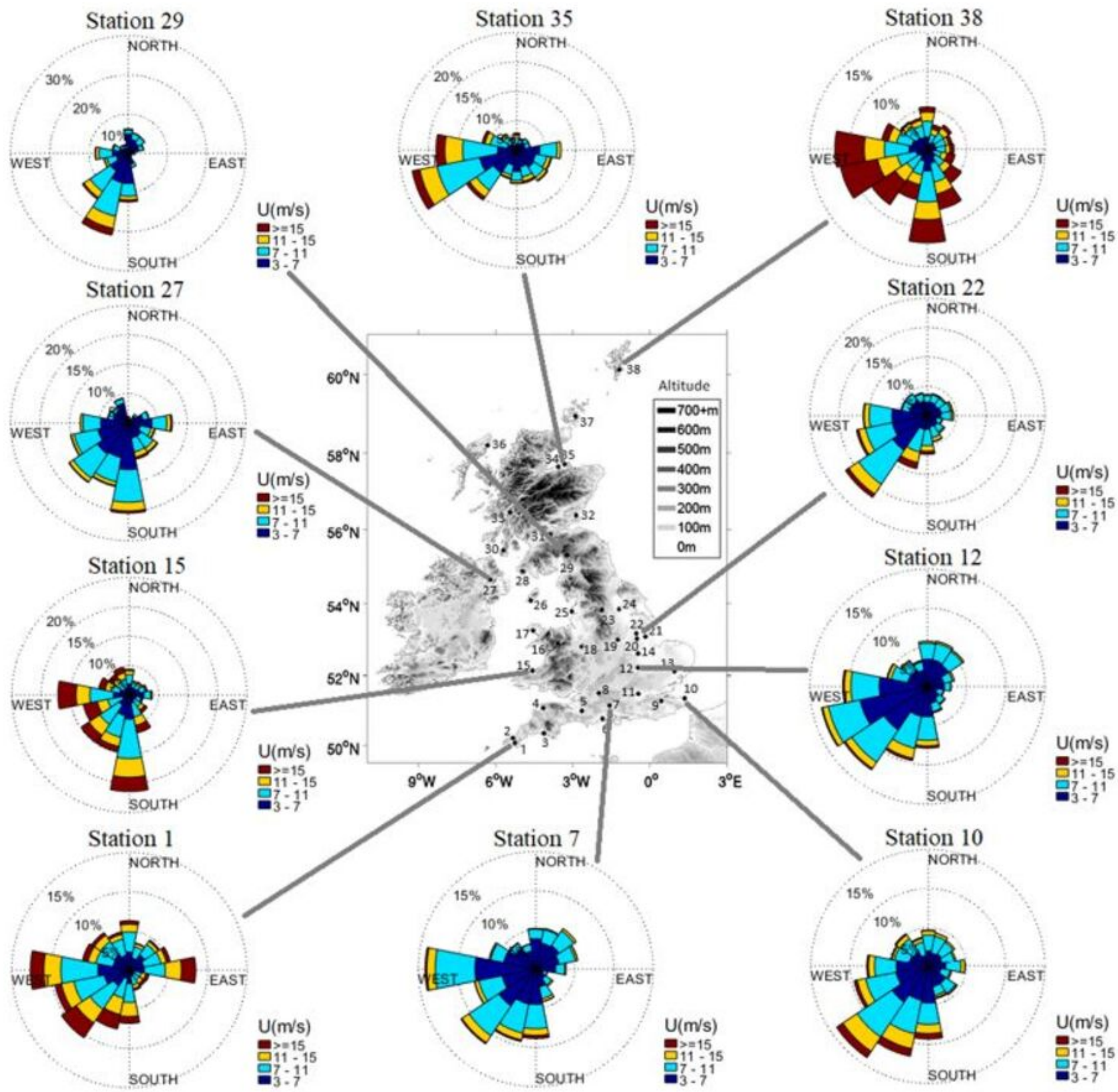
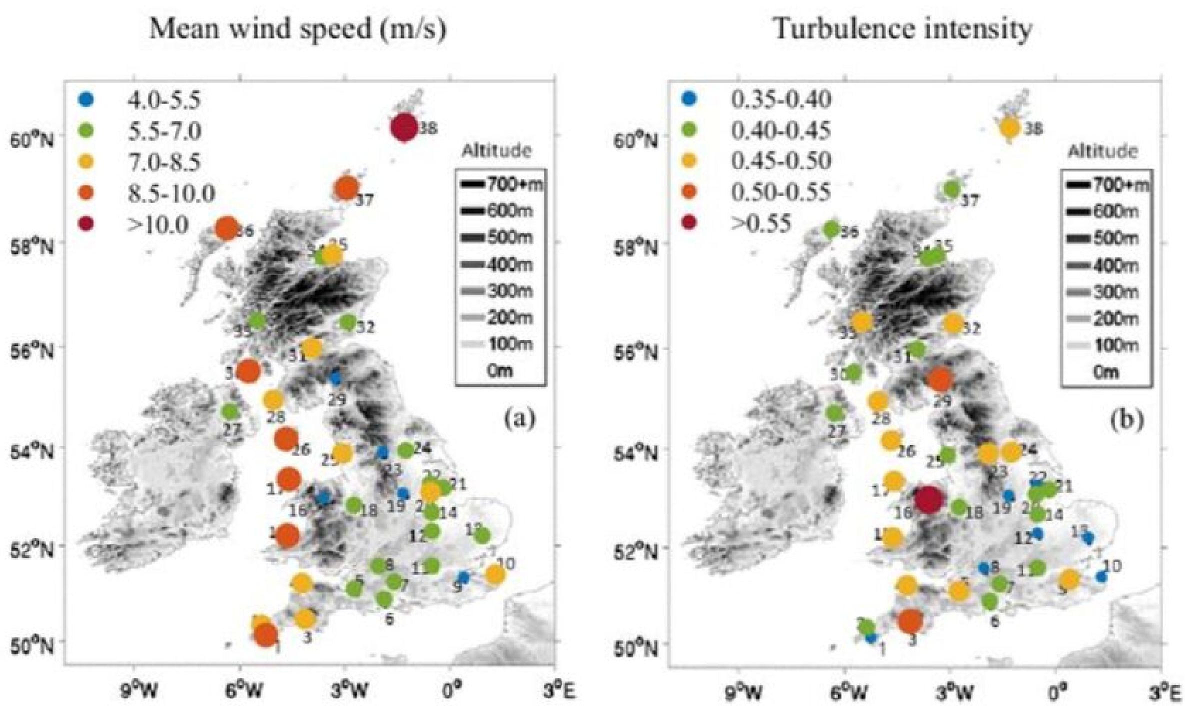
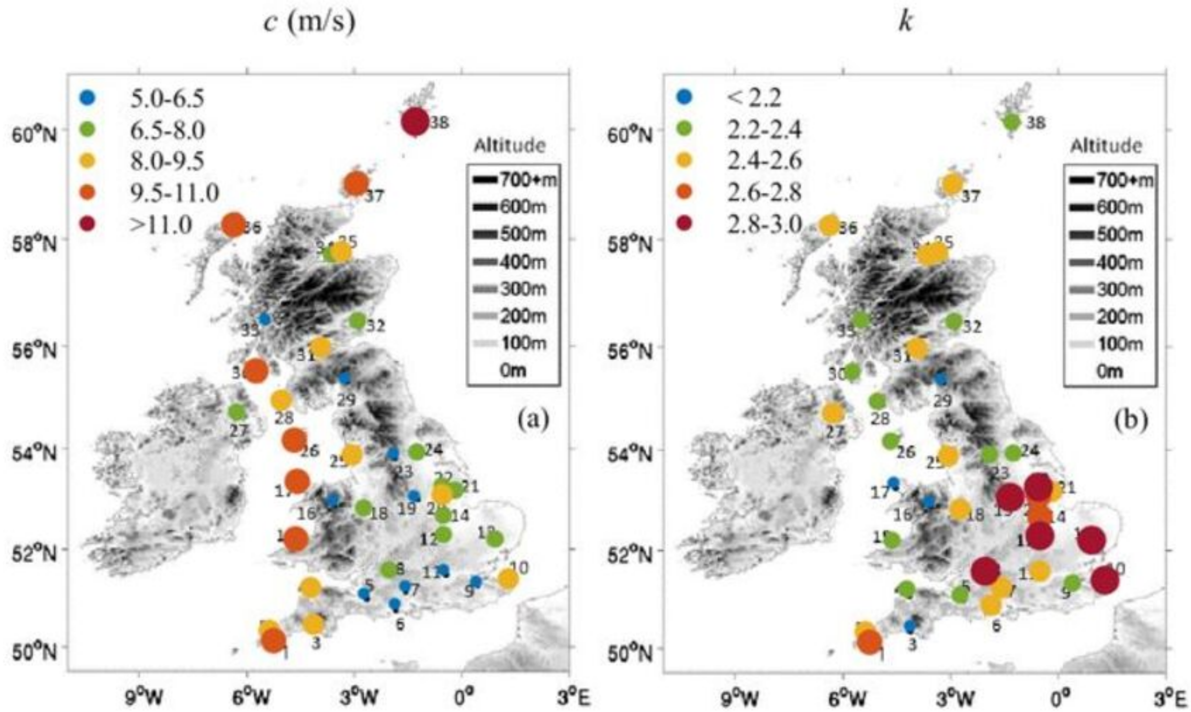
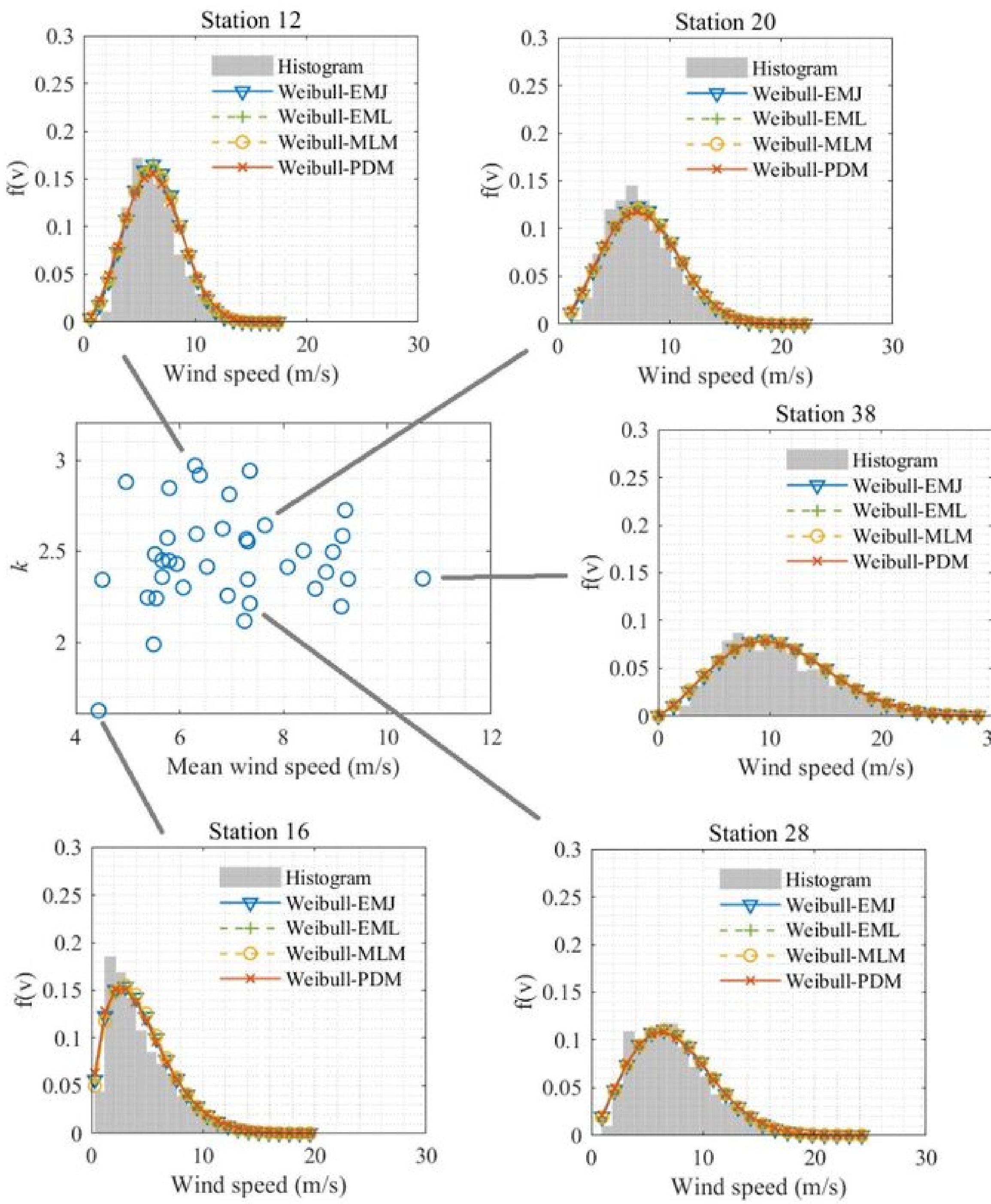

Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
Northern Scotland
Eastern Scotland
Western Scotland
North East England
Northern Ireland
North West England
Eastern England
Wales
Midlands
South West England
South East England
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

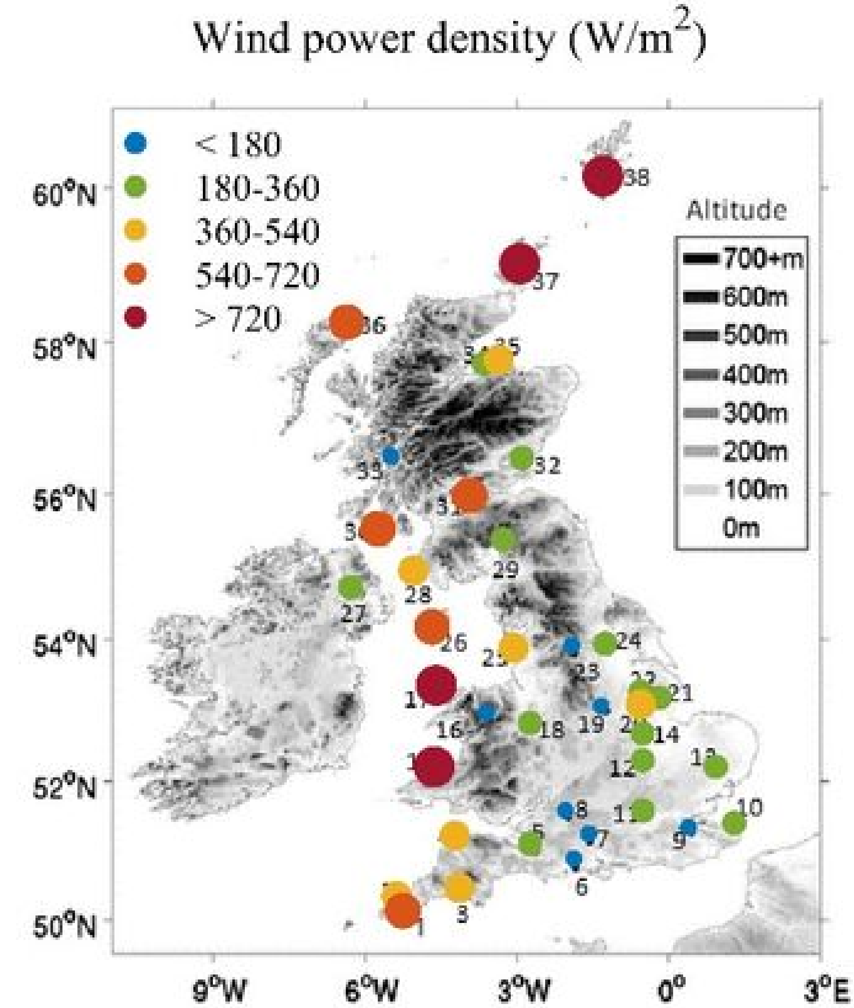

Northern Scotland
(a)
Eastern Scotland
(b)
Western Scotland
(c)
Northern Ireland
(d)
North West England
(e)
North East England
(f)
Midlands
(g)
Eastern England
(h)
South East England
(i)
South West England
(j)
Wales
(k)
Annual Mean Wind Speed (m/s)
Year
Annual Mean Wind Speed (m/s)
Linear Fit
95% Confidence Interval

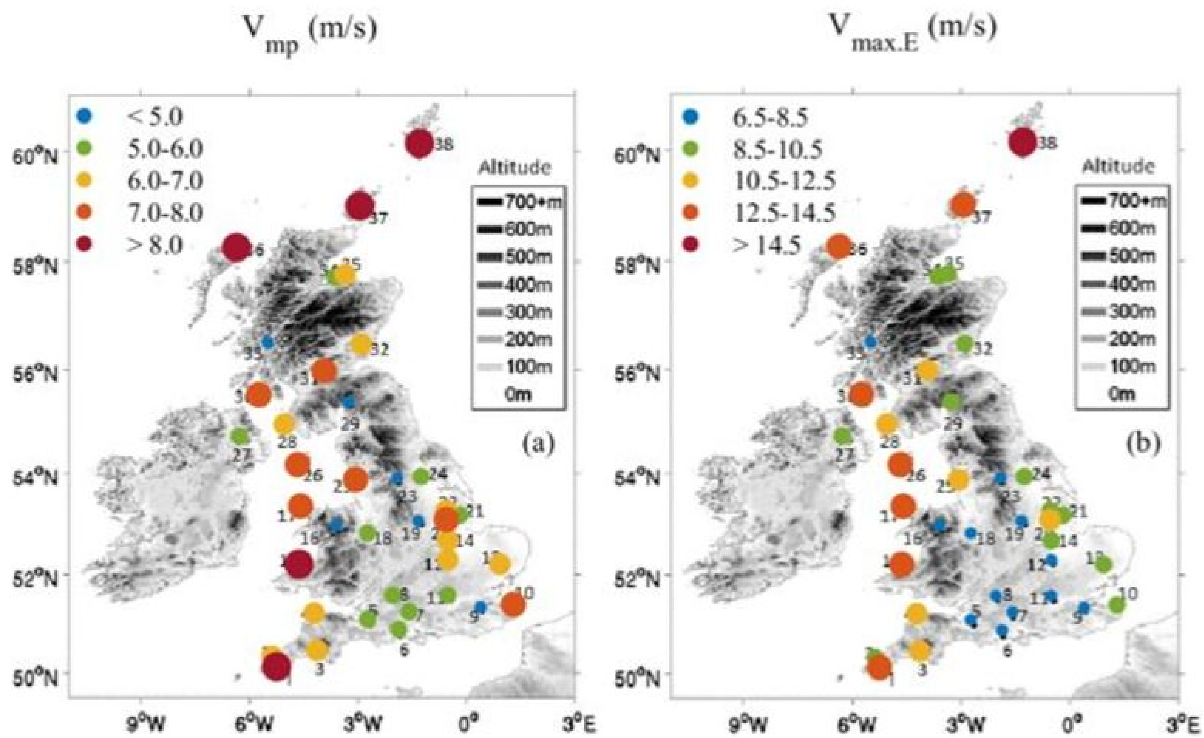

Station 29
Station 35
Station 38
Station 27
Station 22
Station 15
Station 12
Station 1
Station 7
Station 10
NORTH
SOUTH
WEST
EAST
U(m/s)
>=15
11 - 15
7 - 11
3 - 7
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

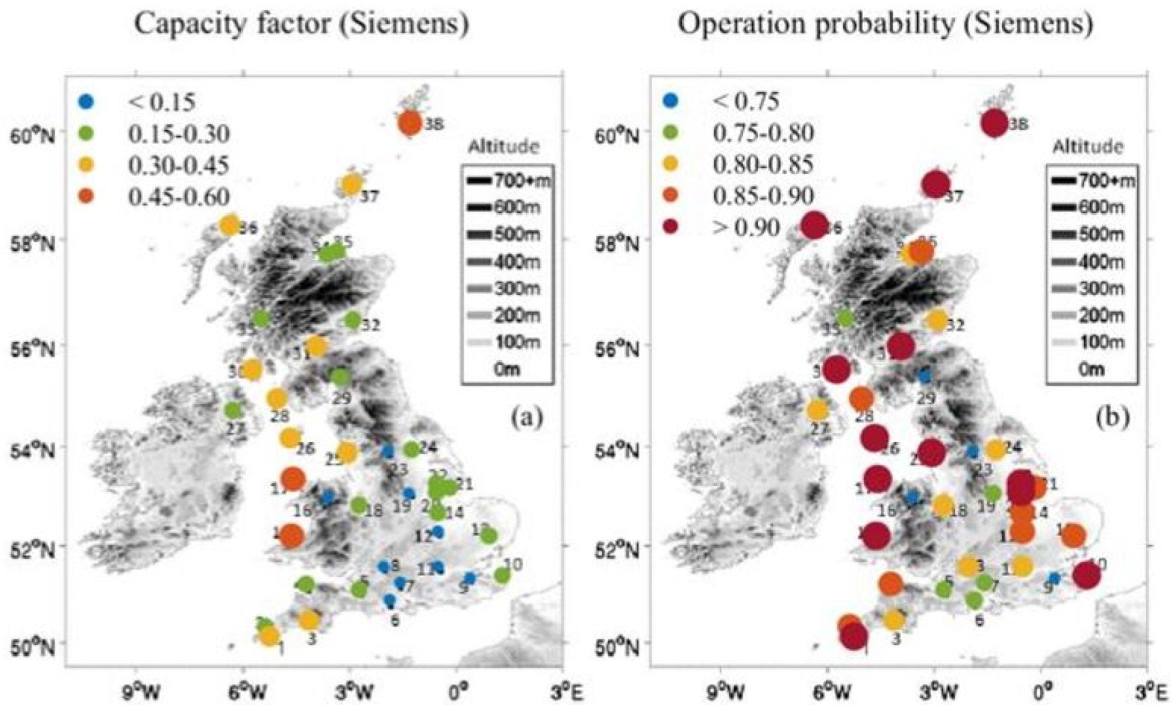

Mean wind speed (m/s)
4.0-5.5
5.5-7.0
7.0-8.5
8.5-10.0
>10.0
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
Turbulence intensity
0.35-0.40
0.40-0.45
0.45-0.50
0.50-0.55
>0.55
(b)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

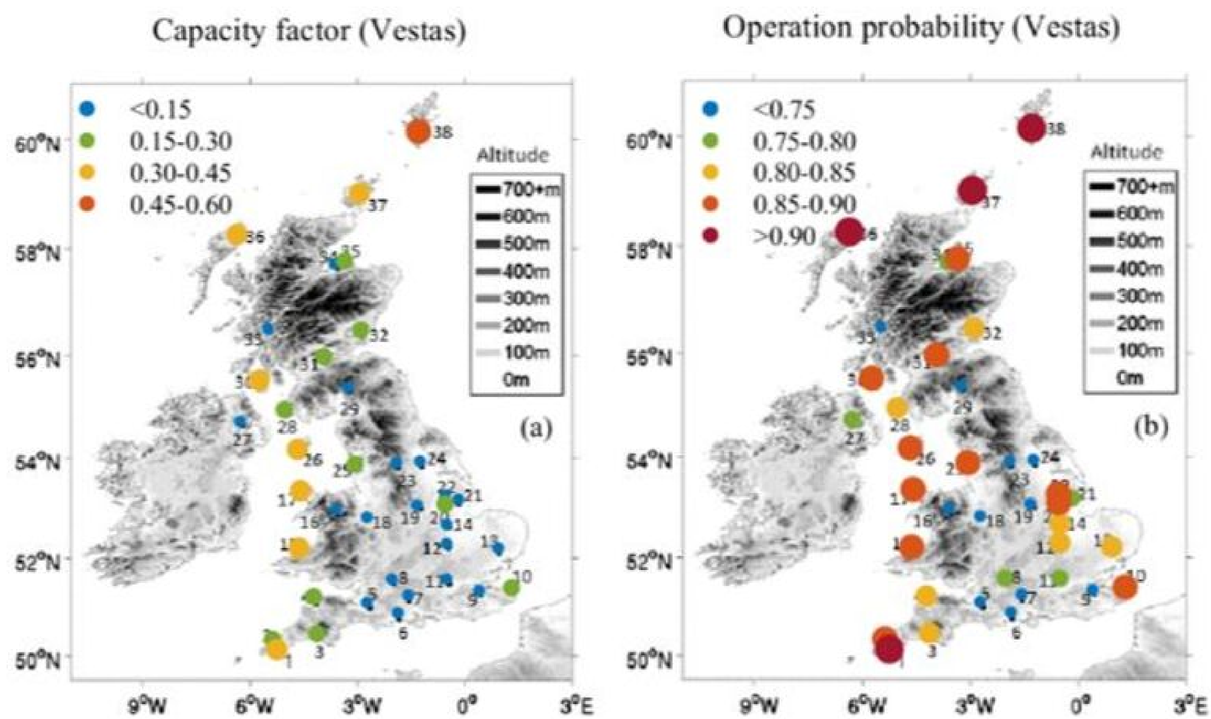

c (m/s)
k
5.0-6.5
6.5-8.0
8.0-9.5
9.5-11.0
>11.0
< 2.2
2.2-2.4
2.4-2.6
2.6-2.8
2.8-3.0
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
(b)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

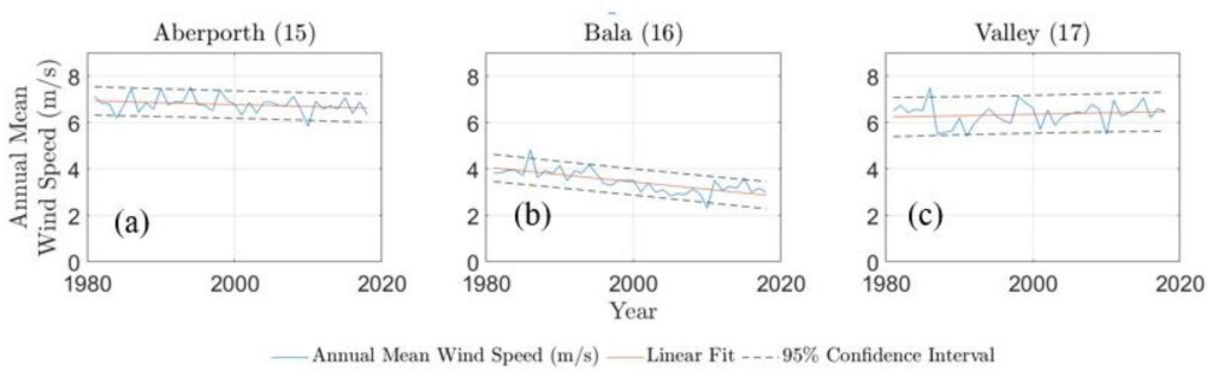

Station 12
Station 20
Station 38
Station 16
Station 28
Histogram
Weibull-EMJ
Weibull-EML
Weibull-MLM
Weibull-PDM
f(v)
Wind speed (m/s)
k
Mean wind speed (m/s)

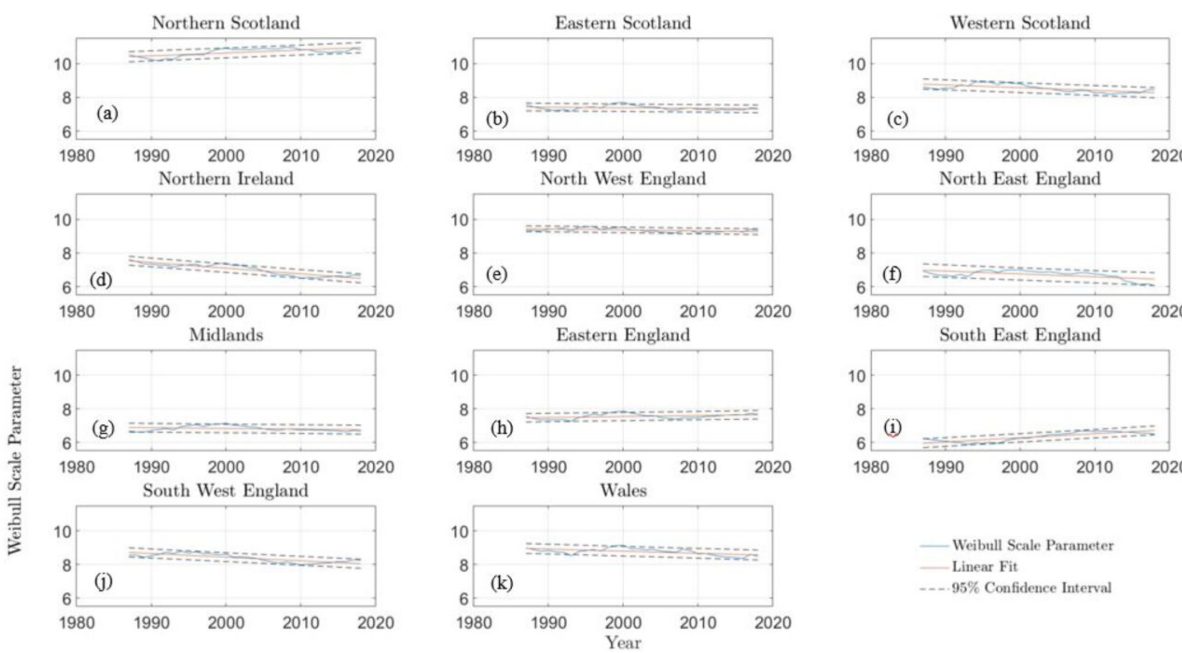

Wind power density (W/m²)
< 180
180-360
360-540
540-720
> 720
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

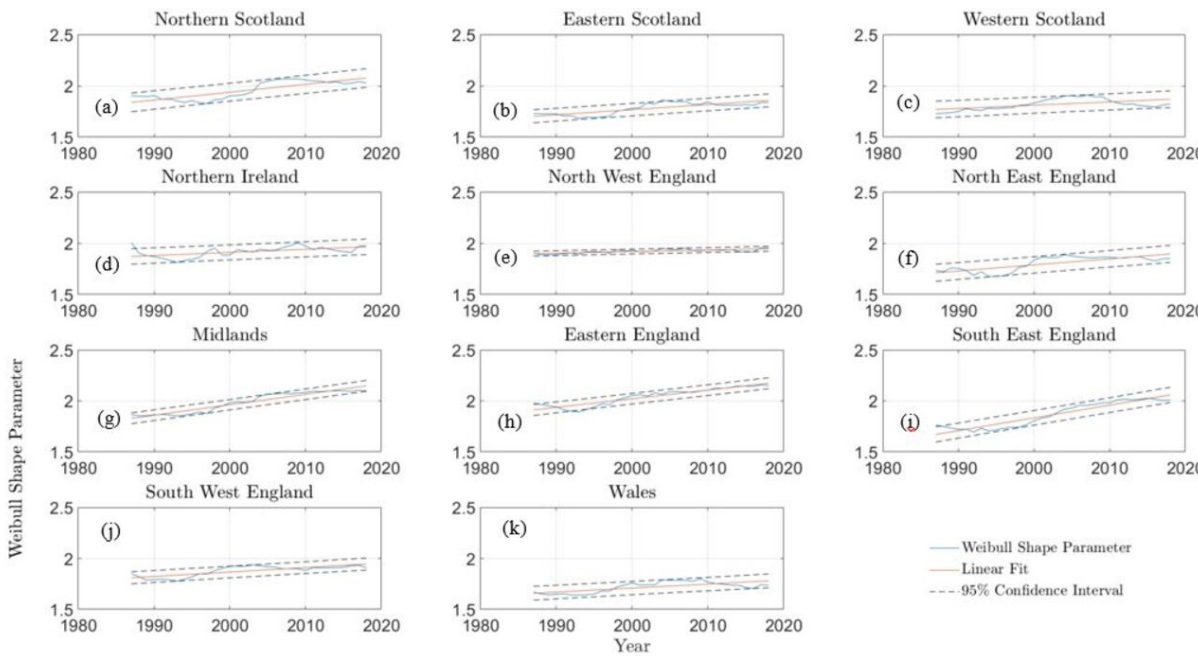

V_mp (m/s)
< 5.0
5.0-6.0
6.0-7.0
7.0-8.0
> 8.0
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
V_max.E (m/s)
6.5-8.5
8.5-10.5
10.5-12.5
12.5-14.5
> 14.5
(b)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

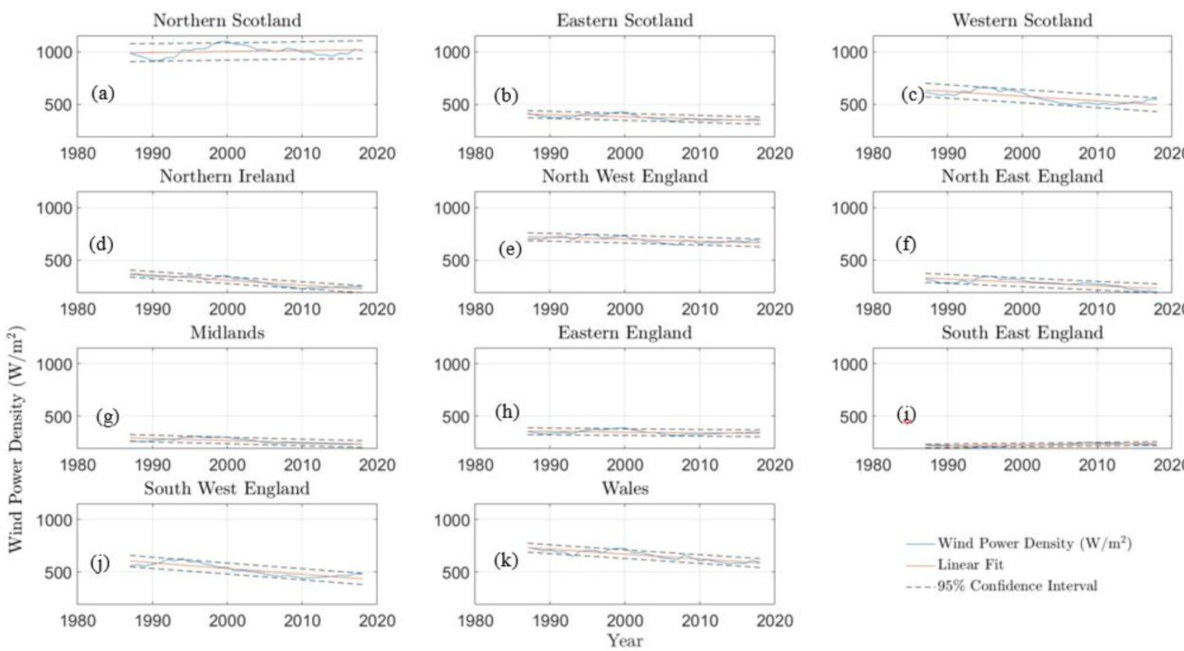

Capacity factor (Siemens)
Operation probability (Siemens)
< 0.15
0.15-0.30
0.30-0.45
0.45-0.60
< 0.75
0.75-0.80
0.80-0.85
0.85-0.90
> 0.90
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
(b)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

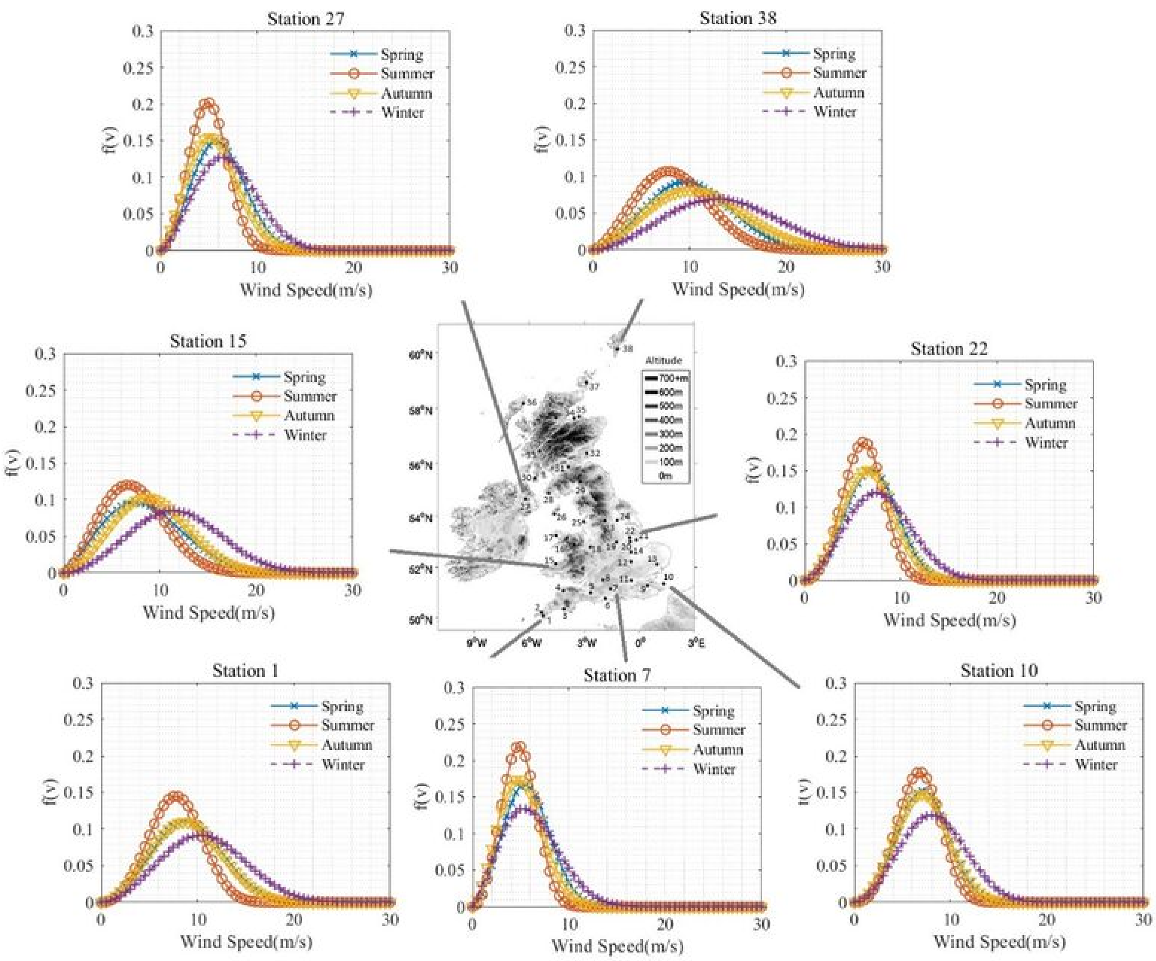

Capacity factor (Vestas)
<0.15
0.15-0.30
0.30-0.45
0.45-0.60
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
Operation probability (Vestas)
<0.75
0.75-0.80
0.80-0.85
0.85-0.90
>0.90
(b)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E

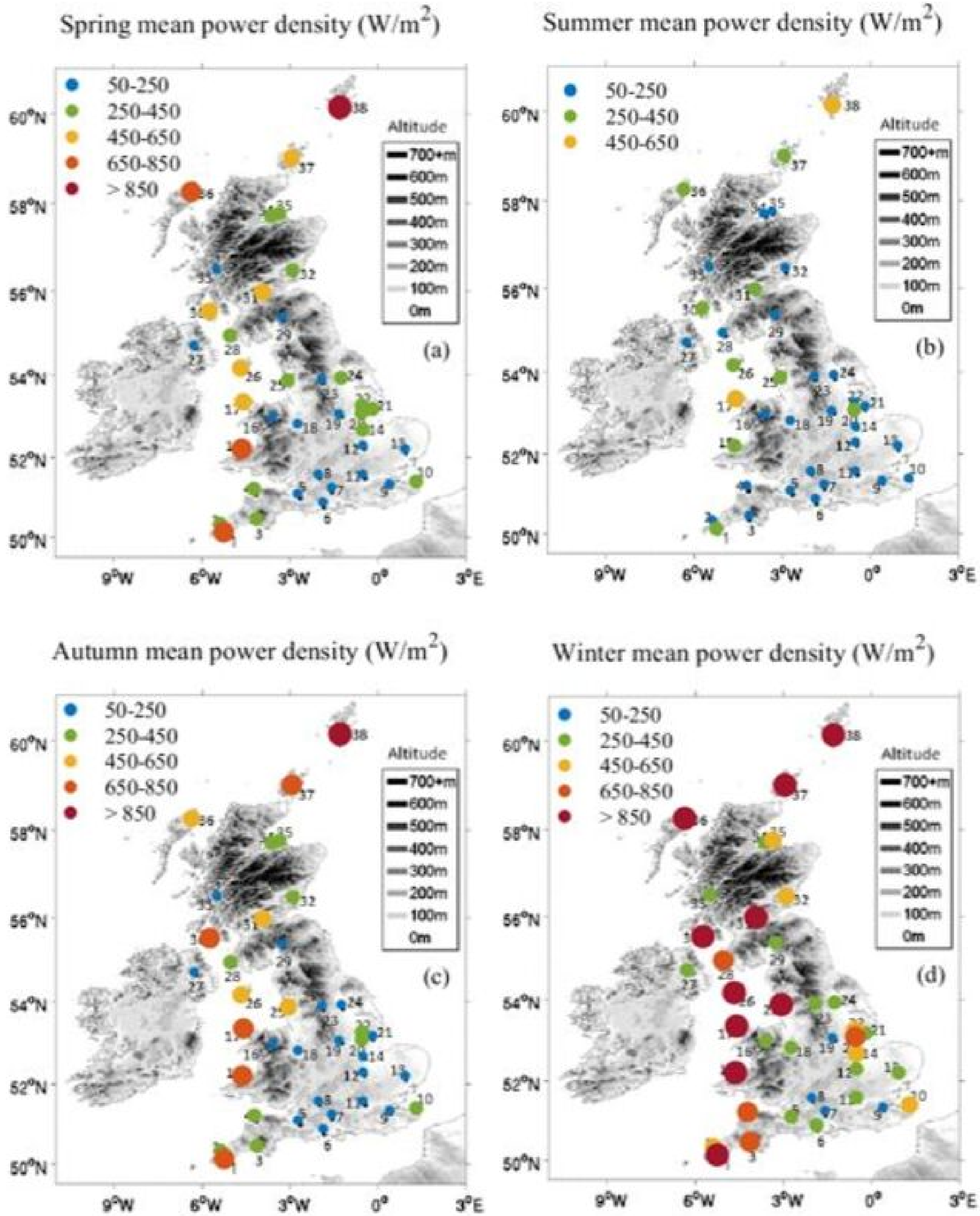

Aberporth (15)
Bala (16)
Valley (17)
Annual Mean Wind Speed (m/s)
(a)
(b)
(c)
Year
Annual Mean Wind Speed (m/s)
Linear Fit
95% Confidence Interval


Northern Scotland
(a)
Eastern Scotland
(b)
Western Scotland
(c)
Northern Ireland
(d)
North West England
(e)
North East England
(f)
Midlands
(g)
Eastern England
(h)
South East England
(i)
South West England
(j)
Wales
(k)
Weibull Scale Parameter
Year
Weibull Scale Parameter
Linear Fit
95% Confidence Interval


Northern Scotland
(a)
Eastern Scotland
(b)
Western Scotland
(c)
Northern Ireland
(d)
North West England
(e)
North East England
(f)
Midlands
(g)
Eastern England
(h)
South East England
(i)
South West England
(j)
Wales
(k)
Weibull Shape Parameter
Year
Weibull Shape Parameter
Linear Fit
95% Confidence Interval


Northern Scotland
(a)
Eastern Scotland
(b)
Western Scotland
(c)
Northern Ireland
(d)
North West England
(e)
North East England
(f)
Midlands
(g)
Eastern England
(h)
South East England
(i)
South West England
(j)
Wales
(k)
Wind Power Density (W/m²)
Year
Wind Power Density (W/m²)
Linear Fit
95% Confidence Interval


Station 27
Station 38
Station 15
Station 22
Station 1
Station 7
Station 10
Spring
Summer
Autumn
Winter
f(v)
Wind Speed(m/s)
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E


Spring mean power density (W/m²)
Summer mean power density (W/m²)
Autumn mean power density (W/m²)
Winter mean power density (W/m²)
50-250
250-450
450-650
650-850
> 850
Altitude
700+m
600m
500m
400m
300m
200m
100m
0m
(a)
(b)
(c)
(d)
60°N
58°N
56°N
54°N
52°N
50°N
9°W
6°W
3°W
0°
3°E