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ABSTRACT

Harvesting wind energy resources is a major part of the UK strategy to diversify the power supply portfolio and mitigate environmental 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 levels and important, turbine-specific wind energy assessment parameters. It is shown that the Weibull distribution function provides satisfactory modeling 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 and 12.06 m/s, and the shape parameter ranges from 1.63 to 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 three of the 11 geographical regions. The seasonal variability of Weibull parameters and wind power density is confirmed and discussed.

I. INTRODUCTION

Harvesting renewable energy resources represents one of a range of strategies to reduce carbon dioxide emission and decelerate environmental 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 5.2 GW in 2010 to 23.9 GW 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 ρ 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 the identification of desirable sites to predicting the economic viability of wind farms 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., Refs. 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,

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

In the UK, estimation of Weibull parameters for wind energy analysis has been carried out previously by Earl *et al.*,[21] Früh,[22] and Brayshaw *et al.*[23] Based on two-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 10 m height ranges from 4.76 m/s to 8.71 m/s. Given that the assertion of Gross *et al.*[24] shows that at least seven years of wind speed data are required due to year-to-year variability (this variability has been estimated as about 4%[25]), the two-year period seems short, but a similar range of shape parameters is also reported by Earl *et al.*[21] from a much longer (31-yr) dataset. 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 to 2010, over which 15 of the 40 observation sites 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 to 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 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 levels, including changes in Weibull distributions and implications for wind power generation. Data from 1981 to 2018 from 38 surface observation stations across the UK are analyzed. The remaining contents in this paper are organized as follows: Sec. II details the data used and their processing. Section III introduces the determination of various parameters involved in this study. The results from statistical analysis are documented and discussed in Sec. IV, and the main conclusions and summary are given in Sec. V.

II. 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., Refs. 19, 20 and 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 (MLM) is most suitable in accordance with 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 the Weibull distribution function. Moreover, Mohammadi and Mostafaeipour[19] and Mohammadi *et al.*[20] concluded that the power density method (PDM) 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 σ_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 Γ 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]

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

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

where v_i is the wind speed data measured at the time interval i and n is the number of non-zero datasets.

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

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

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

where $\overline{v^3}$ is the mean of the cubed wind speed. The scale parameter in the PDM is estimated in 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 cutoff 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 be utilized well to compute the capacity factor (CF) of a wind turbine,

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

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 the 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 as follows:

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

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

III. DATA COLLECTION AND PROCESSING

A. 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 Center (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-min mean speed as used in some contexts. Data covering the period 1981–2018 are used, which are taken from 38 observation stations spread across the country (see Fig. 1 and Table I). All of the observation sites meet the UK Met Office (UKMO) site exposure requirements, which are reasonably representative of open exposure conditions. Wind speed data are recorded using a cup anemometer mounted at a height of 10 m above the local ground, with the wind direction measured by a traditional wind vane at the same height.[41] All the records archived in the 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 with 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.

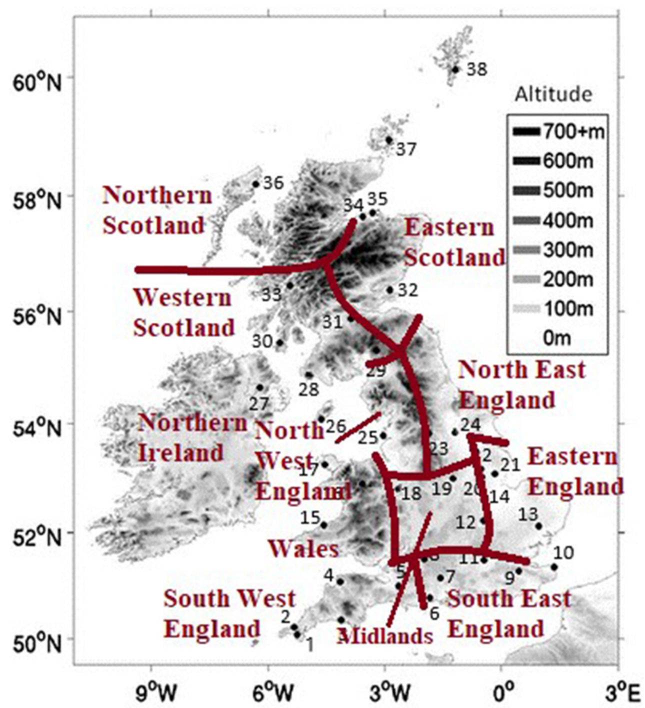

FIG. 1. Surface observation network involved in this study, modified based on Earl *et al.*[21] Marked regions are in accordance with the Met. Office classification for UK regional climate.[40]

Previous statistical analyses of wind energy have been carried out using wind data at various temporal resolutions: 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 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 Sec. IV.

In addition, the UK is one of the countries that are most frequently affected by extratropical cyclones, which are associated predominantly with areas of low atmospheric pressure over the North Atlantic. These cyclonic windstorms are the major contributor in

TABLE I. 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}/yr)	Fit p-value	Significant at 95% level?
Northern Scotland	36	Stornoway 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
South–East England	6	Hurn	10	0.002	0.589	N
	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

TABLE I. (*Continued.*)

Region	Station number	Station name	Altitude (m)	Gradient of linear fit (ms^{-1}/yr)	Fit p-value	Significant at 95% level?
	16	Bala	163	−0.032	0.000	Y
	17	Valley	10	0.006	0.258	N
		Regional mean		−0.011	0.037	Y

terms of 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 windstorms is often considered crucial for extreme wind speed analysis.[46–49] However, given the nature of the present study and the relatively low 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 Fig. 1 and Table I).

To further highlight the necessity of this study, the 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 Fig. 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. Both Earl *et al.*[21] and Hewston and Dorling[26] 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 strategic optimization of the integration of wind power into the UK electricity network, e.g., with increasing integration of wind power in regions where wind speed shows a long-term increase.

B. Extrapolation of wind speed data

It is recognized 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 the 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 the 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 the ground level), v_R is

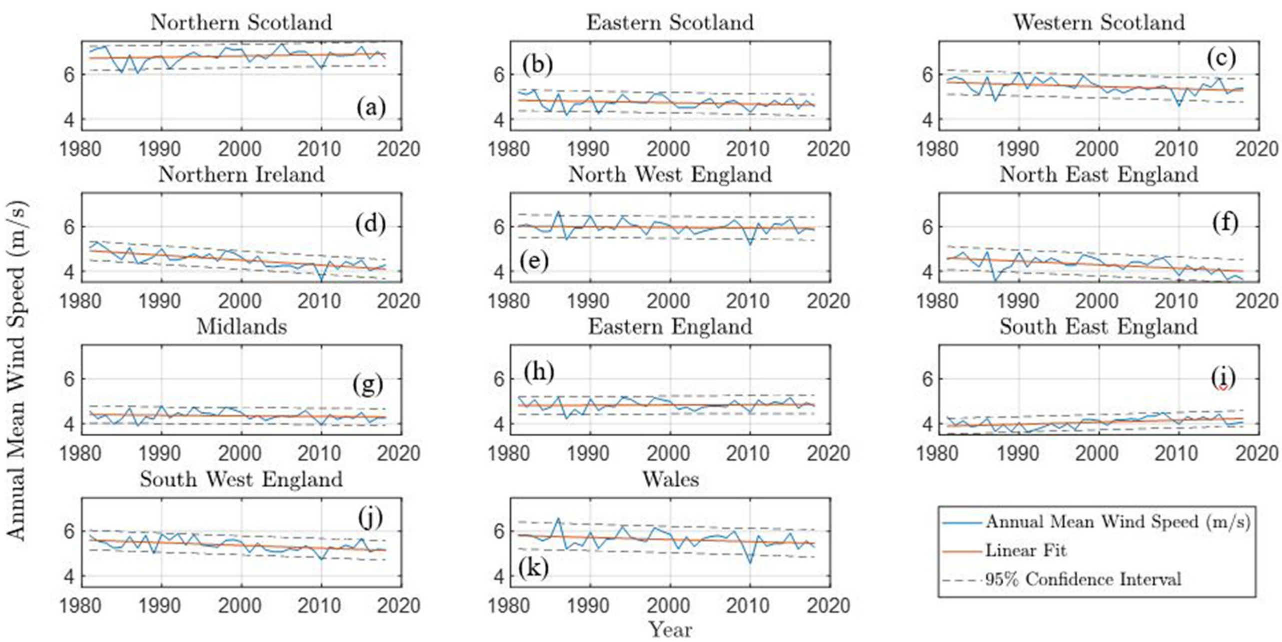

FIG. 2. The variation of annual mean wind speed between 1981 and 2018 across different UK regions. The p-value and slope for the linear regression fit are also demonstrated.

the reference wind speed measured at the reference height z_R (e.g., 10 m above the ground), and α 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 conditions.[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 nighttime and early morning and lower values midday. It should be noted that this study examined wind field characteristics in Saudi Arabia, where thermal effects are likely to be extreme. The common value of the 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 10 m above the ground are converted to a wind turbine hub height of 100 m using the 1/7th power law when applied directly to the wind turbine function. All the graphic representations of analysis results given in this study were produced using MATLAB, unless otherwise specified.

IV. RESULTS AND DISCUSSION

A. Current UK wind climate

The prevailing wind direction over the wind direction is broadly south–west (see Fig. 1) due to the location of the UK at a latitude

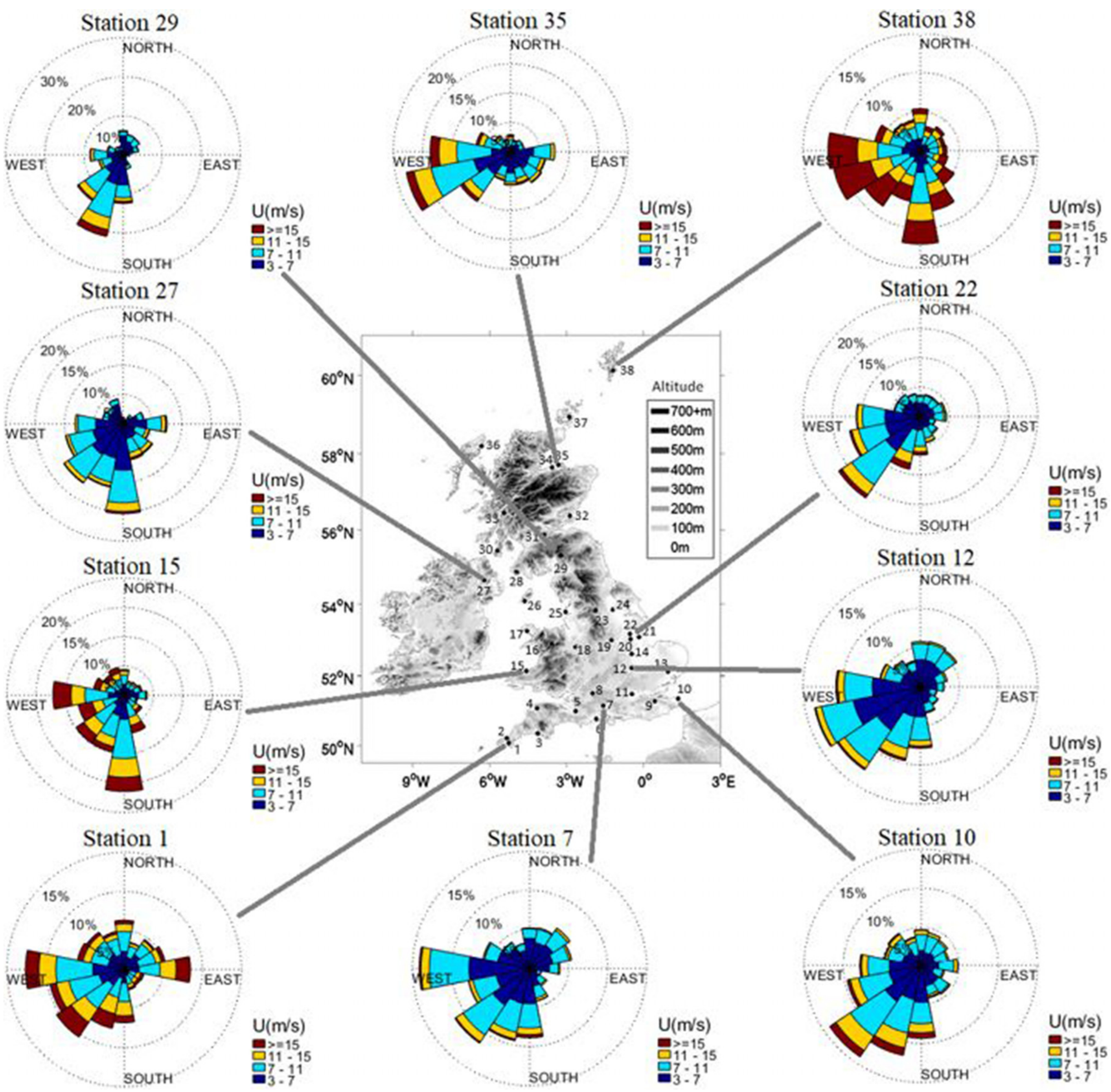

FIG. 3. Wind rose plots at selected locations.

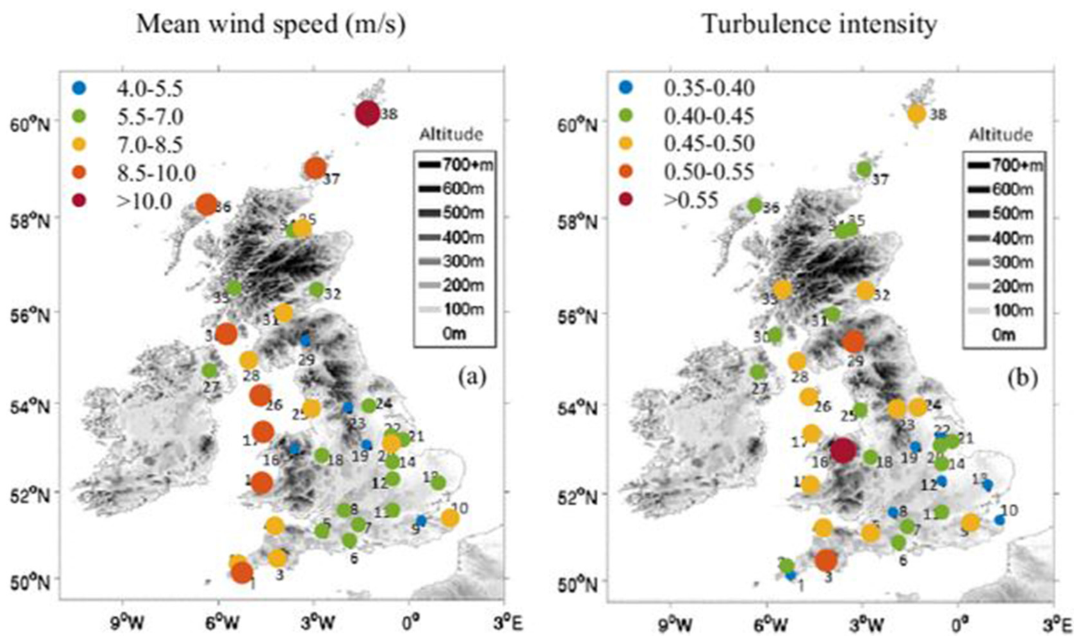

FIG. 4. Distribution of mean wind speed and turbulence intensity.

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 localized 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

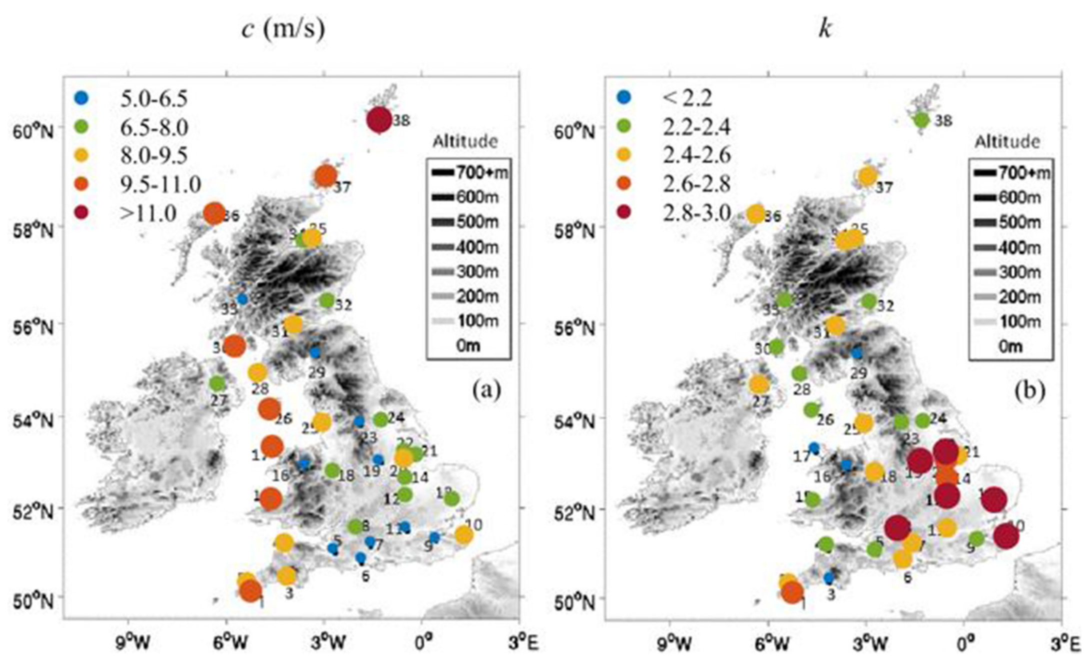

FIG. 5. Distribution of Weibull scale parameter (c) and shape parameter (k).

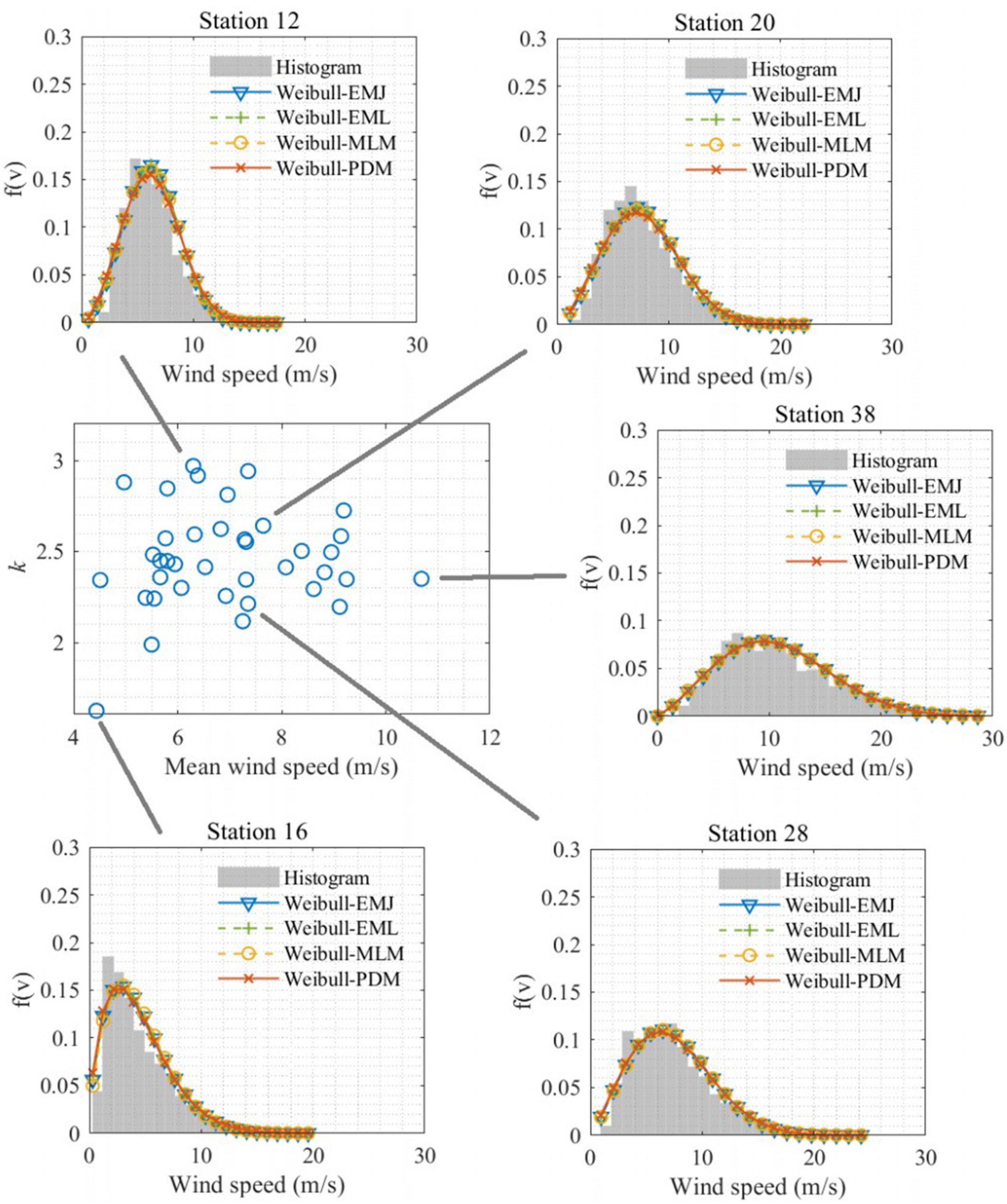

FIG. 6. Comparison of wind data histogram with different Weibull distribution fits.

clearly defined prevailing wind direction, while in south and central England (e.g., Stations 7, 10, and 12), there is a much wider spread (Fig. 3).

The site-to-site variability of mean wind speed [Fig. 4(a)] and turbulence intensity [Fig. 4(b)] 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) and 10.69 m/s at Lerwick (Station 38). Note that extreme low wind speeds (i.e., <5.5 m/s) are found mostly at the observation sites (e.g., Stations 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

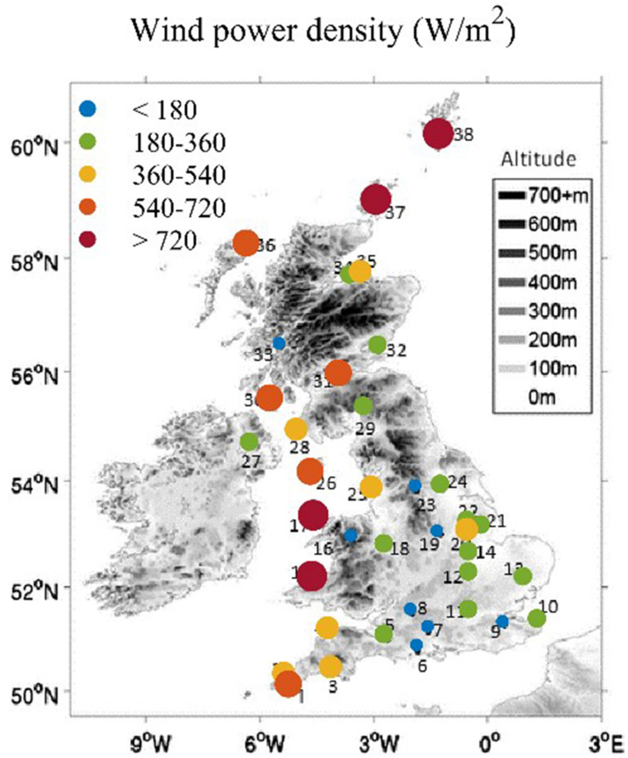

FIG. 7. Distribution of wind power density across the observation network.

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 Fig. 4(b)], 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.

The considerable site-to-site variability in mean wind speed and turbulence intensity leads to variations in the corresponding Weibull parameters (Fig. 5). From a practical point of view, the value of the 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 Fig. 5(a), the distribution of the 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 the southern part of England are generally the smallest. The spread of the 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 variations [Fig. 5(b)], 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 the 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.

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 (Fig. 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 as follows:

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

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. Furthermore, the goodness of fit was found to be an inverse function of the shape parameter (not shown), i.e., the larger the shape parameter, the lower the R^2 value. Furthermore, it is noteworthy that the Weibull distribution fit based on the power density method (PDM) generally possesses 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 the PDM is presented, and it may be considered representative of all.

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/m², with the largest value (1407 W/m²) obtained at Lerwick (Station 38) and the lowest value (125 W/m²) obtained at Nottingham Watnall (Station 19). In terms of the regions defined in Fig. 1, the variation is seen in the mean wind power density over each region, and Northern Scotland has the highest mean value at 1010 W/m², followed by North–West England (677 W/m²), Wales (590 W/m²), and Western Scotland (544 W/m²). North–East England and South–East England have the lowest regional wind power densities, with mean values of 198 and 221 W/m², respectively.

TABLE II. Specifications of the wind turbines considered in this study.

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

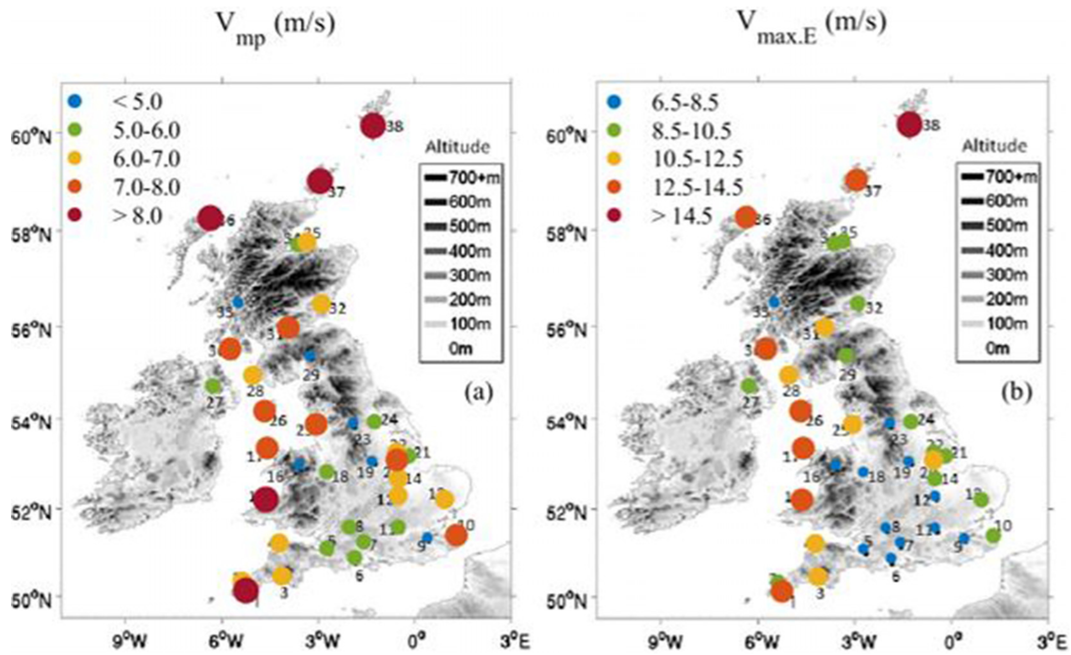

FIG. 8. Distribution of V_{mp} and $V_{max.E}$ across the observation network.

Likewise, Figs. 8(a) and 8(b) demonstrate 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, respectively. The estimated V_{mp} lies in the range between 2.75 and 9.52 m/s, with a network average of 6.30 m/s. As shown in Fig. 8(a), larger V_{mp} values are associated predominantly with sites in the western coast of England, Wales, and Scotland and in the southeast part of England. The distribution of $V_{max.E}$ follows a similar north–-west-to-south–east pattern, the magnitude of which ranges from 6.63 m/s to 15.67 m/s.

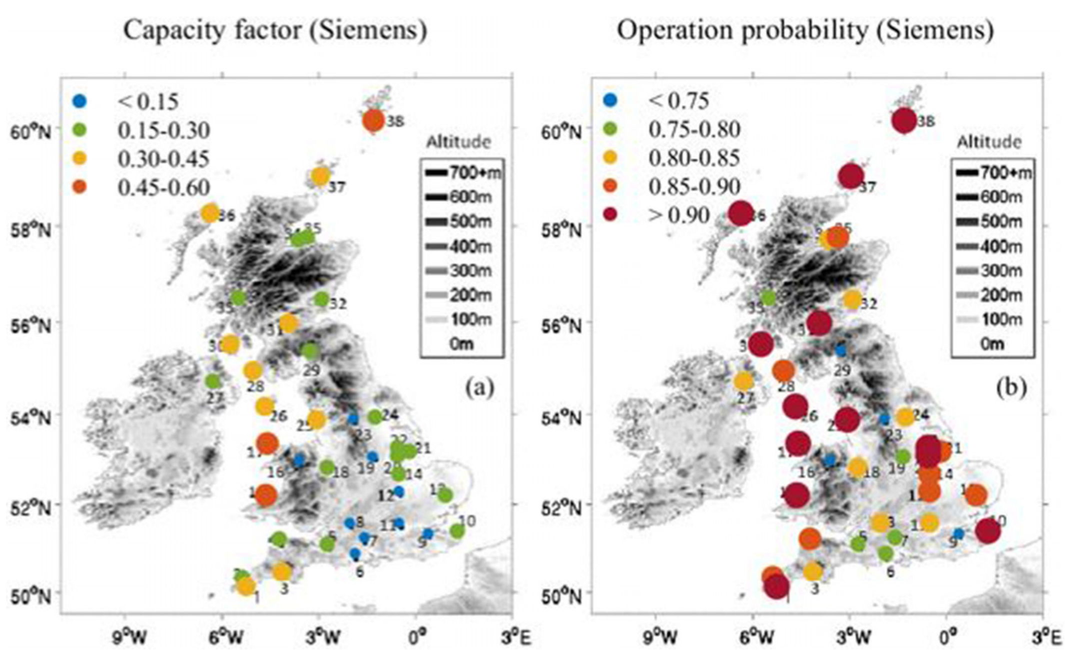

FIG. 9. Distribution of the estimated capacity factor and operation probability of the Siemens SWT-2.3-93 wind turbine.

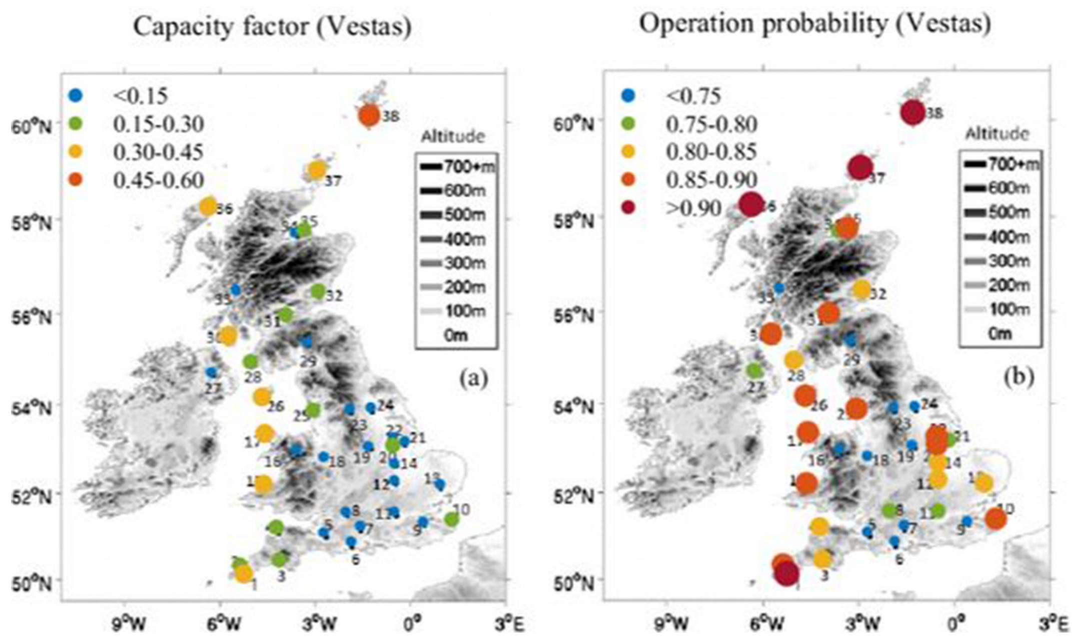

FIG. 10. Distribution of the estimated capacity factor and operation probability of the Vestas V80-2.0 wind turbine.

B. 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 II). The selected wind turbines have similar hub heights and cutoff 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 (Figs. 9 and 10) and generally matches the WPD distribution (Fig. 7). The operation probability is generally the largest in the coastal western and northern regions and the south–east coast of England, though the latter is an area of low capacity factory, including South–East and South–West England, Wales, and Scotland. Notwithstanding the similarities in the spatial pattern, considerable differences can still be found in the magnitude of the capacity factor and operation probability depending on different wind turbines. For example, the spread of the 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 lie between 4% and 46% with a network average of 18.3%. Likewise, the operation probability for Siemens SWT-2.3–93 varies between 57% and 95% and that 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 performances for the same wind characteristics.

C. Long-term trends

As stated in Sec. I, previous studies (e.g., Refs. 21 and 25) have indicated variations 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) changes over the period, determined using the Mann-Kendall test implemented in

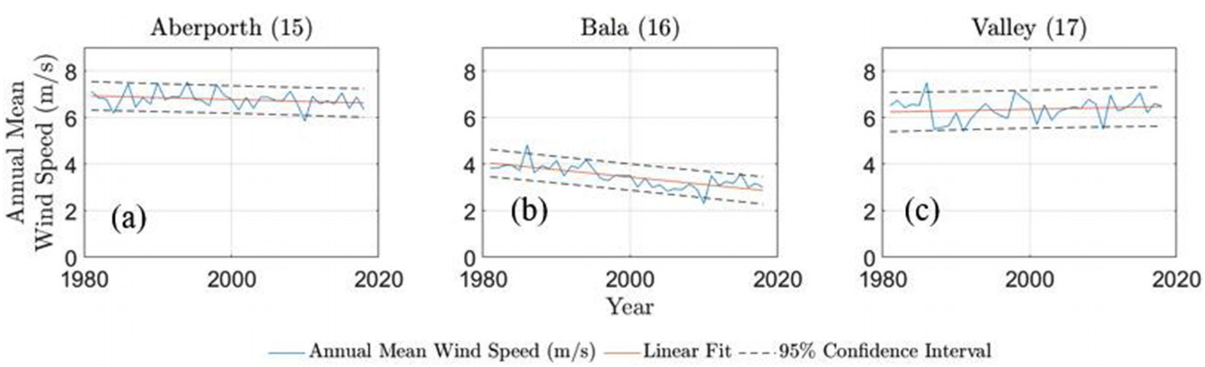

FIG. 11. Annual mean wind speeds at the Wales regional stations.

Ref. 62. However, the variation is only significant in three 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 and construction) cannot be discounted. In South–East England, where Watson *et al.*[25] observed 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}/yr, though this equates to an increase in the mean wind speed of only approximately 0.5 ms^{-1}. In Wales, only the change at Bala is statistically significant, with the remaining two stations not (Fig. 11).

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

The link between the scale parameter and the mean wind speed is clear from comparison of the gradients (Tables III and I), 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 III and Fig. 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 III and Fig. 14). In Northern Scotland, where the 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.

D. 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 (Table IV). The capacity factor decreases 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 increases 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 have 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 I) having a larger impact in bringing the wind speed above the cut-in speed than in other regions.

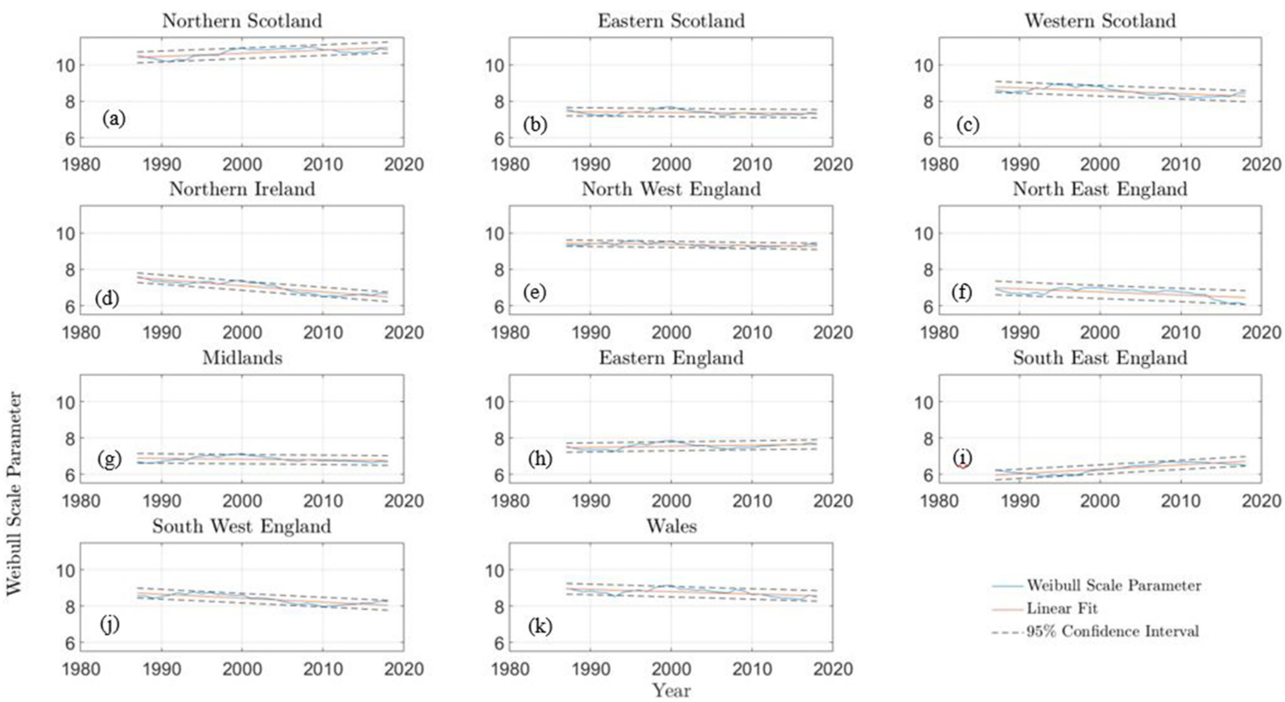

FIG. 12. Seven-year Weibull scale parameter by region.

TABLE III. Trends in the seven-year Weibull parameters.

	Scale parameter (ms^{-1})			Shape parameter			Wind power density				
Region	Gradient of linear fit $(\mathrm{ms}^{-1}/\mathrm{yr})$	Fit p-value	Significant at 95% level?	Gradient of linear fit $(\mathrm{ms}^{-1}/\mathrm{yr})$	Fit p-value	Significant at 95% level?	Gradient of linear fit $(\mathrm{ms}^{-1}/\mathrm{yr})$	Fit p-value	Significant at 95% level?	Mean WPD $(\mathrm{W\,m}^{-2})$	Annual change[a] (%)
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
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

[a]Ratio of the mean annual change (gradient) to mean WPD.

E. 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 the pronounced seasonal variation, in which winter is often the season requiring most electricity power output due to heating and lighting purposes, whereas the 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

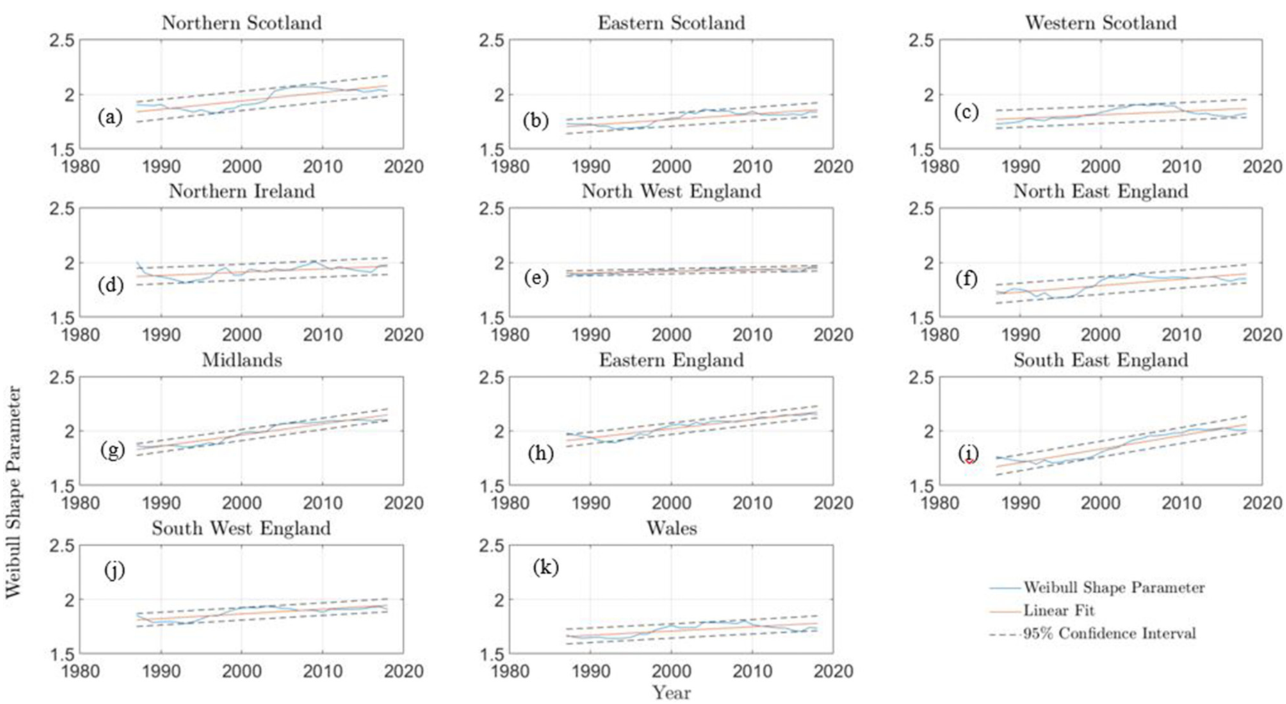

FIG. 13. Seven-year Weibull shape parameter by region.

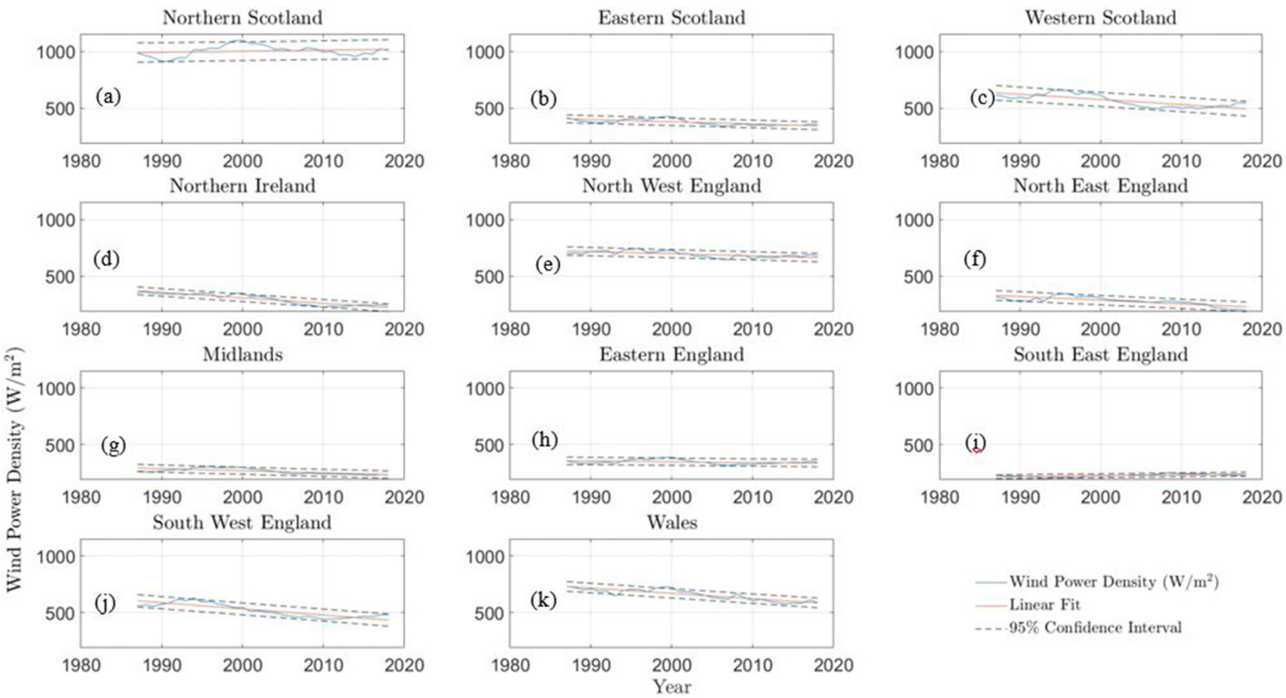

FIG. 14. Seven-year wind power density by region.

winter.[64] In parallel, the 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 Fig. 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 a smaller scale parameter (i.e., abscissa of the distribution peak), whereas those during the winter months of December, January, and February appear to be much wider with lower peaks. Figure 16 reveals that the wind power density during winter is

TABLE IV. Trends in the seven-year capacity factor and operational probability for two example wind turbines.

	Capacity factor						Operational probability					
	Siemens			Vestas			Siemens			Vestas		
Region	Gradient of linear fit (%/yr)	Signif. at 95% level?	Mean (%)	Gradient of linear fit (%/yr)	Signif. at 95% level?	Mean (%)	Gradient of linear fit (%/yr)	Signif. at 95% level?	Mean (%)	Gradient of linear fit (%/yr)	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

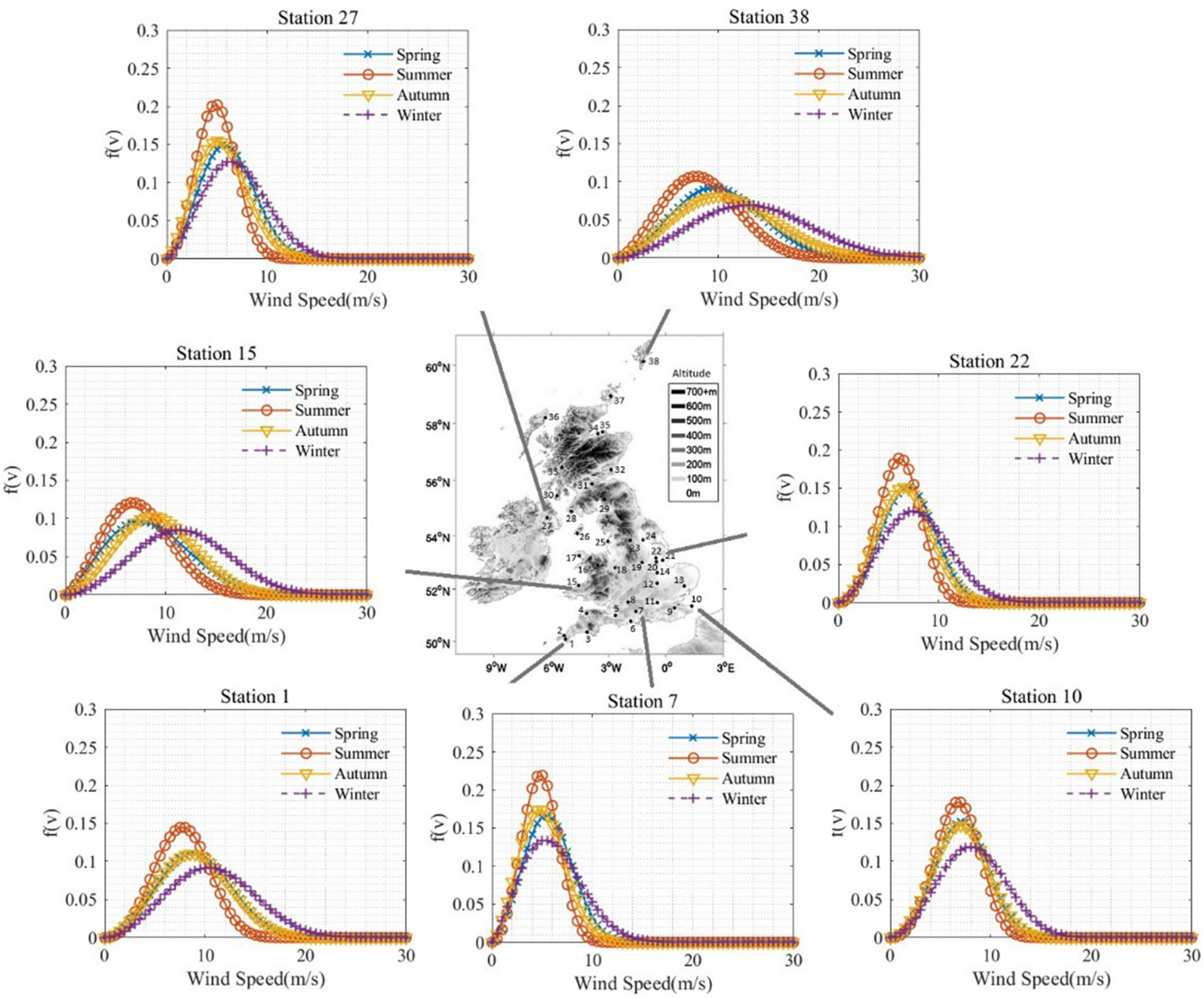

FIG. 15. Weibull distribution of seasonal wind speed at selected stations.

typically higher than those during summer. Quantitatively, the majority of the observation sites (36 of 38) possess twice as much wind power density during winter than that during summer, and 14 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 the 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 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 are encouraging.

V. CONCLUSIONS AND SUMMARY

Given its abundant availability and environment friendly nature, wind energy has been developing at a 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 environmental degradation. To inform this development, this study presents an updated overview of wind speed and wind energy

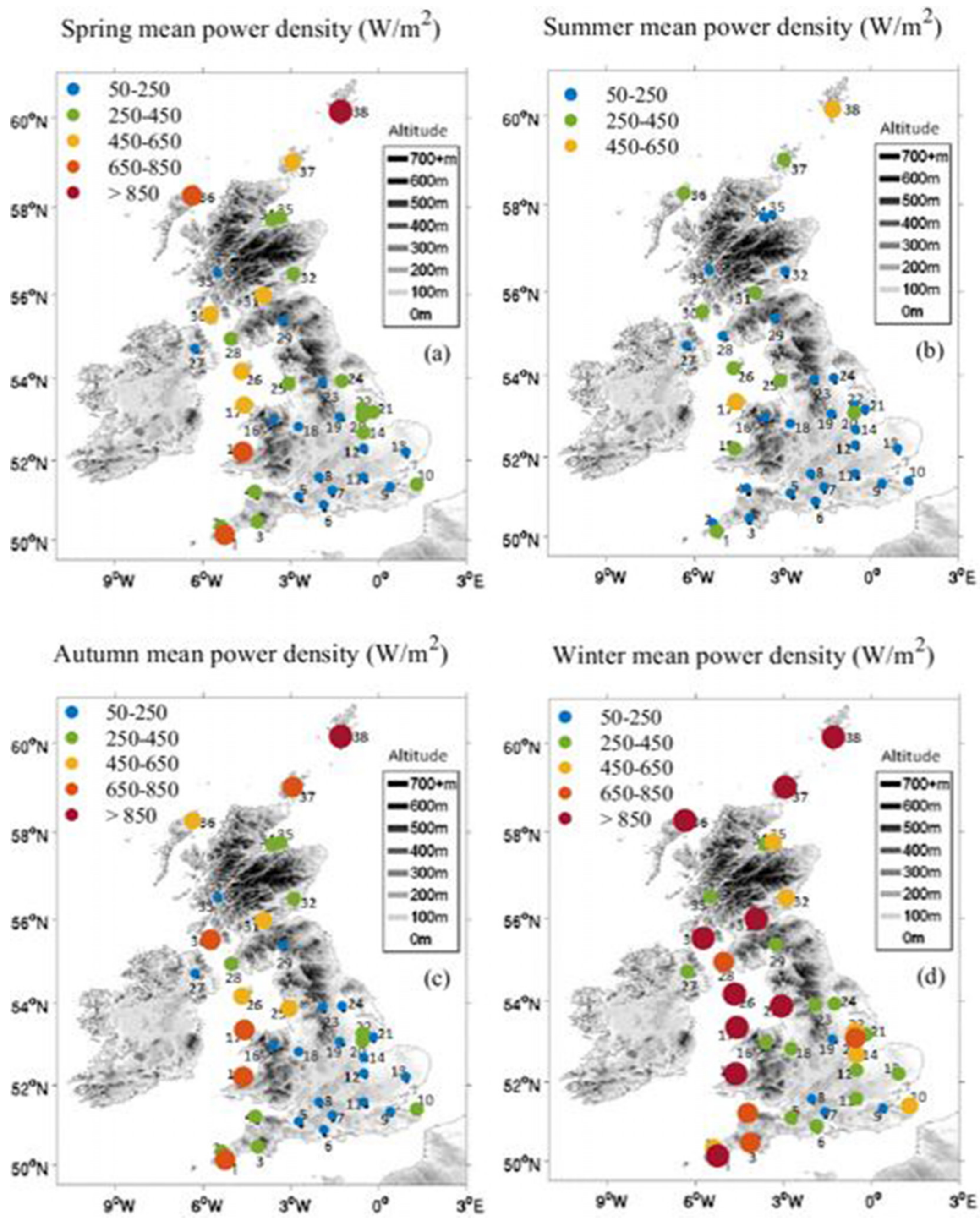

FIG. 16. Distribution of seasonal mean power density.

characteristics across the UK based on the 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 levels, based on the regions defined by the UK Meteorological Office. The important conclusions drawn from this work are as follows:

(1) Statistically significant, long-term changes in annual mean wind speed are seen at 15 of the 38 stations. However, there is

no region that 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 $0.5\,\mathrm{ms}^{-1}$ over the entire period.
(4) The probability distributions are modeled well using a Weibull distribution. The scale parameter follows trends that 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 the 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 the 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 South–East England 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.

AUTHORS' CONTRIBUTIONS

Z.S. conceptualized, performed formal analysis and methodology, and wrote the original draft. M.J. preformed formal analysis and wrote, reviewed, and edited the original draft.

The authors declare no competing interest.

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DATA AVAILABILITY

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

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