Global patterns of offshore wind variability

Chris G. West¹ | Ronald B. Smith²

¹Department of Physics, Yale University, New Haven, Connecticut, USA
²Department of Earth and Planetary Sciences, Yale University, New Haven, Connecticut, USA

Abstract

Using the 40-year hourly gridded ERA5 reanalysis, we study the offshore patterns of wind variability using the probability density function (PDF) and the power spectral density (PSD). To summarize wind variability, we compute the Weibull parameters from the PDF and the PSD for six spectral bands: interannual, annual, multimonth, storm, diurnal, and semidiurnal. We characterize the storm spectral peak using a Gaussian function in log\(_{10}\) frequency space. These parameters are plotted along two pole-to-pole transects through the Atlantic Ocean at 25°W and the Pacific Ocean at 170°W longitude and at 16 current and proposed offshore wind sites. We test the idea that coastal and open-ocean wind statistics may be described by a single set of meridional profiles.

In mid-latitudes, the storm band variance exceeding 20 \(m^2 \cdot s^{-2}\) dominates. The Weibull shape parameter is close to \(k = 2\). The storm interval varies from 4 to 7 days depending on location. In the Northern Hemisphere only, the annual variance is significant, exceeding 3 \(m^2 \cdot s^{-2}\). In the equatorial region, we find steadier winds with small storm variance less than 3 \(m^2 \cdot s^{-2}\). The Weibull shape parameter is \(k = 4\) or greater, suggesting the possibility of a high capacity factor there. The storm interval can exceed 15 days. The equatorial zone has an annual wind variance reaching 2 \(m^2 \cdot s^{-2}\), comparable to the storm variance. In the tropical Pacific, we find interannual variance associated with El Niño-Southern Oscillation (ENSO). Semidiurnal variance is detected in the tropics from the atmospheric tide.

KEYWORDS
global, intermittency, offshore wind, storms, Weibull, wind power, wind spectra

1 | INTRODUCTION

The generation of electrical power from wind has grown rapidly in the past few years, but it still falls far short of the theoretical global totals.¹–³ According to Veers et al.,⁴ the future wind power contribution may reach 30–50% of global demand. For this to happen, offshore wind must play a major role, with its advantages of stronger wind and reduced public resistance. The European Union alone plans to add 300 GW of additional offshore wind by 2050. Several recent technological breakthroughs have made this seem more feasible: larger turbines, deeper or floating...
foundations, and “green hydrogen” from seawater. Long range planning for offshore wind will require a global view of the wind speed variability, especially for optimizing wind turbine design and developing installation, servicing, and energy collection strategies.

The practical use of wind power is limited by its variability. Due to variability, typical capacity factors (i.e., ratio of actual to nameplate power) for wind turbines on land are only about 30–40% but may reach 60% for those offshore. As the penetration of wind power grows, this problematic variability or intermittency will require one or more of the following innovations: additional energy storage, overbuilding the wind generation system to account for periods of calm wind, increased long-distance transmission, or smart-grid intermittent demand reduction (i.e., brownouts). Accurate weather forecasts can only partially mitigate the intermittency problem. These technological developments will benefit from an improved knowledge of the statistics of wind variability. The goal of this report is to summarize global patterns of offshore wind power intermittency with a focus on time scales from 10 h to 10 years.

The existing knowledge of wind speed variability is primarily based on two statistical techniques: (1) the wind speed probability density function (PDF) and (2) the wind speed power spectral density (PSD). The PDF describes the fraction of time, at a given site, that the wind speed falls in each speed range (e.g., 12–13 ms⁻¹). It is usually represented by the two-parameter Weibull distribution. Combined with the turbine power curve, the PDF can be used to estimate the important capacity factor for the installed turbine using the “method of bins” (see Chang et al.). Chang et al.’s method can be used in turbine design to find the optimum cut-in speed and specific power (i.e., ratio of nameplate generator power to rotor disk area). Several authors (i.e., Jung et al.) have shown that the Weibull distribution can be improved upon, especially by tailoring the choice of distribution to the geographic region, but such a method does not suit our goal of global mapping.

The wind speed PSD reveals the time scale of wind fluctuations using the Rayleigh Energy Theorem, also called Parseval’s Theorem. In this approach, the wind speed time series is Fourier transformed, and the square of the Fourier coefficient at each frequency is defined as the PSD. The shape of the PSD curve shows the time-scale contributions to the total variance. That is, how much of the wind variance occurs with periods of 1 day, 1 week, 1 month, 1 year, and so forth. While the PSD cannot be used to compute the capacity factor, it does provide critical information for reducing the negative impact of variability. For example, if a site has a sharp PSD peak at a period of 4 days, then an energy storage system with a 4-day capacity will largely accommodate that variation.

The power spectrum approach is well developed in the literature. Most of these studies used wind data from single meteorological towers. The original spectral diagram of Van der Hoven, based on data from a tower in coastal New York State, sparked a useful controversy about the existence of a spectral gap near a period of 30 minutes, between the storm variance and the variance from boundary layer turbulence. These authors also noted the sharp spectral peaks at 24 and 12 h, that is, the diurnal peak and its semidiurnal harmonic.

There is general agreement that, at least at mid-latitude sites, the dominant wind speed variations occur with periods from 2 to 7 days associated with eastward migrating frontal storms. According to Harris, 89% of the total wind speed variance arises from these storms. The analysis of this spectral “storm peak,” also called the “synoptic peak” by Van der Hoven, requires long time series and significant computation. The shape and central frequency of this peak have not been carefully studied nor has its variation with geographic location. Also, its properties over the sea are largely unknown.

The longer time scales of months and years are also important. Mid-latitude sites usually experience an annual cycle (i.e., the 12-month seasonal cycle) with more frontal storms and wind in winter due to the tilt of the earth’s rotation axis and the variation in differential solar heating of the high and low latitude zones. The tropics, with more constant solar heating, may also have significant seasonal wind speed variations. Inter-annual variations and trends are also relevant to long-term investments in wind power.

For historical context, we note that the study of global patterns of offshore wind variability started during the Age of Discovery with sailing captains like Dias, Columbus, Cabot, da Gama, Magellan, Drake, Hudson, Dampier, Bering, and Cook. Dampier’s book “A Discourse of Winds” in 1699 has several useful insights regarding the variability of trade winds, sea breezes, and storm winds.

In this contribution, we use the new global gridded 40-year hourly ERA5 reanalysis data set. This long duration data set is useful for the statistical analysis of wind variability on time scales from 10 h to 10 years. Its global coverage allows us to investigate the geographical pattern of variability, especially over the sea. We start with a study of the “open ocean” wind statistics to clarify that type of homogeneous environment. Then we look at a set of specific coastal sites that are currently being developed for wind power. As we seek a compact global view of natural variability, we are not able to discuss other important issues of local energy storage, transmission, and demand.

2 | THE ERAS REANALYSIS DATA SET

Climate reanalysis is a method of generating global data sets for large time spans by merging archived observations with a physical climate model. A benefit of a reanalysis data set is that the climate model, and its assumptions are consistent across time and space. A recent and highly regarded reanalysis is the European Centre for Medium-Range Weather Forecasting (ECMWF) ERA5. Recent studies have confirmed the quality of ERA5 data and its value for wind power applications.
All data in this paper are from the ERA5 hourly data set, downloaded from the CS3 Climate Data Store. Wind data were collected for an altitude of 100 m to match the hub height of modern offshore wind turbines. Throughout this paper, we consider wind speed without regard to wind direction.

ERA5 data are available on a global grid with longitudinal and latitudinal resolution of 0.25° (about 27 km). In most cases, the nearest offshore grid position to a given wind farm was used as the effective location for that farm. We analyzed data from January 1, 1980, to December 31, 2019, so all locations had an equal 40-year time span.

3 | WEIBULL PROBABILITY DENSITY FUNCTION

3.1 | Analysis methods

The most popular method for characterizing variability is the PDF. After choosing a reference time interval (say 1 hour) and bin width (dU), a wind speed time series \( U(t) \) is used to determine the fraction of time the wind speed falls into each speed category \( f(U) \). By definition, \( \int_{0}^{\infty} f(U) \, dU = 1 \).

This PDF can be used to estimate the average power generated by a wind turbine

\[
\text{Average Power} = \int_{0}^{\infty} P_{W}(U) f(U) \, dU
\]

where \( P_{W}(U) \) is instantaneous power generated by a turbine exposed to a wind speed \( U \). From average power, the capacity factor can be computed. In the wind power literature, the wind speed PDF is usually approximated by the two-parameter Weibull distribution

\[
f(U) = \left( \frac{k}{\lambda} \right)^{k} \left( \frac{U}{\lambda} \right)^{k-1} \exp \left[ - \left( \frac{U}{\lambda} \right)^{k} \right]
\]

where \( \lambda \) is the scale parameter and \( k \) is the shape parameter. The two parameters \( (\lambda, k) \) are estimated using an error minimization scheme.\(^{13,15,16}\) In our calculations, we use a maximum likelihood method which attempts to maximize the log of the Weibull distribution likelihood function by finding the stationary points, that is, the zeros of the gradient of the log-likelihood function with respect to each parameter.\(^{42}\)

We report the coefficient of determination of the Weibull fit as

\[
R^2 = 1 - \frac{SS_{res}}{SS_{tot}}
\]

where \( SS_{res} \) is the sum of the squared residuals and \( SS_{tot} \) is the sum of the squared differences between these data and the data mean (i.e., a scaled variance). The Weibull scale parameter \( \lambda \) is related to the mean wind speed by

\[
\overline{U} = \left( \frac{1}{\Gamma} \right) \int_{0}^{\infty} U(t) \, dt = \lambda \Gamma \left( 1 + \frac{1}{k} \right).
\]

In Equation (4), \( \Gamma \) is the Gamma Function (i.e., the generalization of the factorial function for non-integers). As an example of Equation (4), if \( k = 2, \overline{U} = 0.8862\lambda \). The variance of the wind speed can be computed from the Weibull parameters using the second form in Equation (5):

\[
s^2 = \left( \frac{1}{\Gamma} \right) \int_{0}^{\infty} (U(t) - \overline{U})^2 \, dt = \lambda^2 \left[ \Gamma \left( 1 + \frac{2}{k} \right) - \left( \Gamma \left( 1 + \frac{1}{k} \right) \right)^2 \right].
\]

In the case \( k = 2, s^2 \approx 0.2146\lambda^2 \). An additional useful parameter is the coefficient of variation (CV) defined as \( CV = \frac{s}{\overline{U}} \). CV is uniquely and inversely related to \( k \), and thus, they are redundant for a Weibull PDF. When \( k = 2, CV \approx 0.5227 \). As \( k \) grows, \( CV \rightarrow 0 \) (Equation 5).

3.2 | Examples of PDF

In Figure 1, we show four examples of PDF from around the world. At Grand Strand off the South Carolina coast (Figure 1A), the Weibull function gives an excellent fit to the data with \( k \approx 2 \). This is a commonly found \( k \) value and corresponds to the one-parameter Rayleigh Function. In Naikun...
our estimated shape factor is smaller $k \approx 1.8$. In the equatorial Pacific and Atlantic (Figures 1C,D) the shape factors are much larger with $k \approx 3.22$ and $k \approx 3.11$. These large $k$ values in the tropics suggest that a unique turbine design should be employed there with altered cut-in speed and specific power. An alternative to the Weibull fit has been proposed by Jung et al. but the $R^2$ values in Figure 1 seem to be satisfactory.

4 | THE POWER SPECTRAL DENSITY

4.1 | Analysis methods

The PSD function describes the time scales of variability. The PSD of a discrete wind speed time series $U(t)$ is computed from the discrete Fourier transform

$$\tilde{U}_r = \left( \frac{1}{N} \right) \sum_{i=1}^{N} U_i \exp \left( \frac{2\pi ir}{N} \right)$$

where the hat denotes the transform, $r$ is the frequency index, and $N$ is the length of $U(t)$. For our 40-year hourly data, $N = 350,640$. Equation (6) has units of $\text{ms}^{-1}$. Before computing (6), the trends were removed from all time series, but this did not make a significant difference in the results. The PSD is then

$$P_r = \tilde{U}_r \tilde{U}_r^*$$

where the asterisk $^*$ denotes complex conjugation. While $\tilde{U}$ is complex-valued, $P$ is real-valued. The $r$ index in $\tilde{U}$ or $P$ corresponds to a frequency $\nu$ according to

$$r = \frac{\nu N}{v_s} \quad \text{or} \quad \nu = \frac{rv_s}{N}$$

where $v_s$ is the sampling rate of the original signal. For our hourly data, $v_s = 1/3600 \text{ Hz}$.
According to Parseval’s Theorem, the variance of $U(t)$ in Equation (5) can be computed from $P_r$

$$s^2_u = \sum_{r=1}^{N} P_r$$

(9)

which is approximately the area under the curve of $P_r$ plotted against $r$. As the frequency index $r$ may range over many orders of magnitude, it is convenient to use

$$X = \log_{10}(v) = \log_{10}(\frac{rv}{N})$$

(10)

as the abscissa instead of $r$ or $v$. In this case, the increment along the abscissa $dX = d\log_{10}(rv/N) = (\log_{10}(10))^{-1}dr$ is uneven so the ordinate value $P_r$ must be weighted by $\log_{10}(10)$ to conserve area. The weighted PSD is $\tilde{P}(X) = \log_{10}(10)P_r$. The total variance (Equation 9) is now written

$$s^2_u = \int \tilde{P}(X)dX = \sum_{r=1}^{N} \tilde{P}_r \Delta X_r$$

(11)

where $\Delta X_r = \log_{10}(r+1/r)$ corresponds to the width of a logarithmic unit increment along the abscissa $X$. Verifying that Equations (9) and (11) are equal amounts to confirming that $\log_{10}(10)\Delta X_r \approx 1$. In other words, calculating the variance (or “area under the curve”) by multiplying the weighted PSD with a logarithmic increment is equivalent to summing over entries of the unweighted PSD.

Even with the 40 years of data from ERA5, the chaotic nature of the winds can cause the PSD plots to be noisy. To make the plots easier to interpret, we have smoothed the spectra. Given the nature of the power spectrum, with a higher resolution at higher frequencies, the width of a good smoother should increase with frequency. Beginning at $X = -8$ in the power spectra, a smoother of width $\Delta r = 7$ is applied through $X = -7.5$. The smoother has weights that correspond to sampling from the distribution $\exp[-x^2/4]$ between $x = -4$ and $x = 4$. The weighting function is normalized so that it always sums to unity. With each increase of 0.5X in the PSD, the new smoother width is calculated from the old width w as $2w - 3$. For example, from $X = -7.5$ to $-7$, the smoother has width $\Delta r = 11$, and from $X = -4.5$ to $-4$, the smoother has width $\Delta r = 515$. Note that the width is always odd so that the center position is given the largest weight.

To characterize the storm peak, a Gaussian curve is fitted to the weighted PSD between periods of 1 month to 18 h,

$$\tilde{P}(X) = a \cdot \exp\left(-\frac{(X-b)^2}{2\sigma^2}\right)$$

(12)

where $a$, $b$, and $c$ are independent parameters. For this fit, we exclude the diurnal peak at 24 h. The (weighted) storm peak height is $a$ with units $m^2s^{-2}$. The storm peak frequency location is $b$ (in X coordinates). The full width at half maximum is

$$W = 2\sqrt{2 \ln(2)c} = 2.35c$$

(13)

in units of $X$. A typical value for $W$ is unity, meaning that the width of the storm peak is about a factor of ten in frequency or period (e.g., 2–20 days or 1–10 weeks).

A convenient estimate of the total wind speed variance caused by storms is the integral (Equation 11) of Equation (12),

$$\text{Total Storm Variance} = a\sqrt{2c}$$

(14)

in units of $m^2s^{-2}$. We report the coefficient of determination $R^2$ calculated in the same way as for the Weibull fit to the PDF (Equation 3).

4.2 Examples of PSD

In Figure 2, we show six examples of PSD functions from around the world. Figure 2A shows the spectrum for Hornsea in the North Sea. It has a massive broad asymmetric storm peak centered on a period of about 5 days. There is also a strong sharp annual peak and barely detectable diurnal and semidiurnal peaks. There is little if any interannual variance. The area under the curve is the total variance.

The spectrum at Sunrise Wind off the New England (USA) coast (Figure 2B) has a narrower more symmetric storm peak than Hornsea and is centered on 3.5 days. The diurnal peak is significant, perhaps because the site is close enough to shore to feel a continental effect. The annual variance is still strong, but again, there is little long period variance. The Grand Strand site in Figure 2C is located off the South Carolina coast in the
United States. The storm variance is weaker than at Sunrise Wind and shifted to 4.8 days. The diurnal peak is stronger, but the annual peak is weaker than at Sunrise.

The Oahu, Hawaii site (Figure 2D) at latitude 21.5° N has a much smaller storm peak and shifted to 12 days. No annual peak is evident. The semidiurnal peak is evidence of the atmospheric tide (see Section 7).

Spectra for two open-ocean equatorial sites are shown in Figure 2E,F. Both sites have weak storm peaks centered at about 10 days. In other respects, the spectra are different. The Pacific Ocean site has some interannual variance, associated with ENSO. The Atlantic Ocean site has no interannual variance but a large annual variance. This feature is caused by the seasonal shift in the South East Trade Winds in the equatorial Atlantic. The contributions from defined frequency bands are discussed in the next section.

5 | BAND VARIANCE ESTIMATES

The PSD calculations described in Section 4 allow us to define spectral bands and estimate their contributions to the total wind speed variance, that is, their “Band Variances” (BV). We define six spectral bands in Table 1 with band limits given as periods and using our frequency variable

---

**Figure 2** Six examples of power spectral density (PSD) functions computed from ERA5: (A) Hornsea, (B) Sunrise Wind, (C) Grand Strand, (D) Oahu, (E) Pacific Transect, and (F) Atlantic Transect [Colour figure can be viewed at wileyonlinelibrary.com]
Our choice of bands in Table 1 is somewhat similar to the five bands defined by Harris: annual, unidentified long period, broadband random (our “storm peak”), diurnal, and semidiurnal. His 30-year record came from a single onshore site in Wiltshire, UK. Table 1 also identifies the source of the variance as either “astronomical” or “internal.” BV can be envisioned as an equivalent sinusoid with amplitude $A = \sqrt{2} BV$; for example, $BV = 8 \text{ m}^2 \text{s}^{-2}$ gives $A = 4 \text{ m s}^{-1}$.

We do not try to estimate the variance from boundary layer turbulence as the ERA5 model only parameterizes turbulence, and the hourly outputs would not resolve turbulent fluctuations anyway. Previous work suggests that the variance from turbulence has significant power at periods from 3 s to 3 min, that is, $0.33 \text{–} 0.006 \text{ Hz}$. Neither does our data fully capture the controversial spectral gap between 3 min and 12 h. In the range of periods from 8 to 24 h, the ERA5 model only partially resolves relevant processes such as fronts. Olauson shows that reanalyses underestimate wind variance with periods less than 18 h compared to tower data (Olauson, his fig. 7). In Sections 5.1–5.5, we discuss the physics behind each band in Table 1.

### 5.1 | The diurnal and semidiurnal bands

Each power spectrum in Figure 2 shows spikes at periods of 24 and 12 h (i.e., $X = \log_{10}(v) = -4.9$ and $-4.6$). In Table 1, no bandwidth is specified as these two spikes have finite width only when smoothed. These diurnal cycles play a relatively minor role in offshore wind, usually less than 1% of total variance (see Section 6). Let’s consider the reason for this.

From the literature on atmospheric dynamics, we can identify five thermally driven diurnal wind processes: atmospheric boundary layer (ABL) stratification cycles, low level jet, slope and valley winds, sea breeze, and thermal tides. The ERA5 reanalysis probably captures all five of these processes to some degree.

The ABL stratification cycle is very common over land and has a peculiar signature of reversing its phase with height in the boundary layer. During the day, the winds weaken at turbine level (say 100 m) and strengthen near the surface. At night, the winds at turbine level increase due to “lubrication” by the stable surface inversion. This phenomenon is well-known in the wind power community. Low level jets and slope and valley winds are absent over the sea unless very close to a sloping coastal terrain. An exception might be an offshore low level jet described by Wagner et al.

Many coastal wind turbines draw power from the diurnal sea breeze. While the sea breeze circulation may extend 10 or 20 km offshore, they often do not reach true “offshore” wind farms. The term “offshore” is sometimes defined as “below the horizon” due to the earth surface curvature, requiring a distance of about 30 km. Finally, there is the global thermal tide driven by solar absorption in the stratosphere. This phenomenon gives both diurnal and semidiurnal wind variance, mostly in the tropics.

### 5.2 | The storm band

The storm band, defined here as periods from 18 h to 1 month, captures most of the variance shown in Figure 2, except at equatorial sites. These peaks arise from the eastward migrating frontal storms in mid-latitudes. In the tropics, the much smaller storm variance is caused by other phenomena such as easterly waves, tropical cyclones, or the Madden–Julian oscillation.

### 5.3 | The MMB

The “Multi-Month” band (MMB) is defined here as the variance between 1.1 and 11 months. Several types of dynamics may contribute to this band. In some instances, the MMB may just be the long-period spectral tail of the storm peak. Another contributor might be persistent weather conditions.
patterns such as jet stream “blocking” or the effect of persistent oceanic temperature anomalies such as ENSO. In other cases, the MMB contains a sharp semiannual peak. A semiannual (i.e., 6 months) peak can be caused by the meridional shift of a narrow zonal jet or an annual wind reversal.

5.4 | The annual band

The annual peak (i.e., 12-month period) is narrow and easily identified. It is driven by the tilt of the earth’s rotation axis relative to the plane of the ecliptic. While annual cycles are expected at high latitudes due to the seasonal insolation cycle, they may also be large in the tropics (e.g., Figure 2F).

5.5 | The interannual band

We define the interannual band as variance with periods from 1.1 to 11 years. Our long 40-year ERA5 data set constrains this band pretty well. Interannual variance in the Pacific (Figure 2E) is driven by the 4- to 7-year ENSO cycle.

6 | ONSHORE VERSUS OFFSHORE WIND

Before studying the global distribution of offshore wind variance, we show one example of how offshore and onshore winds are different in the ERA5 database. In Figure 3, we plot three spectral BVs (Table 1) along an east-west transect at 33.5°N with origin at the coast of South Carolina, USA. This transect crosses the Grand Strand wind farm site in Figure 4, whose PDF is shown in Figure 1A and full PSD in Figure 2C. At this latitude, the average wind speed increases from about 6 m/s over land to 8 m/s offshore due to reduced roughness.

The annual variance (Figure 3A) jumps from 0.5 m² s⁻² to about 1.7 m² s⁻² while the CV remains nearly constant. We conclude that the jump in variance scales with the jump in mean wind. A similar association is seen with the important storm variance (Figure 3B). The diurnal variance (Figure 3C) behaves differently however, dropping sharply from 0.15 m² s⁻² to nearly zero in spite of the increase in mean wind.

Over land, the boundary layer parameterization in ERA5 captures the diurnal stratification cycle. During the night, the wind speed at 100 m increases due to the “lubrication” by the ground level inversion. At sea, the large heat capacity of the ocean mixed layer suppresses this stratification cycle, and the diurnal wind variance is barely detectable. No coastally localized sea breeze is seen in Figure 3. The 25-km ERA5 resolution may fail to fully resolve it. The implications of the strong coastal gradient in diurnal cycle will be discussed again in Section 8.

Not shown in Figure 3 is that the Weibull shape parameter decreases from $k=2.25$ to 2.05 moving offshore, indicating a slight broadening of the PDF.

7 | VARIABILITY ALONG POLE-TO-POLE TRANSECTS

We describe the geographic patterns of variability by constructing pole-to-pole mid-ocean transects of Weibull and spectral parameters. For the Atlantic Ocean, we choose the 25°W meridian with an eastward jog at 62°N, continuing north along the Greenwich meridian (Figure 4). For the Pacific Ocean, we choose the 170°W meridian for all latitudes. Along these transects, we plot several variability parameters (Figures 5–7).

Parameters that can be computed in the time domain are shown in Figure 5. Included are mean wind speed, variance, maximum wind speed, and the Weibull shape parameter ($k$). These four parameters are given by season, clustered in the usual way: DJF, MAM, JJA, and SON. Note that the Atlantic and Pacific transects are similar to each other and that in most cases, the seasons reverse across the equator as expected. That is, DJF in the Northern Hemisphere is similar to JJA in the Southern Hemisphere. Generally, there is less seasonality in the Southern Hemisphere than the Northern Hemisphere.

In Figure 5A, we see the well-known maxima in mean wind in mid-latitudes from 30°N to 60°N and 40°S to 70°S (Zheng et al. and many others). The profile of the 40-year maximum wind in Figure 5B qualitatively resembles the mean wind profile in Figure 5A. These maxima may be underestimated as the ERA5 grid does not fully resolve storm structure. The total variances shown in Figure 5C have an even stronger mid-latitude maximum. The variance at 50°N and 50°S is a full order of magnitude greater than at the equator. Note especially in Figure 5A the smooth jets reaching 9 m/s adjacent to the equator in both oceans and both hemispheres, except in the south Pacific.

Another measure of the variability is the shape parameter ($k$) in the Weibull distribution (Figure 5D). In mid-latitudes, $k \approx 2$ while in the tropics much larger values are seen, reaching $k \approx 4$–6. These peaks are the steady “trade winds” where the winds are seldom very weak (see Figure 1C,D). According to Chang et al., large $k$ values like this can give extraordinary capacity factors for a properly selected wind
turbine. Note (Figure 5D) that the peak in shape parameters adjacent to the equator is missing in the south Pacific. The missing k peak (Figure 5D) reflects mostly the missing wind jet (Figure 5A) in the tropical south Pacific. Both CV and k are related to the ratio of variance to mean wind.

We now turn to a discussion of the BVs (Table 1) along the pole-to-pole ocean transects (Figure 6). The interannual variance (Figure 6A) is small everywhere except in the equatorial Pacific, due to ENSO. Note however the small peaks in interannual variance at 60 degrees north and south in both oceans.

The annual BVs in Figure 6 show a dramatic north–south asymmetry. Both ocean transects show powerful annual cycles in the northern mid-latitudes and almost none in the southern mid-latitudes (see also Figure 5A). The phase of this cycle brings strong winds in winter and weaker in summer. The hemispheric asymmetry in seasons arises from the larger ocean fraction in the Southern Hemisphere with its greater heat capacity and fewer mountains. The significant annual variance in the equatorial zone in both oceans arises from shifting tradewinds. There is little annual variation in solar insolation; in fact, insolation is semiannual between the Tropics of Cancer and Capricorn, so the annual forcing must come from higher latitudes.

The MMB and storm BVs (Figure 6C,D) are qualitatively similar in both oceans and in both hemispheres. They dominate the total variance and have the biggest impact on wind power, except in the tropics where they compete with the annual variance.
Figure 6E,F shows the diurnal and semidiurnal variances. These variances are generally small but irregular. There is a small spike where the Atlantic transect crosses the Azores at 38°N picking up a diurnal sea breeze cycle from those islands. The general dominance of semidiurnal over diurnal variance in low latitudes suggests that these signals are caused by thermally driven tides.49,50

We finish our analysis of the pole-to-pole transects by looking at spectral properties of storms (Figure 7). The peak storm period (Figure 7A) is derived from the Gaussian fit to the PSD. It indicates roughly the time between storms. In mid-latitudes, it varies from 2 to 6 days. In the
subtropics, where storms are less frequent, this peak period can exceed 15 days. Note the surprising asymmetry between the two oceans and two hemispheres (Figure 7A).

The integrated “storm variance” in Figure 7B slightly exceeds the “storm band variance” in Figure 6D (i.e., 18 h to 1 month) as it includes the spectral “wings” of the storm peak, estimated by the Gaussian fit (Figure 2). Thus, it might be a better measure of the full effect of storms.

The relevance of the pole-to-pole transects in Figures 5–7 is that they probably represent the vast majority of the world ocean. Only when one approaches coastline closer than 50 km or so (Figure 3) will sea breezes and other continental effects be felt (see Section 6). To test this hypothesis, we examine 16 actual coastal wind power sites in the next section.

8 | VARIABILITY AT CURRENT AND PROPOSED WIND FARMS

Our detailed discussion in Section 7 of the pole-to-pole transects may seem abstract and idealized to the reader as we do not anticipate the actual construction of wind farms at these mid-ocean sites. Our decision to approach the subject in this way was partly based on the hypothesis that latitude is the dominant control of wind variability, and thus, actual coastal wind farm sites would be similar to corresponding transect points at the same latitude. To test this hypothesis, we investigated the wind speed variability at 16 current or proposed offshore wind sites (Tables 2 and 3). The site locations are shown in Figure 4.
Six sites in northern Europe near latitude 50N were studied: Hornsea, London Array, and Walney Extension in the United Kingdom; Horns Rev III in Denmark, Hohe See in Germany, and Borssele in Holland. Hornsea was already discussed in Section 2. For the east coast of the United States, we examined Sunrise Wind, Ocean Wind, Skipjack, and Grand Strand ordered from NE to SW. For the west coast, we examine Diablo Canyon off California and Niakun Strait off British Columbia, Canada. In the central and western north Pacific Ocean, we looked at Oahu in Hawaii, Akita Yurihonjo in Japan, and Huaneng Rudong in China. The only southern hemisphere site is Caucala off Brazil.
The six nearby sites from northern Europe are not redundant. We computed the Pearson correlation coefficient (CC) for the wind speed time series between all pairs of these stations and found that $CC \approx \exp(-d/L)$ where $d$ is the distance between sites and $L$ is a de-correlation distance; and $L \approx 700$ km. For example, Walney Extension (3.75/C14 W) and Horns Rev III (7.75/C14 E) are about 750 km apart, so $CC \approx 0.3$. In spite of significant de-correlation of their time series, the PSD and PDF for these six sites were very similar, except for the PSD in the diurnal band (Tables 2 and 3).

The comparison of mid-ocean and coastal sites is shown in Figures 6 and 7. The colored dots denote the ocean of the site. Overall, the agreement between coastal site and transect is good, especially for the storm variance that dominates the total variance. The glaring exception is the diurnal and semidiurnal variance (Figure 6E,F) where we see a large scatter and values far exceeding the open ocean transect. As shown in Figure 3, this scatter is due to the large coastal gradient in diurnal variance. We conclude that to a first approximation, the wind speed variability at coastal wind farm sites is similar to that at mid-ocean sites at the same latitude with the exception of the diurnal band.

In Tables 2 and 3, we also include two sites (#17 and 18) where the transects cross the equator (see also Figures 1 and 2). These two are not coastal wind farm sites, but data from those points help to contrast the stormy mid-latitudes with the steady condition in the equatorial zone. The CV for these equatorial sites is only about $CV = 0.35$, compared to $CV = 0.5$ for mid-latitude sites. The shape parameter exceeds $k = 3$. Table 3 shows large values for annual and inter-annual BV.

### 9 | CONCLUSIONS

In this report, we have used the new 40-year ERA5 reanalysis along with the conventional statistical tools of PDF and the PSD to characterize the wind speed variability at a level 100 m above the ocean's surface. The former tool (PDF) allows a capacity factor to be estimated and turbine design to be optimized. The latter tool (PSD) describes the time scale of variability and allows one to optimize deployment strategies. These two indicators are related to each other. In the stormy mid-latitudes, the wind speed variance is high, and the Weibull shape factor ($k$) is low indicating a wide range of wind speeds. In the quiescent tropics, the storm variance is smaller, and the $k$ is larger indicating a narrower range of wind speeds.

Our main goal was to describe the global pattern of wind speed variability over the sea. To simplify this task, we assumed that latitude is the dominant control on variability. We tested this idea by comparing mid-ocean transects with coastal sites. The primary exception to this rule is the diurnal frequency $BV$, which is very sensitive to the distance from the land.

To define the open ocean environment, we examined pole-to-pole meridional transects at 25°W and 170°W. The variability patterns in the Atlantic and Pacific transects are qualitatively similar in some respects. Each ocean transect has a striking mid-latitude maximum in mean wind,
total variance, storm variance, and multimonth variance. The pattern of Weibull shape factor \( k \) also appears to be universal. It has values near \( k = 2 \) in mid-latitudes but reaches \( k = 4 \) and higher in the tropics.

Due to the dominance of storm variance at most sites, we devised a method for characterizing the PSD storm peak. We fitted a Gaussian curve in \( \log_{10} \) frequency coordinates, allowing us to estimate the peak height, width, period, and total storm variance. We found that the period between storms varies considerably, from 3 to 7 days, even within the mid-latitude region. In tropical zones, the period between storms is much larger, often exceeding 15 days.

While latitude is a dominant factor for wind speed variability, there are many important anomalies and asymmetries between oceans and between hemispheres. First we note the strong steady tradewinds at 10° north and south in the Atlantic Ocean and 10° north in the Pacific. These locations have small storm variance, small CV, and large Weibull shape factor. With a properly designed turbine,20 these locations might offer the highest capacity factor on earth. Second is the strong asymmetry in annual variance between the Northern and Southern Hemispheres. At 40-60° north, the seasonal cycle in wind speed is much larger than in the corresponding southern latitudes. Also, there are isolated tropical regions with large annual variance in spite of locally steady insolation. Third, due to ENSO, the equatorial Pacific is the only place with interannual variance exceeding 10% of total variance. Fourth, the tropics, especially over the Pacific Ocean, have a detectable semidiurnal variance from the stratospherically driven thermal tide. Otherwise, diurnal variance nearly vanishes offshore.

Our analysis of global wind variability fails to take into account the variability in energy demand. Mostly, this limitation is due to the broad geographic scope of our study and the unknown strategies that may be used in the future to collect, store, and distribute offshore wind power. A good example is Dvorak et al.40 that examined the match between resource and demand along the east coast of the United States. As we can see in Figures 2B, 5A, and 6B, this region has a strong summer minimum in wind resource that unfortunately coincides with the summer demand maximum for air conditioning. Using more a more detailed meteorological model and demand data, they looked for ways to minimize this conflict.

We hope that this broad summary of global wind variability will improve future plans for offshore wind power development. The principle of latitude control of wind statistics allows a single set of open-ocean meridional profiles to be applied approximately to coastal sites. Coastal wind farms will dominate the immediate future of offshore wind due to transmission constraints and the proximity to power consumers. In the long run, open ocean “blue water” sites may be developed using green hydrogen technology and tanker ship collection.

ACKNOWLEDGEMENTS

We thank the Yale Office of Career Strategy for supporting CW over the pandemic summer of 2020. The extraordinary ERA5 data were made available by the ECMWF and were generated using Copernicus Climate Change Service information 2020. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus information or data it contains. Three reviewers made helpful comments.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1002/we.2641.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in “ERA5 hourly data on single levels from 1979 to present” at http://doi.org/10.24381/cds.adbb2d47, reference Hersbach et al. (2018).

ORCID

Chris G. West https://orcid.org/0000-0001-7264-8007
Ronald B. Smith https://orcid.org/0000-0002-9567-8572

REFERENCES

1. Jacobson MZ, Archer CL. Evaluation of global wind power. J Geophys Res: Atmos. 2005;110(D12):D12110.
2. Lu X, McElroy MB, Kiviluoma J. Global potential for wind-generated electricity. Proc Natl Acad Sci. 2009;106(27):10933-10938.
3. Jacobson MZ, Archer CL. Saturation wind potential and its implications for wind energy. Proc Natl Acad Sci. 2012;109:15679-15684.
4. Veers P, Dykes K, Lantz E, Barth S, Bottasso CL, Carlson O, Clifton A, Green J, Green P, Holtinnen H, Laird D, Lehtomäki V, Lundquist JK, Manwell J, Marquis M, Meneveau C, Moriarty P, Munduate X, Musculus M, Naughton J, Pao L, Paquette J, Peinke J, Robertson A, Sanz Rodrigo J, Sempreviva AM, Smith JC, Tuohy A, Wiser R. Grand challenges in the science of wind energy. Science. 2019;366(6464).
5. Kuang Y, Kenney MJ, Meng Y, Hung W-H, Liu Y, Huang JE, Prasanna R, Li P, Li Y, Wang L, Lin M-C, McGehee MD, Sun X, Dai H. Solar-driven, highly sustained splitting of seawater into hydrogen and oxygen fuels. Proc Natl Acad Sci. 2019;116(14):6624-6629.
6. Yu L, Zhu Q, Song S, McElhenny B, Wang D, Wu C, Qin Z, Bao J, Yu Y, Chen S, Ren Z. Non-noble metal-nitride based electrocatalysts for high-performance alkaline seawater electrolysis. Nat Commun. 2019;10(5106):1-10.
7. Al-Badi M, El-Saadany E. Wind turbines capacity factor modeling a novel approach. IEEE Trans Power Syst. 2009;24(3):1637-1638.
8. Tarroja B, Mueller F, Eichman JD, Brouwer J, Samuelsen S. Spatial and temporal analysis of electric wind generation intermittency and dynamics. Renew Energy. 2016;36(12):3424-3432.
9. Ren G, Wan J, Liu J, Yu D, Soder L. Analysis of wind power intermittency based on historical wind power data. Energy. 2018;150:482-492.
10. Weibull W. A statistical distribution function of wide applicability. *J Appl Mech.* 1951;18:293-297.
11. Seguro JV, Lambert TW. Modern estimation of the parameters of the weibull wind speed distribution for wind energy analysis. *J Wind Eng Ind Aerodyn.* 2000;85:75-84.
12. Belu R, Koracin D. Statistical and spectral analysis of wind characteristics relevant to wind energy assessment using tower measurements in complex terrain. *J Wind Energy.* 2013;7:39162. https://doi.org/10.1155/2013/739162
13. Kantar YM, Usta I. Analysis of the upper-truncated weibull distribution for wind speed. *Energy Convers Manag.* 2015;96:81-88.
14. Murthy KR, Rahi OP. A comprehensive review of wind resource assessment. *Renew Sustain Energy Rev.* 2016;72:1320-1342.
15. Pobocikova I, Sediackova Z, Michalkova M. Application of four probability distributions for wind speed modeling. *Procedia Eng.* 2017;192:713-718.
16. Chaurasiya PK, Ahmed S, Warudkar V. Comparative analysis of weibull parameters for wind data measured from met-mast and remote sensing techniques. *Renew Energy.* 2018;115:1153-1165.
17. El-Sharkawy MM, Attib MA, Abdelaziz AY, Kanwar N. Impact of wind farm disturbance on power system performance. In: Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM); 2019:75-84.
18. Paraschiv L-S, Paraschiv S, Ion I. Investigation of wind power density distribution using rayleigh probability density function. *Energy Procedia.* 2019;157:1546-1522.
19. Bidaoui H, Abbassi IE, Bouardie AE, Darcherif A. Wind speed data analysis using Weibull and rayleigh distribution functions, case study: Five cities northern morocco. *Procedia Manuf.* 2019;32:786-793.
20. Chang T-P, Liu F-J, Ko H-H, Cheng S-P, Sun L-C, Kuo S-C. Comparative analysis on power curve models of wind turbine generator in estimating capacity factor. *Energy.* 2014;73:88-95.
21. Jung C, Schindler D, Liable J, Buchholz A. Introducing a system of wind speed distributions for modeling properties of wind speed regimes around the world. *Energy Convers Manag.* 2017;144:181-192.
22. Paatero JV, Lund PD. Effect of energy storage on variations in wind power. *Wind Energy.* 2005;8(4):421-441.
23. Van der Hoven I. Power spectrum of horizontal wind speed in the frequency range from 0.0007 to 900 cycles per hour. *Meteorol.* 1957;14(2):160-164.
24. Pierson Jr. WJ. The measurement of the synoptic scale wind over the ocean. *J Geophys Res: Oceans.* 1983;88(C3):1683-1708.
25. Eggleston ED, Clark RN. Wind speed power spectrum analysis for Bushland, Texas, USA. *Wind Eng.* 2000;24(1):49-52.
26. Apt J. The spectrum of power from wind turbines. *J Power Sources.* 2007;169(2):369-374.
27. Harris RI. The macrometeorological spectrum a preliminary study. *J Wind Eng Ind Aerodyn.* 2008;96(12):2294-2307.
28. Vincent CL, Pinson P, Giebela G. Wind fluctuations over the north sea. *Int J Climatol.* 2011;31(11):1584-1595.
29. Soberanis MAE, Mrida W. Regarding the influence of the Van der Hoven spectrum on wind energy assessment in the meteorological mesoscale and microscale. *Renew Energy.* 2015;81:286-292.
30. Kang S-L, Won H. Spectral structure of 5 year time series of horizontal wind speed at the boulder atmospheric observatory. *J Geophys Res: Atmos.* 2016;121(20):11,946-11,967.
31. Larsn XG, Larsen SE, Petersen EL. Full-scale spectrum of boundary-layer winds. *Bound-Layer Meteorol.* 2016;159:349-371.
32. Zheng CW, Li CY, Li X. Recent decadal trend in the north atlantic wind energy resources. *Adv Meteorol.* 2017;2017:7257492. https://doi.org/10.1155/2017/7257492.
33. Dampier W. A discourse of winds: V. *Tomes Press.* 1699. 2010, ISBN-13: 978-1978149953.
34. Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balmaseda MA, Balsamo G, Bauer P, Bechtold P, Beljaars ACM, Berg L, Bidlot J, Bormann N, Delsol C, Dragani R, Fuentes M, Geer AA, Haimberger L, Healy SB, Hersbach H, Holm EV, Isaksoen S, Kallberg P, Kohler M, Matricardi M, McNally A, Monge-Sanz BM, Moncet J-J, Park B-K, Peubey C, Rosnay P, Tavolato C, Thepaut J-N, Vitart F. The era interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc.* 2011;137(656):102-113.
35. [Dataset] Hersbach H, Bell B, Berrisford P, Biavati G, Dee D, Dragani R, Fuentes M, Geer AA, Haimberger L, Healy SB, Hersbach H, Holm EV, Isaksoen S, Kallberg P, Kohler M, McNally A, Monge-Sanz BM, Moncet J-J, Park B-K, Peubey C, Rosnay P, Tavolato C, Thepaut J-N, Vitart F. The era interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc.* 2011;137(656):102-113.
36. Olauson J. Era5: The new champion of wind power modelling? *Renew Energy.* 2018;126:322-331.
37. Hoffmann L, Gunther G, Li D, Stein O, Wu X, Griessbach S, Heng Y, Konopka P, Muller R, Vogel B, Wright JS. From era-interim to era5: the considerable impact of ECMWF's next-generation reanalysis on Lagrangian transport simulations. *Atmos Chem Phys.* 2019;19(5):3097-3124.
38. Ramon J, Lleo D, Torralba V, Soret A, Doblas-Reyes FJ. What global reanalysis best represents near surface winds? *Q J R Meteorol Soc.* 2019;145(724):3236-3251.
39. Archer CL, Jacobson MZ. Supplying baseload power and reducing transmission requirements by interconnecting wind farms. *J Appl Meteorol Climatol.* 2007;46(11):1701-1717.
40. Dvorak MJ, Corcoran BA, Ten Hoeve JE, McIntyre NG, Jacobson M. US East Coast offshore wind energy resources and their relationship to peak-time electricity demand: US East Coast OWE resources and their relationship to peak-time electricity demand. *Wind Energy.* 2013;16(7):977-997. https://doi.org/10.1002/we.1524.
41. Kalnay E, Kanamitsu M, Kistler R, Collins W, Deaven D, Gandin L, Iredell M, Saha S, White G, Woollen J, Zhu Y, Chelliah M, Ebisuzaki W, Higgins W, Janowiak J, Mo K, Ropelewski C, Wang J, Leetmaa A, Reynolds R, Jenne R, Joseph D. The ncep/ncar 40-year reanalysis project. *Bull Am Meteorol Soc.* 1996;77(3):3437-472.
42. Coria VH, Maximov S, Rivas-Davalos F, Melchor-Hernandez CL. Perturbative method for maximum likelihood estimation of the weibull distribution parameters. *Springer Plus.* 2016;5(1):1-16.
43. Engblom A, Dornbrack A. The impact of the diurnal cycle of the atmospheric boundary layer on physical variables relevant for wind energy applications. *Atmospheric Chemistry Physics Discussion;* 2016. https://doi.org/10.5194/acp-2015-995
44. Smith EN, Gebauer JG, Klein PM, Fedorovich E, Gibbs JA. The great plains low-level jet during pecan: observed and simulated characteristics. *Mon Weather Rev.* 2019;147:1845-1869.
45. Whiteman CD, Zhong S. Downslope flows on a low-angle slope and their interactions with valley inversions. part i: Observations. *J Appl Meteorol Climatol.* 2008;47:2023-2038.
46. Wagner D, Steinfeld G, Withe B, Wrups H, Reuder J. Low level jets over the southern north sea. *Meteorol Z.* 2019;28(5):389-415.
47. Banta RM, Olivier LD, Levinson DH. Evolution of the monterey bay sea-breeze layer as observed by pulsed doppler lidar. J Atmos Sci. 1993;50(24):3959-3982.

48. Birch CE, Roberts MJ, Garcia-Carreras L, Ackerley D, Reeder MJ, Lock AP, Schiemann R. Sea-breeze dynamics and convection initiation: the influence of convective parameterization in weather and climate model biases. J Clim. 2015;28:8093-8108.

49. Lindzen RS. Thermally driven diurnal tide in the atmosphere. Q J R Meteorol Soc. 1967;93(395):18-42.

50. Ueyama R, Deser C. A climatology of diurnal and semidiurnal surface wind variations over the tropical pacific ocean based on the tropical atmosphere ocean moored buoy array. J Clim. 2008;21(4):593-607.

51. Daz-Argandoa J, Ezcurra A, Senz J, Ibarra-Berastegi G, Errasti I. Climatology and temporal evolution of the atmospheric semidiurnal tide in present-day reanalyses. J Geophys Res: Atmos. 2016;121(9):4614-4626.

52. Parding KM, Benestad R, Mezghani A, Erlandsen HB. Statistical projection of the north atlantic storm tracks. J Appl Meteorol Climatol. 2019;58(7):1509-1522.

53. Matsueda M, Endo H. Verification of medium range mjo forecasts with tigge. Geophys Res Lett. 2011;38(11):L11801.

54. Yu S, Fedorov AV. The role of westerly wind bursts during different seasons versus ocean heat recharge in the development of extreme el niño in climate models. Geophys Res Lett. 2020;47(16):e2020GL088381. https://doi.org/10.1029/2020GL088381

55. Battisti DS, Vimont DJ, Kirtman BP. 100 years of progress in understanding the dynamics of coupled atmosphere-ocean variability. Meteorol Monogr. 2019;59:8.1-8.57.

56. Horel JD. On the annual cycle of the tropical pacific atmosphere and ocean. Mon Weather Rev. 1982;110:1863-1878.

57. Wang B. On the annual cycle in the tropical eastern central pacific. J Clim. 1994;7(12):1926-1942.

58. Trenberth KE. What are the seasons? Bull Am Meteorol Soc. 1983;64(11):1276-1282.

59. Archer C, Jacobson M. Spatial and temporal distributions of U.S. winds and wind power at 80 m derived from measurements. J Geophys Res. 2003;108:4289.

60. Lee JA, Hacker JP, Monache LD, Kosovi B, Clifton A, Vandenberghhe F, Rodrigo JS. Improving wind predictions in the marine atmospheric boundary layer through parameter estimation in a single-column model. Mon Weather Rev. 2017;145(1):5-24.

61. Trenberth KE. Seasonality in southern hemisphere eddy statistics at 500 mb. J Atmos Sci. 1982;39(11):2507-2520.

How to cite this article: West CG, Smith RB. Global patterns of offshore wind variability. Wind Energy. 2021;1–16. https://doi.org/10.1002/we.2641