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Statistical and spectral analysis of wind over a strategic location

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ABSTRACT

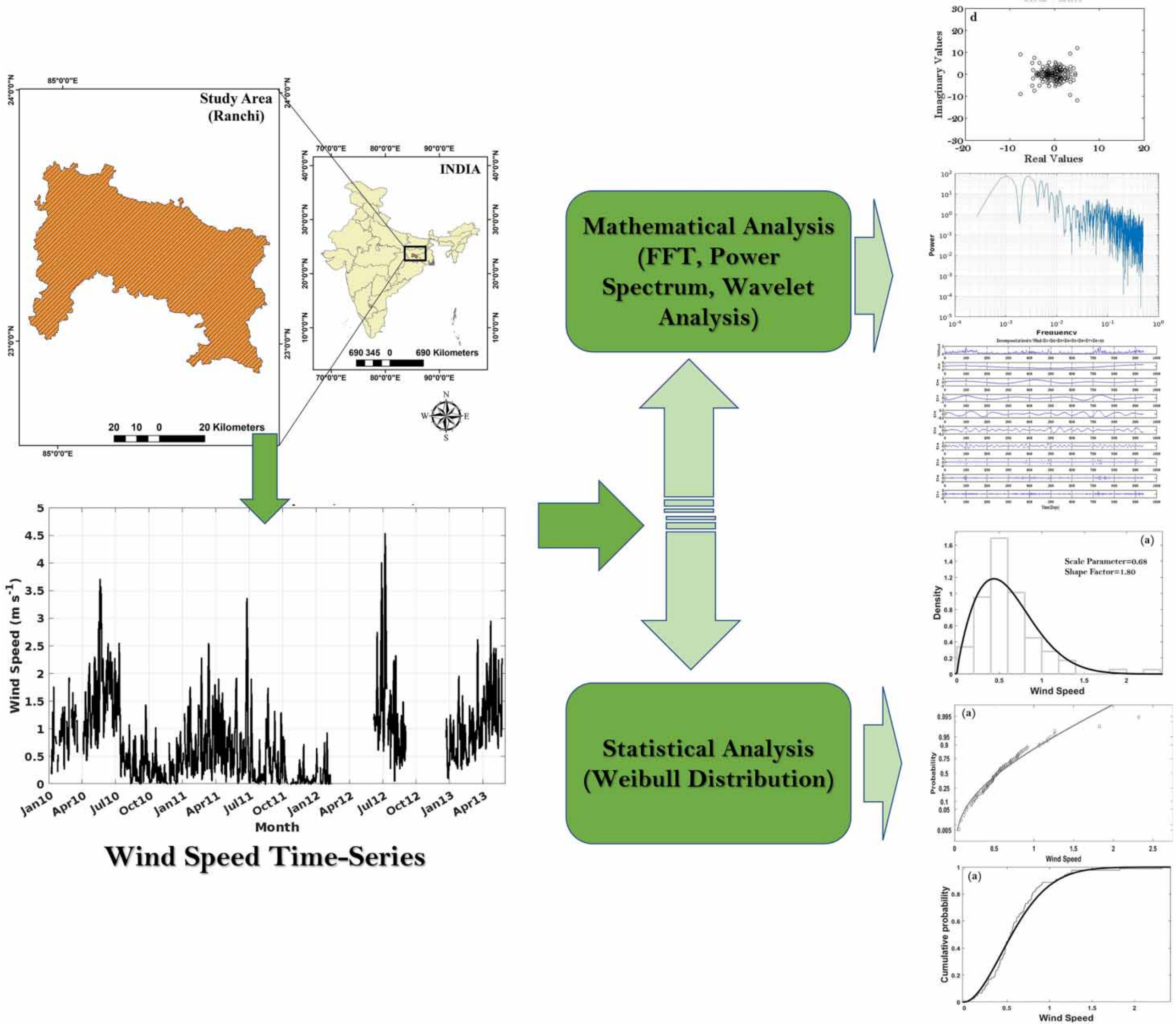
In the present work, we explored the inherent characteristics of the wind over a complex terrain site 'Ranchi' situated near a strategic location of the monsoon trough with various mathematical and statistical tools, i.e., time-series analysis, Fast Fourier transform (FFT), FFT coefficients, wavelet decomposition, and Weibull distribution. The time-series analysis showed a rapid day-to-day variability with a seasonal variation with a peak during summer. Fourier coefficients were concentrated for the winter/post-monsoon, indicating lower wind conditions, while wide spreads of the points indicate agility, i.e., high wind during the summer. The spectral features obtained using FFTs infer that wind has a prominent peak at a frequency f=0.00106724 (day^{-1}) and f=0.00266809 (day^{-1}). The power spectrum and wavelet decomposition show that the prominent frequencies correspond to yearly, eight, six, and four months. Weibull probability density function, cumulative probability distributions, and probability profiles are studied. Results show that the Weibull distribution function reasonably models the probability distribution of daily wind speed. Weibull scale parameter varied between 0.26 and 1.33 m/s, and the shape parameter ranged between 1.09 and 2.88. Results from various analyses indicate that the seasonal variation of wind speed over Ranchi is mainly associated with the development of monsoon trough over the site.

Key words: Fast Fourier transform, power spectrum, time series, Weibull distribution, wind speed

HIGHLIGHTS

- Inherence characteristics of wind over a site in the Indian trough region have been investigated.
- The highest mean speeds are observed just before the onset of monsoon and the lowest just after its departure in the post-monsoon season.
- Shape and scale parameters indicate more robust and variable winds in summer.
- Seasonal wind speed variation over Ranchi is mainly associated with the development of monsoon trough.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Wind energy is a primary renewable energy source and plays a crucial role in the energy production industry. The wind is the principal component of the weather system and governs the weather/climate at any location. Wind speed affects weather forecasting, aircraft motion, and maritime operations and has numerous other effects. Thus, the wind is a fundamental atmospheric variable and has an essential role in the renewable energy production industry (Yu *et al.* 2009), along with various meteorological significance. The prime meteorological importance of wind is in transporting moisture, heat, and pollutants. The wind transports the moisture and heat from one place to another, influencing the weather pattern. Wind also plays a crucial role in the dilution and transport of pollutants over a location, thus essential for air pollution monitoring and assessments. As a rising trend in wind energy, power efficacies need to plan the adaptation of wind power (Li & Jin 2018). Therefore, an accurate measurement of wind speed prediction is ideal for showing the behavior and trend of historical wind patterns and future projected patterns. Forecasting the wind speed is essential for the reliable and efficient operation of the wind generation system, an integral component of weather determination and forecasting (Lei *et al.* 2009). Detailed knowledge of wind distribution on various time scales is required for meteorological applications and optimization of wind energy systems (Jaramillo & Borja 2004).

Recently, statistical and mathematical modeling of wind dynamics/characteristics has drawn attention from scientists worldwide due to immense growth in opportunities in the wind energy sectors (Belu & Koracin 2009). It is essential to understand wind dynamics and characteristics in the atmosphere's boundary layer to manage wind resources effectively and to understand urban topography, air pollutants dispersion, building structures, and wind energy. The periodicity of wind speed over various time scales can be determined by analyzing the long-term time series of wind properties. Due to various meteorological and energy-related reasons, estimating the inherent properties of the wind speed at different time scales is crucial. Knowledge about temporal variability in wind speed time series is vital from the meteorological and practical point of view. Information about any abrupt or gradual change in wind speed is essential for the scientific world. To give any conclusive statement about such changes, a study of long-term time series of wind is required. Scientists have extensively explored wind energy as an effective alternative for power requirements and the possibilities of improvements in the wind energy power system. The wind is vital to study concerning climatic and weather conditions and environmental issues and is a significant source of renewable energy (Koracin *et al.* 2012). The wind energy sector is one of the growing renewable energy sectors. In addition to wind energy, renewable energy production can be integrated with water treatment applications such as desalination and brine treatment (Panagopoulos *et al.* 2019; Panagopoulos 2020, 2021; Panagopoulos & Haralambous 2020).

Numerous studies have been performed over various locations of the world to study the wind's inherent characteristics using multiple techniques that incorporate the time-series analysis; Fast Fourier transforms (FFTs), power spectrum study, and the statistical analysis of the time-series data (Koracin *et al.* 2012; Belu & Koracin 2013; Alam *et al.* 2014).

Koracin *et al.* (2012) performed an extensive study of weather and climate parameters governing environmental conditions. It is essential to study wind characteristics and other meteorological parameters to forecast probabilities of extreme events. Belu & Koracin (2013) performed a statistical study of wind properties important for wind power evaluation with tower observations in complex terrain. They investigated the spatio-temporal properties of wind speed and direction, crucial for wind energy/power-related system operation and maintenance. They used the Weibull and the von Mises distribution function to model the wind speed and direction. Their study showed that regional/local synoptic processes primarily govern wind variability over the study site. They studied boundary layer effects, such as turbulence and stability, on the wind energy.

Alam *et al.* (2014) used the FFT power spectrum and wavelet analysis methods to study wind variability, significantly affecting wind energy generation. Their work demonstrated the need to understand wind properties' spatial and temporal variation over any location for substantial wind power generation. Ismail *et al.* (2003) have used the FFT technique to transform the wind speed data from the time regime to the frequency regime for wind speed data over about 31 weather stations in Malaysia. Their work studied the parameters, such as cyclicities, frequency components, magnitude and phase of transformed data, and power spectrum density for wind power estimation.

Basumatary *et al.* (2005) explored the feasibility of the Weibull probability function in modeling wind speed. They performed a comparative study of the Weibull probability function with different methods for wind speed time-series data. They found the Weibull probability function as the best tool among all studied techniques to model various wind regimes. Gan *et al.* (2015) proposed a hybrid system that integrated the wind energy and electrical system. Gan *et al.* (2015) studied hybrid wind-photovoltaic diesel battery system sizing tool development with an empirical method. In their work, they also estimated the life cycle cost and efficiency of the proposed approach. Their study emphasized the benefits of the time-series analysis as it reflects a much more accurate condition.

Omer & Akinci (2020) studied signal processing techniques for wind speed analysis. Their work reported the manufacturing steps with wind energy and the production of electrical power with wind energy. They used mathematical, statistical, and signal processing techniques to estimate wind energy efficiency and compared the findings. Nie *et al.* (2020) used artificial intelligence and a double prediction scheme to simulate wind speed and energy. As a forecast of wind speed is a difficult task due to the randomness and nonlinearity involved, their study developed a double prediction system comprising a point prediction module and interval prediction module to overcome the deficiencies of these techniques. Their findings demonstrated the efficacy of the proposed strategies for engineering application and power system planning.

Santhosh *et al.* (2020) have extensively reviewed various approaches and advancements in wind speed and wind power for improved renewable energy. Their work studied the techniques used to improve and overcome the shortcomings of existing methods and explored future research directives. Nazir *et al.* (2020) also reviewed emerging research trends in wind power in the last few years. Their work revealed the wind forecasting methods and artificial intelligence applications in the wind energy field. Their work emphasizes the proper handling and calibration of wind forecasting instruments and methods for higher accuracy. Ben *et al.* (2021) analyzed 10 years of wind speed data over various parts of Nigeria to assess wind energy potential with integrated techniques. They used different techniques to estimate Weibull parameters. Their study rated the performance of multiple methods by evaluating the wind characteristics, variation pattern, and wind power potential.

In the present work, we studied the inherent nature of wind speed data with mathematical and statistical techniques. We selected Ranchi for this study, situated in the eastern part of India. The studies for wind characterization over the Eastern Part of India are very sparse, and no such analysis has been performed over this site. This study will provide us with an overview of the characteristics of wind variation over this region. Ranchi has a very strategic location as it falls over the site of the monsoon trough line, which is very important concerning various meteorological phenomena. The monsoon trough is one of the semi-permanent characteristics of monsoon circulation. The development and movement of the monsoon trough line govern the movement of the monsoon over the continent. Weather condition causes a frequent shift in the location of the monsoon trough. The wind is one of the essential features of weather; thus, it is necessary to investigate the wind characteristics over this region. This study will provide us with an overview of the change in wind pattern and its features associated with the development of monsoon trough. We used FFT, wavelet analysis, power spectrum, and Weibull distribution methods to understand, examine, and review the fluctuating nature of the wind. This paper is structured as follows: We start with an introduction section where we provide a brief literature review of the field, followed by a short introduction of the study site. The following section provides the details regarding the mathematical and statistical techniques used in this work. Furthermore, the observations and data analysis outcomes are provided in the results section, followed by conclusions from the work.

2. DATA AND STUDY SITE

The region selected for the study is Ranchi in Eastern India, which is situated on a plateau and falls over the trough line of the Indian summer monsoon. Figure 1(a) shows the geographical location of Ranchi over the Indian subcontinent, and Figure 1(b) gives the elevation map of Ranchi. The average elevation of this site is 651 m above sea level and is positioned in the southern part of the Chota Nagpur plateau, the eastern segment of the Deccan plateau. The Tropic of Cancer passes just a few kilometers away from it. Ranchi has a mountainous landscape and is surrounded by dense tropical forests. The position of Ranchi falls near the monsoon trough line during the monsoon season, which is an essential feature for the monsoon system and progress. It is a part of inter tropical convergence zone that proceeds up to mid of Indian landmass during the monsoon and is very helpful for the monsoonal wind circulation. The location of the trough line changes following the weather conditions. The monsoon trough migration is one factor controlling the monsoonal rainfall activities over the continent. The present work uses station data for the wind from the observational site established at BIT-Mesra, Ranchi (23 °25′N; 85 °24′E). The study is performed with the daily observation of wind speed, direction, and temperature; the data spans from January 2010 to May 2013.

3. MATHEMATICAL AND STATISTICAL BACKGROUND

We analyzed the wind with various mathematical and statistical techniques in the present work, including FFT, Power Spectrum analysis, Wavelet Analysis, and Weibull Distribution. Brief details about these techniques are provided in this section.

3.1. Mathematical techniques (FFT, power spectrum, wavelet analysis)

The Fourier transform technique extracts information from the signal and converts it from the time sphere to the frequency sphere. FFT is a very effective algorithm for estimating discrete Fourier transform, where the signal is composed of sine and cosine series (Ismail *et al.* 2003; Alam *et al.* 2014). FFT is a mathematical approach to convert a function from time-space to frequency space. FFT has been applied for all-season wind data to observe the Fourier coefficient and its distribution in the Fourier plane.

Next, we studied the power spectral density. A time-series's power spectrum represents the power variation in terms of frequency segments of that signal. The power spectral density function is a very useful tool that tells us at which frequency range the variation is substantial. Power spectrum analysis helps determine the presence of intra-seasonal oscillations in the data. Researchers widely use this technique to study the inherent frequency present in the data (Chellali *et al.* 2010; Giorgi *et al.* 2011).

To represent a discrete signal in a more representative form, we used the discrete wavelet transform. It is often used as preconditioning for data compression. Furthermore, wavelet analysis has been employed to analyze localized power variations within a time series (Daubechies 1992; Mellit *et al.* 2006). The dominant modes of variability and the time dependence of

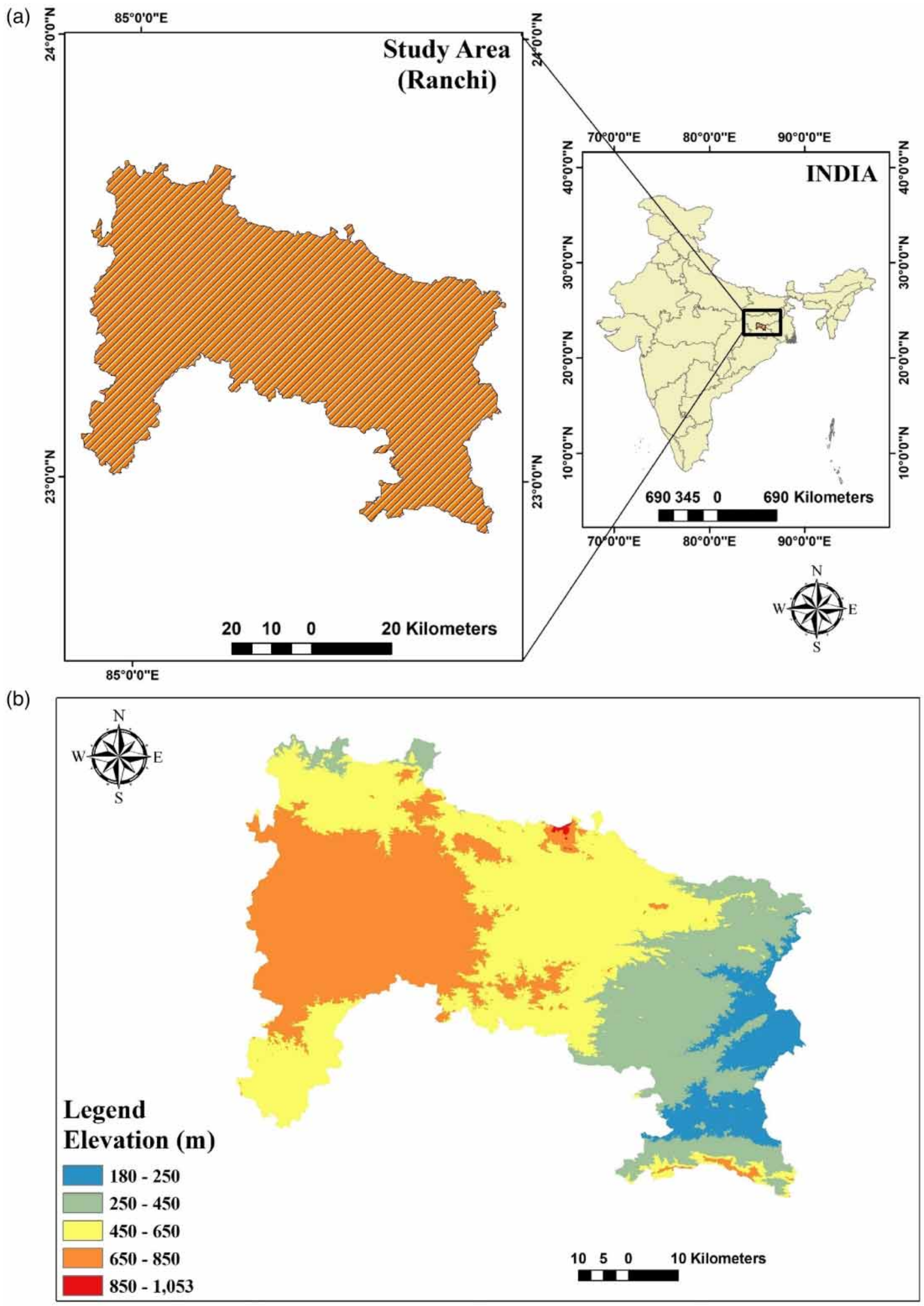


Figure 1 | (a) Geographical location of Ranchi (23 °25′N; 85 °24′E) over the Indian subcontinent. (b) Elevation map of Ranchi.

those modes are obtained by decomposing the time-series into time-frequency space (Siddiqi *et al.* 2005; Turbelin *et al.* 2009). Owing to the higher efficiency of the wavelet analysis method than Fourier transforms for detecting dominating frequencies in a signal, we employed wavelet analysis in our case along with the FFT analysis.

3.2. Statistical techniques (Weibull distribution)

It is helpful to perform a statistical analysis to explore the complete information from the wind data. The Weibull distribution function is one of the best conventional techniques to compute density functions related to wind variation (Stevens &

Smulders 1979). For the wind with low speed, this statistical technique is found most suitable (Alizadeh *et al.* 2015). With this technique, the wind speed fluctuations can be analyzed significantly. The shape and scale factors are the essential parameters in the Weibull distribution. Researchers have widely utilized the Weibull probability density function to model the wind speed distribution on various time scales (Chang 2011; Bagiorgas *et al.* 2012; Belu & Koracin 2019). The Weibull distribution is given by:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^{k}}$$

where v is the wind speed, f is the frequency, k is the shape parameter, and c is the Weibull scale parameter. We analyzed the seasonal variation of wind with the help of this distribution.

4. RESULTS AND DISCUSSION

In the present work, we studied the intrinsic properties of wind speed using various mathematical and statistical tools, including statistical distribution, FFT analysis, power spectra analysis, wavelet analysis, and Weibull distribution. The whole year is divided into four seasons, and primarily the analysis is performed for these seasons. The seasons are Winter (December, January, February), Pre-Monsoon (March, April, May), Monsoon (June, July, August), and Post-monsoon (September, October, November). First, we discuss the wind characteristics, then the mathematical analysis findings are discussed, and lastly, the statistical analysis results are discussed.

4.1. Wind characteristics

Time-series analyses of meteorological data have an increasing interest in many fields. Time-series studies are especially essential for a better understanding of atmospheric phenomena to model them, determine the climate of a geographical area, or forecast the occurrence of some extreme situations. Therefore, the time-series analysis of meteorological data series is helpful in various fields such as agriculture, air, sea traffic control, structural engineering calculations, global change studies, solar and wind resources estimation. Here, we have performed the time-series analysis for wind and temperature on daily data.

To observe the temporal changes in the wind speed, we studied its variation with the help of time series (Figure 2(a)). The daily wind showed drastic fluctuations from one day to another, but a long-term time-series plot provides the idea of wind's seasonal and interannual variation. In the time-series variation, an apparent seasonal effect could be seen. The highest wind speed was observed in the summer (pre-monsoon and monsoon), while low wind was observed in the winter and post-monsoon seasons. During the summer season, heating causes a change in pressure, and thus wind conditions change accordingly. The change over this site is also associated with the development of the monsoon trough over this region during the summer (i.e., pre-monsoon and monsoon season). The change in wind condition from winter/post-monsoon to pre-monsoon/monsoon indicates the development of a monsoon trough over the region; thus, increased wind could be noticed during the summer. As mentioned before, the study site falls near the monsoon trough region during the monsoon season, and its development could be seen as increased wind speed over this site. In the winter and post-monsoon seasons, the wind was in the calm to light air speed range, while in the pre-monsoon and monsoon seasons, it was in the range of light to gentle breeze speed range according to the Beaufort wind scale. In the post-monsoon season, very light wind (~0–1 m/s) was noticed frequently. Statistical parameters (mean, maximum, minimum, standard deviation, and variance) for the whole dataset and all seasons have been calculated, and details about the same are given in Table 1.

Next, we analyzed the time series of temperature data as the temperature is a significant moderator factor for the wind, thus crucial to study (Figure 2(b)). An apparent seasonal effect can be seen in the time-series variation of temperature data. The maximum temperature observed over Ranchi was about 42.5 °C, and the minimum was about 17.5 °C. The standard deviation for temperature data was about 5°. Temperature data indicates that Ranchi has a pleasant winter with a mean temperature of about 24 °C and a moderately hot summer with a mean temperature of about ~34 °C. Pre-monsoon season is hotter than monsoon season. The details regarding the mean, maximum, minimum, and other statistical parameters are given in Table 2. Both time-series plots, i.e., wind speed and temperature, have clear seasonality, and high wind speed was observed during the summer when the temperature was higher. High wind is observed during a similar period of high temperature, indicating

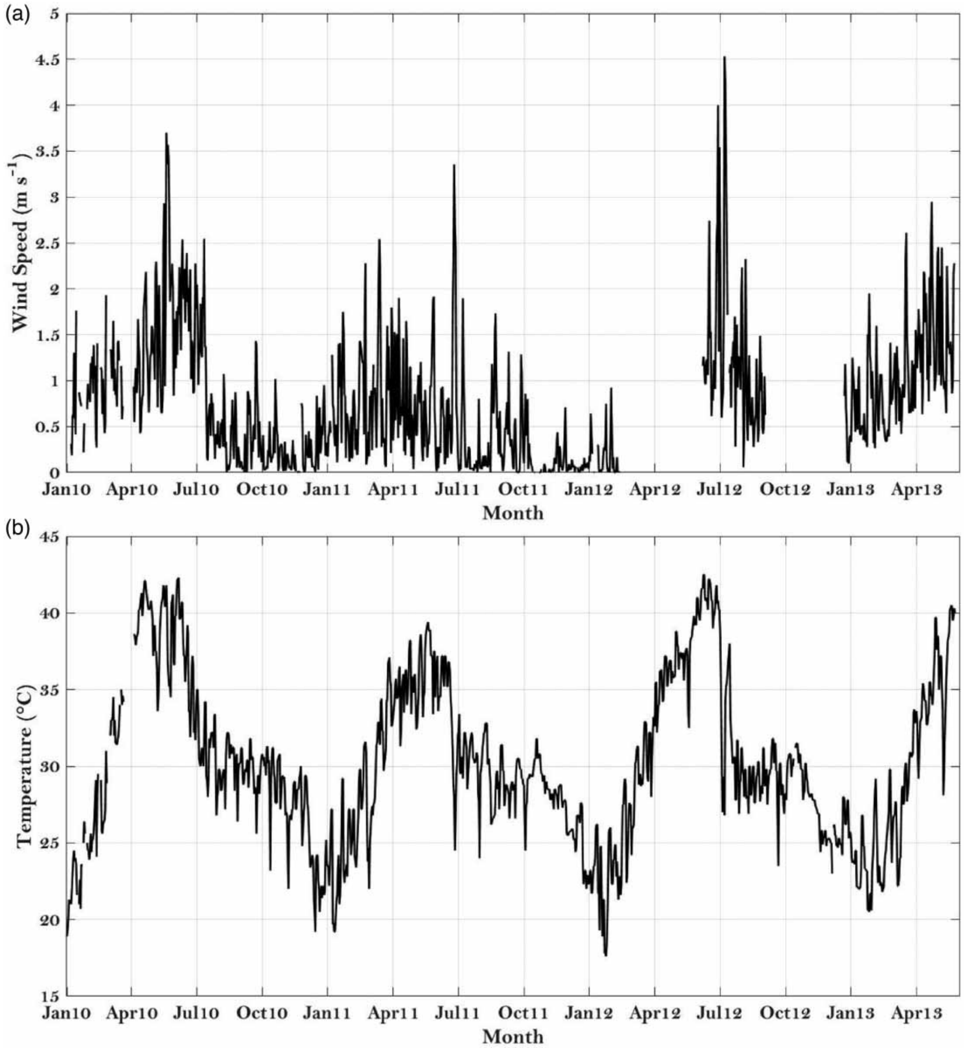


Figure 2 | Time series of the composite 2010–2013 datasets over the study site: (a) wind speed and (b) temperature.

the change in pressure over the region, which leads to the wind. The correlation between these two parameters was about 0.5, which is significant over a 99% confidence level.

Next, we explored the prominent direction of wind over Ranchi. The distribution of the wind direction can be shown effectively with the help of a wind rose plot, which indicates the occurrence of wind in a particular direction. This plot is a symbolic depiction of wind speed, frequency of occurrence, and wind direction over 360° in a circular manner of a specific location. The spoke length gives information regarding the strength of occurrence of wind in a particular direction. These

Table 1 | Main statistical characteristics of wind at the study site

Variables/Season	All data	Winter	Pre-monsoon	Monsoon	Post-monsoon
Mean	0.7666	0.5284	1.1767	0.9012	0.2560
Standard deviation	0.7096	0.4613	0.6950	0.8397	0.3025
Max	4.5308	2.2781	3.7012	4.5308	1.4312
Min	0.0012	0.0012	0.0139	0.0012	0.0012
Variance	0.5036	0.2128	0.4830	0.7052	0.0915

Table 2 | Main statistical characteristics of temperature at the study site

Variables/Season	All data	Winter	Pre-monsoon	Monsoon	Post-monsoon
Mean	30.2	24.7	35.9	31.9	28.3
Standard deviation	5.3	2.9	3.4	4.0	1.9
Max	42.5	31.6	42.5	42.3	31.8
Min	17.6	17.6	27.7	24.0	22.0
Variance	28.3	8.2	11.6	16.0	3.8

plots can also be used to depict information regarding the average speed and the power information in each direction. Figure 3 gives wind direction, and speed information over Ranchi in the form of a wind rose with 16 directions. The 16 directions include four cardinal directions (north, south, east, and west), four intercardinal directions (north-east, south-east, south-west, and north-west), and eight half wind directions in between these prime directions. As the length of each spoke provides information about the frequency of the wind coming from a specific direction, this figure indicates that over Ranchi, the wind was primarily from the north-northeast (NNE) direction. Nearly 500 times, the wind was in the NNE direction within the speed of less than 1 m/s, while about 200 times wind was in the range of 1–2 m/s in the same direction. In the same order, the wind reached 2–3 m/s about 50 times and very few times (~20) 3–5 m/s. Other than the NNE direction, the wind was blowing in the north (N) direction about 150 times, of which about 120 times it was within 1 m/s limits, and for the rest, it was 1–2 m/s. Another prominent direction is northeast (NE), and in this direction, about 100 times wind was blowing in which approximately 50% times it was below 1–3 m/s and other times between 1 and 3 m/s.

4.2. FFT analysis

The FFT analysis is performed with the help of MATLAB software, which facilitates an inbuilt algorithm for FFT estimation. With the help of this, we can obtain the inherent properties of the wind data, such as periodicity, frequency components,

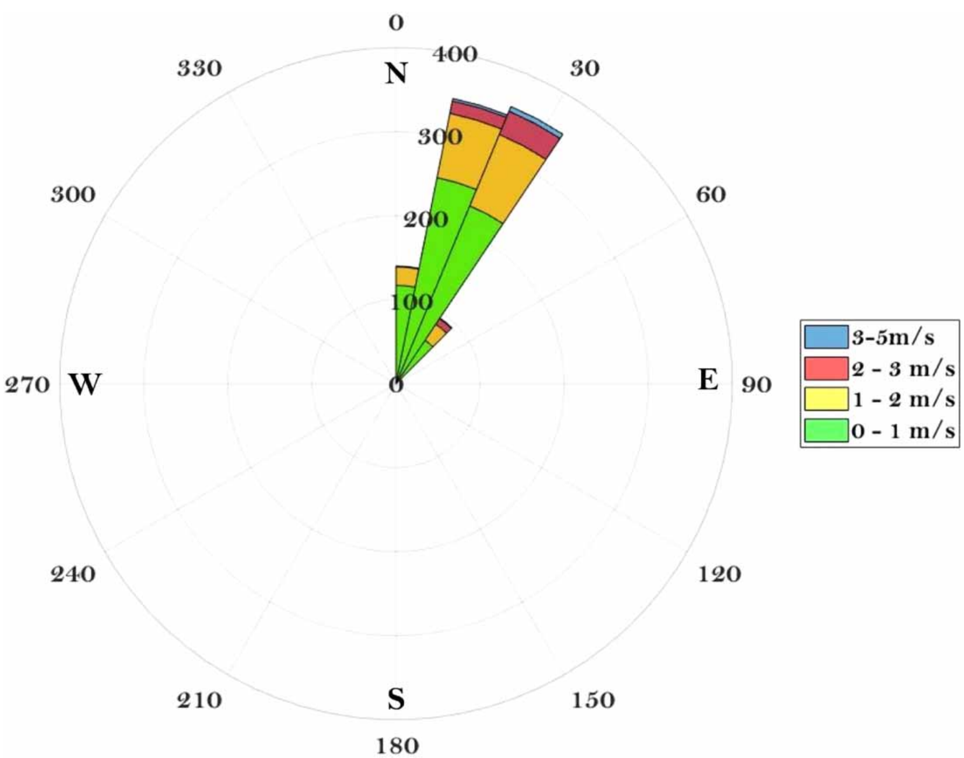


Figure 3 | Wind Rose diagram for the composite 2010–2013 datasets over the study site.

magnitude, and phase of renovated data, along with several other properties, including power spectral density. We have estimated the Fourier coefficients and power spectral density in the present work with the FFT analysis. In this section, we discussed the findings from the FFT analysis of wind speed over the study site.

4.2.1. Fourier coefficient distribution

Fourier coefficient distribution in the Fourier plane was studied to predict the agility of the wind particles in different seasons. The Fourier coefficients were calculated with the help of FFT analysis, where we can decompose a signal into its constituent frequencies over a continuous range. FFT has been applied to seasonal wind speed data to estimate the Fourier coefficient. Figure 4 shows the Fourier coefficient distribution in the Fourier plane. Figure 4(a) shows the Fourier coefficient distribution for winter, Figure 4(b) for pre-monsoon, Figure 4(c) for monsoon, and Figure 4(d) for the post-monsoon season. These plots provide us with information regarding the agility of the atmosphere.

In the summer, the atmosphere is quite hot in the region and enhances the convective activities due to hot weather. With the start of the summer season, the monsoon trough also starts developing over this region, and an increase is noticed in the wind speed, which is reflected in the plot regarding wind agility. In the pre-monsoon and monsoon season, the Fourier coefficients plots showed wide scatter; it predicts wind agility during summer due to the rapid convection process (Figure 4(b) and 4(c)).

The time-series analysis showed that the wind speed was low in the winter season, and the Fourier coefficients distribution for the winter season also indicates the same (Figure 4(a)). The scatter of the coefficients was low in this season. The lowest wind conditions were observed in the post-monsoon season; thus, significantly less scattering was observed in Fourier coefficients (Figure 4(d)). Time-series analysis observed the calmest conditions for wind in the post-monsoon season; and the Fourier coefficient plot also showed the lowest scatter in this season. The concentrated plot of Fourier coefficients showed that atmospheric agility was lowest in this season. Statistical information for the wind and temperature in this season indicated the lowest variance, i.e., the atmosphere is stable. As the monsoon retreats, the monsoon trough also disappears, and the region becomes calm.

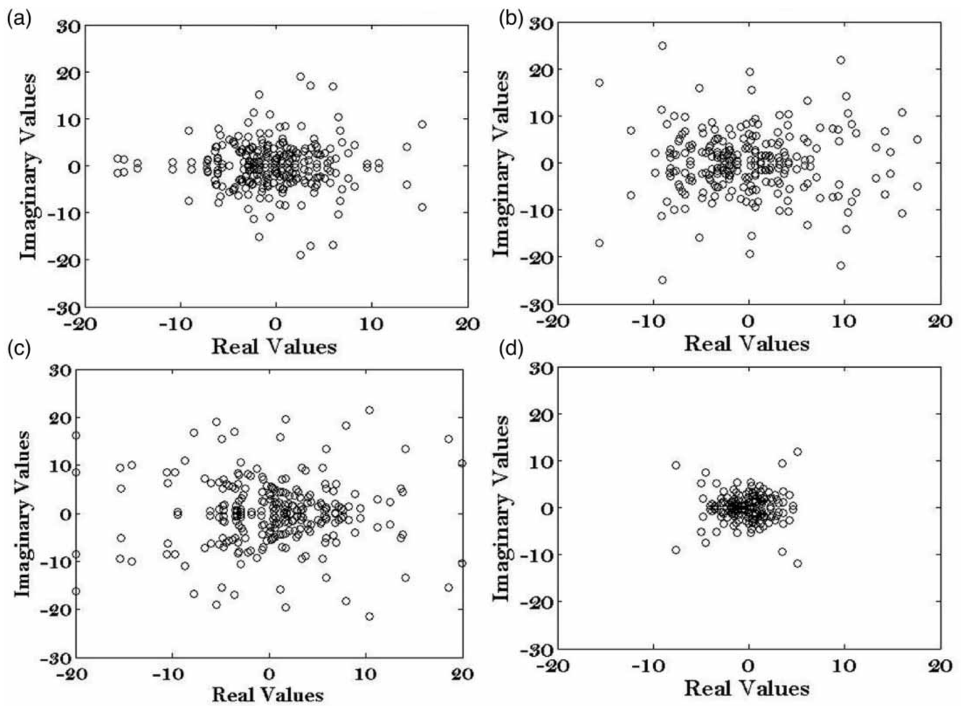


Figure 4 | Fourier coefficients distribution plot. (a) Winter, (b) pre-monsoon, (c) monsoon, and (d) post-monsoon.

4.2.2. FFT power spectrum density

Next, we studied the power spectral density of the wind data. The power spectral density of wind provides information on the nature of fluctuations in the time-series data. The power spectrum of a time series represents the power distribution in terms of its constituent frequency components. The power spectral density function is a very useful tool that tells us at which frequency range the variation is substantial. Figure 5 shows the power spectral density function of the daily wind speed and indicates the most prominent frequencies in the data. This plot showed that spectral power energy was mainly focused at f=0.00106724 (day^{-1}) and f=0.00266809 (day^{-1}). The time period corresponding to these frequencies is about T=1/f=937 days and 374 days. The period of 374 days indicates that wind speed in a year is similar to other year's variations. The period of 374 days is closely equal to Julian's year 365 days, but not exactly. The possible reason for this difference could be the natural phenomenon that the wind speed year is marginally lengthier than the typical year due to the early or late arrival of the seasons. Other prominent peaks were observed at f=0.00480256 (day^{-1}), 0.00571 (day^{-1}), and 0.00773746 (day^{-1}), which corresponds to a period of about 208, 175, and 129 days, respectively. These periods correspond to approximately eight, six, and four months. This analysis indicates that the prominent frequencies correspond to the time-period of a year, eight, six, and four months.

4.3. Inherent characteristics of wind with wavelet decomposition

The wavelet decomposition gives a more enlightening representation of the time-frequency localization of signals. In contrast, FFT provides the averaged spectral coefficients independent of time and is essential to recognize the dominant frequencies in a signal. Data used in the study has the daily frequency, and as per the Nyquist Frequency criteria, these signals will capture the evidence for a span larger than 2 days. The discrete wavelet analysis has been performed using db8 for the daily wind speed data and decomposed into eight levels at various temporal scales. These temporal scales include an extended period (more than a year), yearly, half-yearly, quarterly, bimonthly, monthly, biweekly, weekly, and half-weekly, respectively. These periods are widely used to characterize wind speed fluctuations. Figure 6 shows the study period's decomposed wind speed time series and comprises 10 signals. The first segment 's' shows the raw signal, and the second segment 'A8' corresponds to the raw signal for Daubechies wavelets at level8 (db8), which corresponds to more than 512 days. The other segments (i.e., D1–D8) detail the decomposed signals, which correspond to periods of 2–4, 4–8, 8–16, 16–32, 32–64, 64, 128, 128–256, and 256–512 days, respectively. The signal A8 corresponds to the approximation of the raw signal corresponding to a period longer than 512 days. The mean of signal A8 was about 0.77 m/s which is very close to the mean value of

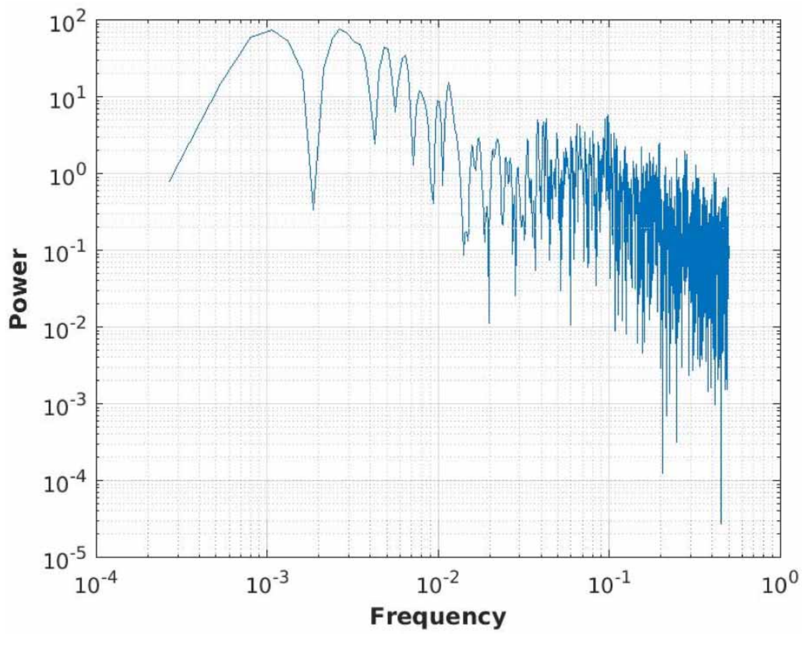


Figure 5 | The variation of power spectra for daily wind speed data over the study site.

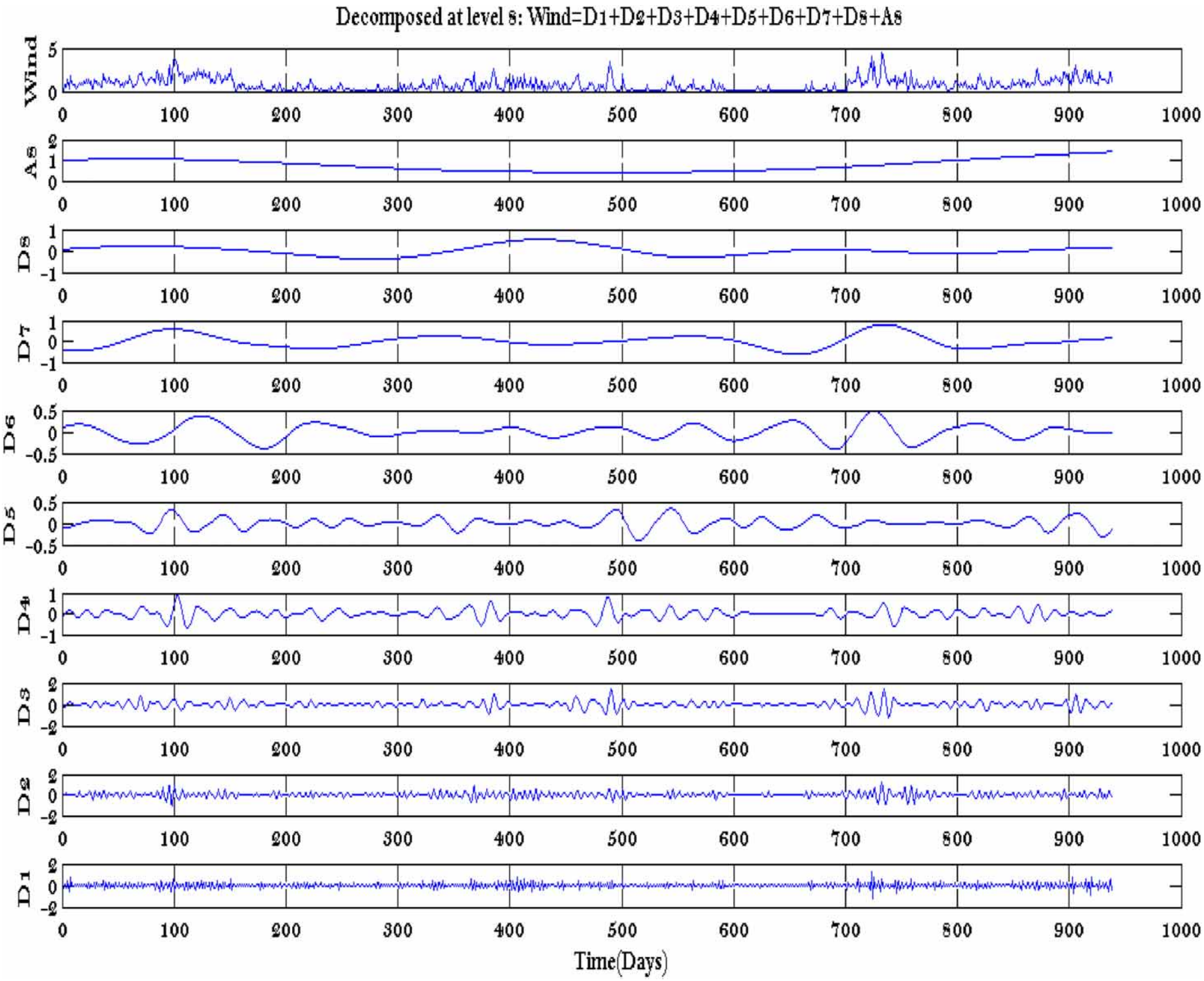


Figure 6 | Decomposition of daily wind speed time-series data (2010–2013) at the study site.

the primary data. The signal A8 oscillates between ±1.5 m/s with standard deviations between~±0.3 m/s. Signal D8 shows the periodicity of about one year and peaks in the summer and winter months. The periodicity of the data was approximately one year, and the signal oscillated between ±0.5 m/s. The signal D7 oscillates between ±1.0 m/s with a time period of about half a year, and signal D6 oscillates between ±0.5 m/s with a time period of approximately a quarter year. The standard deviation of these signal's oscillations was ±0.32 and ±0.17 m/s, respectively. The signal D5 has roughly similar oscillations as D6, i.e., the signal oscillates between ±0.4 m/s with a standard deviation of ±0.17 m/s. The signal D4 has some larger amplitude of variation, and here signal oscillates between ±0.9 m/s with a standard deviation of ±0.23 m/s. The observation insinuates that the monthly variation in the wind speed is more substantial than the bimonthly variation, which occurs in the peak season (May–August) of wind. The D3 and D2 signal oscillate between ±1.4 and ±1.1 m/s with a standard deviation of ±0.28 and ±0.24 m/s, respectively. Overall, wind speed variation is more substantial for a period of one year (D8), half a year (D7), monthly (D4), bimonthly (D3), and less than 8 days (D1 and D2) but is weaker for a period of a quarter year (D6) and bimonthly (D5).

Figure 7 gives us the power spectrum of the decomposed signals, i.e., the power spectrum for D1–D8. From the figure, it is clear that the D8 signal shows a very prominent peak at f (=0.0028 day^{-1}), which corresponds to about one year (~358 days) (Figure 7(a)). A superharmonic peak (f=0.0057 day^{-1}) was also observed in the D8 power spectrum through a weak peak. The signals D7 and D6 showed an oscillation frequency of about 175 and ~90 days, corresponding to about half a year

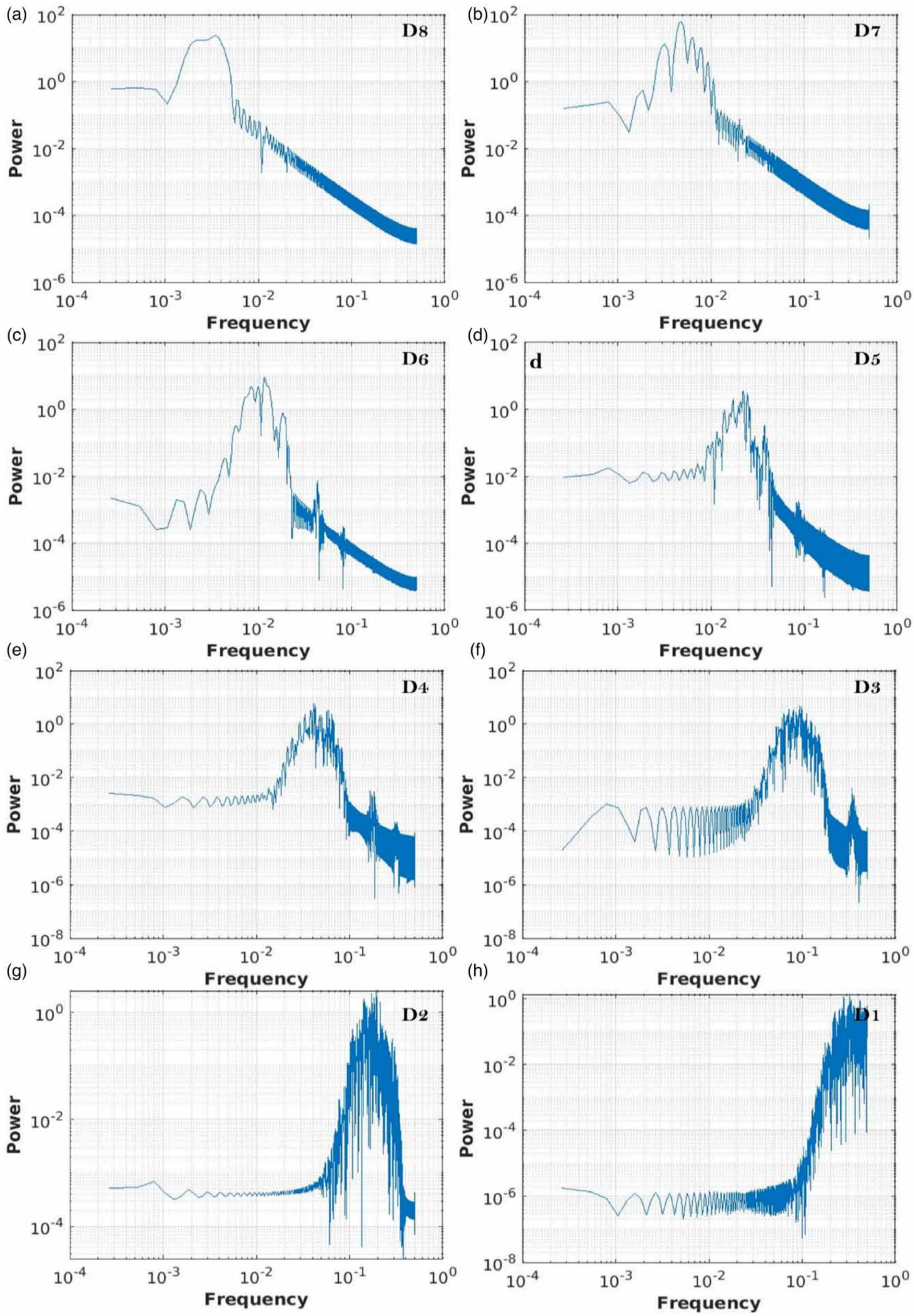


Figure 7 | The power spectra of the decomposed signals at the study site. (a) D8, (b) D7, (c) D6, (d) D5, (e) D4, (f) D3, (g) D2, and (h) D1.

and a quarter of a year. The peak in the D7 was observed at a frequency (f=0.0057 day^{-1}), while the peak for the D6 signal showed an unsharpened peak at a frequency (f=0.0112 day^{-1}). Next, we estimated the power spectrum of D4 and D5 signals, where the fluctuations are low. The peaks of these signals were also blunt, with frequency values about f (=0.0218 day^{-1}) and f (=0.041 day^{-1}) for D5 and D4, respectively, corresponding to about 45 and 24 days. The D3 and D2 showed the peaks at frequency f (=0.0949 day^{-1}) and f (=0.1728 day^{-1}), which is about 10 and 6 days, respectively. We also studied the power spectrum of decomposed signal D1, which showed its peak at a frequency of about f (=0.33 day^{-1}), which stood for about 3 days. This information is essential for long-term wind forecast and energy industries; and also emphasizes the need for long-term wind speed analysis before setting up a wind power production unit.

4.4. Weibull distribution

The wind variation at any site is often described using a Weibull distribution. The Weibull distribution function is the standard function for calculating wind distribution and probability density in wind analyses. In low wind speed conditions, the Weibull distribution provides a reasonable estimate for wind speed distribution. Primarily, low wind speed was observed over Ranchi; thus, this distribution is the most appropriate statistic for wind speed analysis.

The scale parameter is the governing factor for the entire distribution, i.e., the distribution gets compressed or stretched according to its value. If the scale parameter values increase while holding the shape factor constant, the distribution gets stretched out to the right, and its height decreases. Similarly, if scale parameter values decrease while keeping the shape factor constant, the distribution gets pushed toward the left, and its height increases. A higher scale parameter value indicates a more significant departure from the mean value (Bhattacharya 2011). The shape factor 'k' governs the skewness of the distribution and thus changes the shape of the distribution. Smaller k values indicate highly fluctuating winds, and higher values indicate reasonably stable wind conditions (Bhattacharya 2011).

The statistical distribution of wind varies from season to season, and its apparent impact could be seen in Weibull probability density distribution plots (Figure 8). Figure 8 shows the Weibull probability density distribution for all seasons with wind histograms, i.e., Figure 8(a) for winter, Figure 8(b) for pre-monsoon, Figure 8(c) for monsoon, and Figure 8(d) for post-monsoon, respectively. The corresponding shape factor and scale parameters of the Weibull distribution are provided in Table 3. Suppose the scale parameter has a small value, the distribution shifts toward the left while the peak shifts toward the right with the larger value. The same behavior can be observed in all the Weibull distribution plots. We could observe the lowest value of the scale parameter for the post-monsoon season; for this, the peak is toward the left. As the scale parameter value increases, the distribution's peak gets flattened and shifts toward the right. We noticed the largest scale parameter for the pre-monsoon season, and the distribution is near normal distribution with a relatively flat curve.

The seasonal variation of wind speed over the Ranchi is mainly driven by depression, i.e., associated with the development of monsoon trough during the summer season. The monsoon trough appears during the summer season and disappears after it. The low associated with the monsoon trough is vital in summer; consequently, winds are stronger during summer than in other seasons. Correspondingly, the seasonal variation of the Weibull distribution fit is clearly distinguishable when the wind speed distribution peaked with smaller values of scale parameter during the winter and post-monsoon season. In contrast, those during the summer months appear to be wider (i.e., larger scale parameter) with lower peaks.

The shape factor reveals the extent of the distribution of wind speed. Generally, a larger shape factor value indicates that wind speed is primarily confined in a smaller range, while the lower value indicates the broader wind speed distributions. At the same time, the larger value (~3) of the shape factor represents a normal distribution while the lower value shows a skewed-shaped variation. In the winter, the shape parameter was moderately high (1.8), and the scale parameter was relatively low (0.68); thus, the wind during this season showed variable wind conditions (Figure 8(a)). During the pre-monsoon, as heating starts over the land, the development of low starts and causes increased wind conditions. In this season, the shape parameter was very high (2.88), and the scale parameter was also high (1.33), representing high winds with wide distribution (Figure 8(b)). During the monsoon season, the monsoon trough is fully developed over the region, and thus highest winds are seen during the monsoon season over this site. During monsoon, the shape parameter was moderately high (1.69), and the scale parameter was also moderately high (0.99), representing gusty wind with high variance (Figure 8(c)). After the withdrawal of the monsoon, the monsoon trough dissolves; thus, in the post-monsoon season, the lightest wind was observed over the site. During the post-monsoon, the shape parameter was low (1.09), and the scale parameter was also low (0.26), representing light wind (Figure 8(d)).

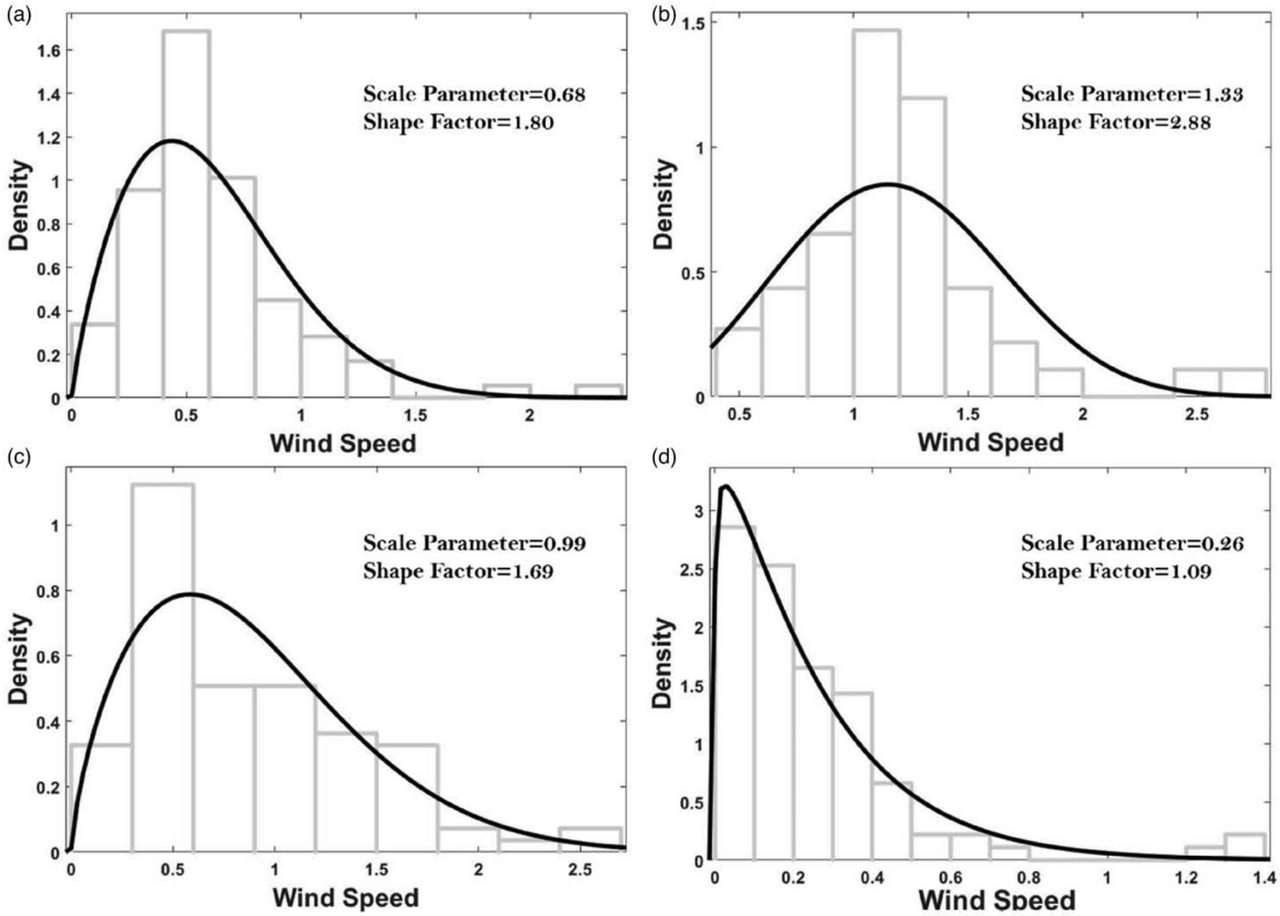


Figure 8 | Weibull probability density function profile for Ranchi. (a) Winter, (b) pre-monsoon, (c) monsoon, and (d) post-monsoon.

Table 3 | Scale parameter and shape factor details for Weibull distribution of various seasons

Season	Scale parameter	Shape factor
Winter	0.68	1.80
Pre-monsoon	1.33	2.88
Monsoon	0.99	1.69
Post-monsoon	0.26	1.09

Figure 9 shows the Weibull probability plot for all seasons, i.e., Figure 9(a) for winter, Figure 9(b) for pre-monsoon, Figure 9(c) for monsoon, and Figure 9(d) for post-monsoon. The scale parameter can also be estimated from these plots. The scale parameter values lie where the best fit line intersects the 63.2% level of the y-axis, and these values were similar to those estimated in the previous plots. From the probability plot, we can notice that in the winter and post-monsoon season, in the lower velocity range, the probability of wind is sharply increasing with wind speed, then varies almost linearly with wind speed. For pre-monsoon and monsoon seasons, probability varies almost linearly with wind speed.

Next, we have shown the Weibull cumulative probability distribution profile for all seasons (Figure 10), i.e., Figure 10(a) for winter, Figure 10(b) for pre-monsoon, and Figure 10(c) for monsoon, and Figure 10(d) for post-monsoon, respectively. Cumulative probability plots show that during the wintertime, maximum probability occurs for the wind speed between 0.5 and 1.0 m/s, and in the post-monsoon season, the maximum probability is for 0.2–0.6 m/s wind speed. While in the pre-monsoon

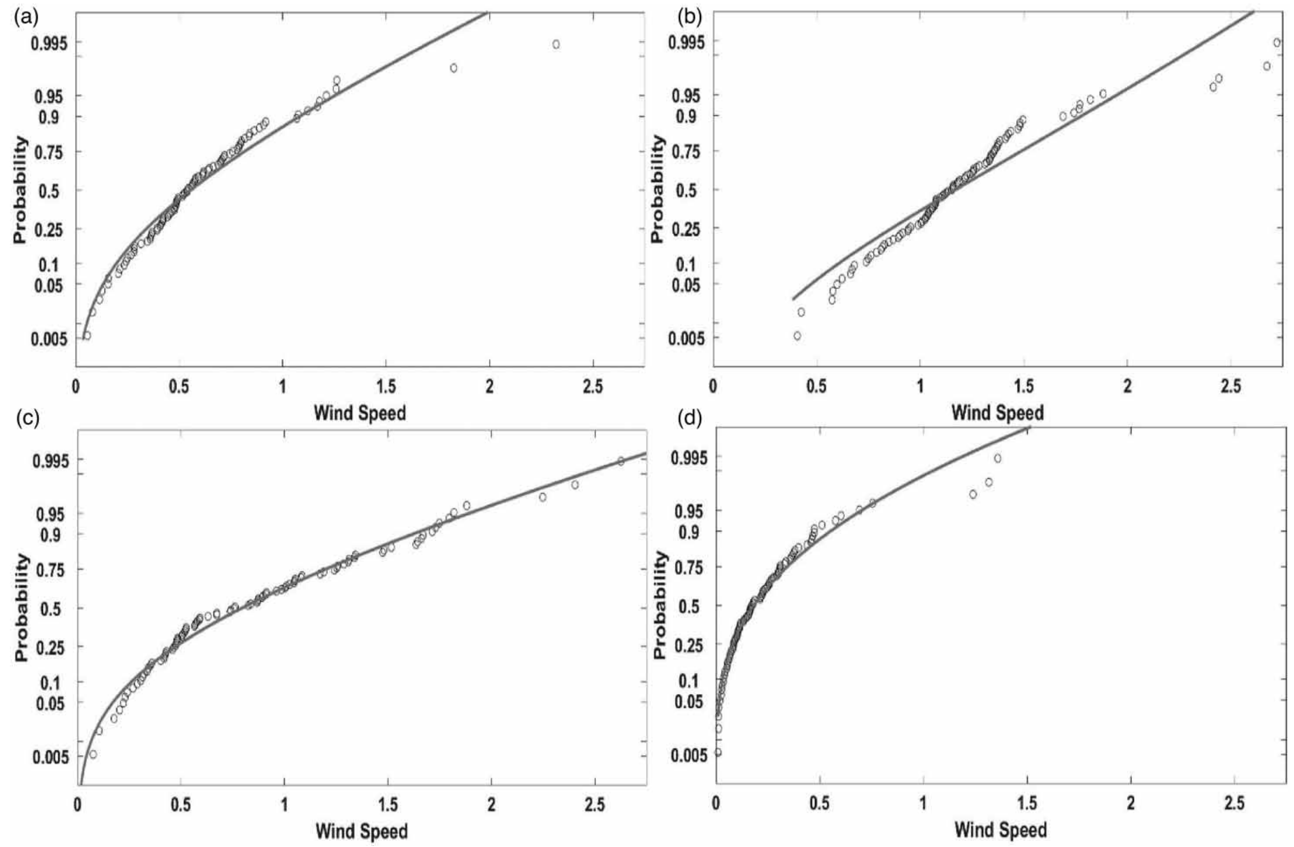


Figure 9 | Weibull probability plot for Ranchi. (a) Winter, (b) pre-monsoon, (c) monsoon, and (d) post-monsoon.

and monsoon season, this plot indicates that wind speed is almost equally probable for all the wind speeds between 0.5 and 2 m/s.

5. CONCLUSION

Wind speed and wind power have received increasing attention all around the globe due to their renewable nature as well as meteorological importance. This study represents an overview of the various inherent properties of the wind over Ranchi with the help of mathematical and statistical methods. The essential conclusions of the work are discussed here.

- The time-series analysis of the wind speed data showed a rapid day-to-day variability with a typical wind speed of ~0.76 m/s, indicating that wind was primarily in the light air range. The monsoon trough starts developing with the heating of the land during the summer season. In association with it, the wind speed increases with the start of summer and reaches its maximum during the peak summer season. Seasonal wind peaks were observed in the pre-monsoon/monsoon season. The statistical parameters also indicate that the wind speed is high in the pre-monsoon and monsoon seasons. These parameters also suggested that the wind speed ranges from light air to gentle breeze.
- Fourier coefficient distribution plots reflected the agility of winds and showed that convective activities are more during pre-monsoon and monsoon months. The agility of the atmosphere is also associated with the development of monsoon trough over this region. As a result, we could see a high scatter of Fourier coefficients in the pre-monsoon and monsoon season and less scatter in the winter and post-monsoon season.
- The power spectrum analysis showed that the most prominent wind speed frequencies were yearly, eight-, six-, and four-monthly. Wavelet analysis indicates that wind speed variation is more substantial for one year, half a year, monthly, bimonthly, and less than 8 days but weaker for a quarter year and bimonthly timescale.
- The Weibull Distribution is a very suitable function to study the statistical features of the wind and subsequently understand its behavior in a given region. The Weibull distribution was used to model the probability distribution of wind speed.

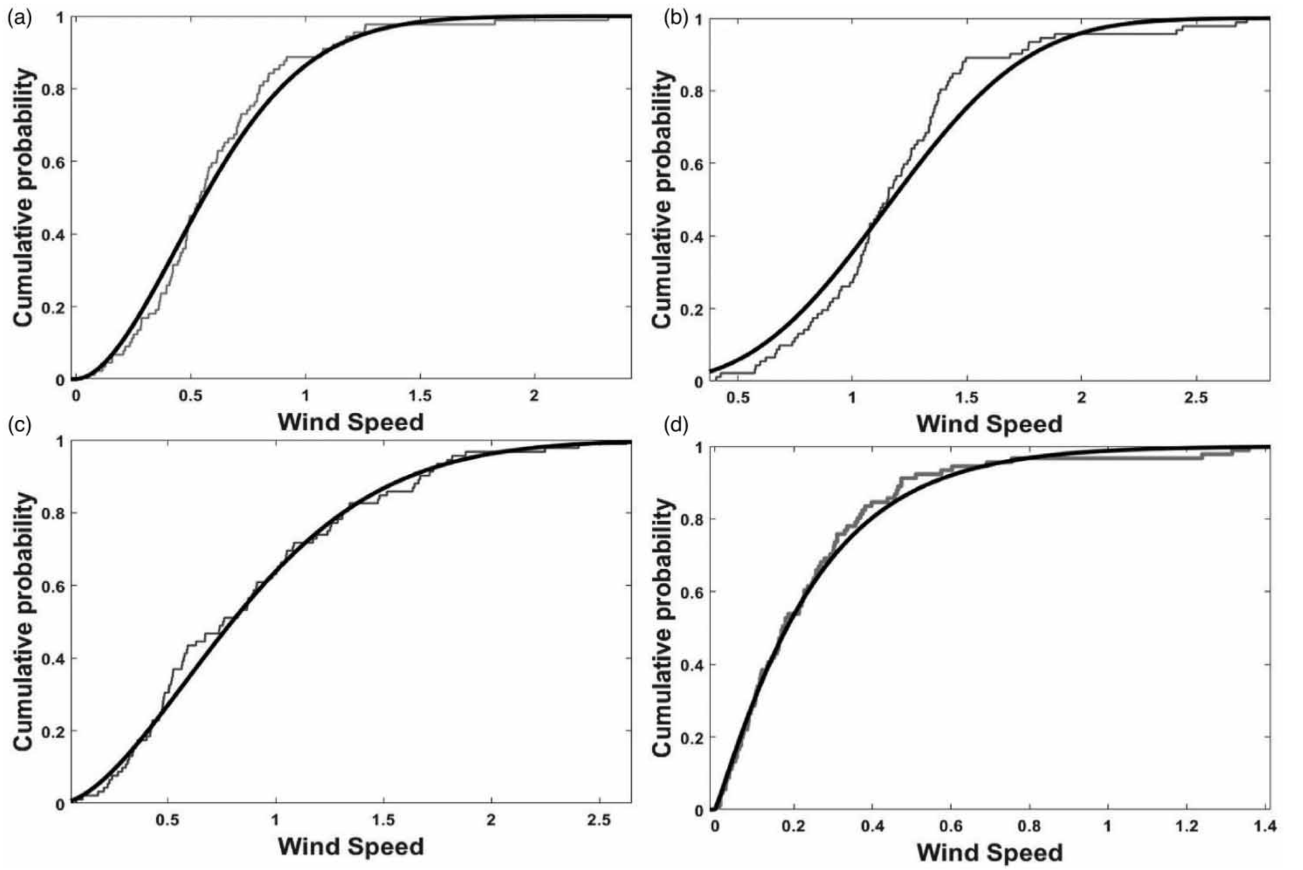


Figure 10 | Weibull cumulative probability distribution profile for Ranchi. (a) Winter, (b) pre-monsoon, (c) monsoon, and (d) post-monsoon.

Probability density function, cumulative probability distributions, and probability profiles are studied. The seasonal variation of wind speed over the Ranchi is associated with the development of monsoon trough during the summer season. The low associated with the monsoon trough is vital in summer, causing more substantial winds during this season than in other seasons. Correspondingly, the seasonal variation of the Weibull distribution fit is clearly distinguishable when the wind speed distribution peaked with smaller values of scale parameter during the winter and post-monsoon season. In contrast, those during the summer months appear to be wider (i.e., larger scale parameter) with lower peaks. In response, the seasonal variation of the Weibull distribution appears to be wider (i.e., larger scale parameter) with lower peaks during the summer months, indicating gusty and high wind conditions. The wind speed distribution peaked with smaller scale parameter values during the winter and post-monsoon season, representing lower and calm wind conditions.

- These studies are essential to understand the nature of wind variation and atmospheric dynamics over a site, which is a crucial component of urban modeling and wind energy generation.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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