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Long-Term Statistical Modelling of Near-Surface Wind Speed in Abuja, Nigeria Using Skewed Probability Distribution

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Abstract: Reliable characterisation of wind speed variability is essential for assessing wind energy potential, particularly in regions where low-speed regimes dominate and resource uncertainty is high. In this study, long-term near-surface wind speed behaviour in Abuja, Nigeria, was statistically modelled using 46 years (1980–2025) of monthly mean Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) reanalysis data at a height of 10 m above ground level. Descriptive statistical properties, including mean, standard deviation, skewness, and kurtosis, were first evaluated to characterise distributional features and deviations from Gaussian behaviour. Three skewed probability density functions (PDFs)—Weibull, Gamma, and Lognormal distributions—were subsequently fitted using Maximum Likelihood Estimation (MLE) and the Method of Moments (MOM). Model performance was assessed through graphical and statistical diagnostics, including probability density histograms, quantile–quantile (Q-Q) plots, and Cullen–Frey skewness–kurtosis analysis, enabling comparative evaluation of tail behaviour and modal structure. The wind regime in Abuja was found to be relatively stable and dominated by low wind speeds, with the principal mode located between 1.5 and 2.0 m/s. Approximately 80% of observed wind speeds were below 2.2 m/s, indicating a persistent low-energy environment. The Weibull and Gamma distributions provided the most accurate representation of the empirical data, successfully capturing the moderate positive skewness, limited tail extent, and weak bimodal tendency. In contrast, the Lognormal distribution systematically overestimated probability density at lower wind speed intervals and exhibited poorer agreement in upper quantiles. These findings demonstrate that skewed distribution modelling significantly improves representation of low-speed wind regimes and highlight the importance of site-specific statistical parameterisation for wind resource assessment in semi-arid Sub-Saharan environments. The results provide a robust statistical basis for wind energy feasibility analysis, micro-siting considerations, and hybrid renewable system design in regions characterised by marginal wind resources.

Keywords: Wind speed modelling; Modern-Era Retrospective Analysis for Research and Applications version 2 reanalysis; Weibull distribution; Gamma distribution; Lognormal distribution; Statistical fitting; Wind resource assessment

1 Introduction

Wind power is one of the planet's most abundant and promising renewable energy sources. Its increasing significance is primarily driven by the depletion of fossil fuel reserves, rising global energy consumption, and the urgent need to mitigate the effects of climate change [1–3]. Growing concerns about climate change have led several countries to transition to renewable energy sources, particularly wind power, which has quickly spread over the globe [4–6]. Wind energy offers several key advantages, including the absence of fuel costs, reduced exposure to fuel price volatility, and enhanced energy security, however, its effective utilisation is constrained by the inherent intermittency and stochastic nature of wind resources, which limit predictability and complicate reliable energy planning [7–9].

With a roughly 300-fold rise since 1990, wind energy is today the most commonly used renewable source for power generation, with China, the US, Germany, Spain, and India leading the way in worldwide development [10, 11]. Huge hydropower is not included in this.

In parallel environmental modelling research, the study [6, 12] used Weibull and Lognormal models across thirteen parameters to analyze water pollutant distributions from two important rivers in Oyo State in order to assess water safety. The investigation demonstrated that several contaminants did not exhibit right-skewed characteristics, and goodness-of-fit (GOF) tests indicated that the lognormal distribution provided a superior fit to the Weibull distribution [13].

To adequately represent temporal variability and long-term patterns, multi-year datasets are required for effective modelling of wind speed distributions in wind resource assessment. In order to minimize the time and computational expense associated with processing long-term data, probability density functions (PDFs) are widely employed to characterize wind speed behaviour [2, 3, 14]. Model parameters are typically estimated using the Maximum Likelihood Estimation (MLE) technique. Conventional distributions like Weibull, Lognormal, Gamma, and Generalized Extreme Value (GEV) as well as mixture models like Weibull–Lognormal and GEV–Lognormal, have been shown to adequately capture wind speed variability [15, 16].

Furthermore, it has been demonstrated that including both wind speed and wind direction improves modelling robustness and adaptability under changing climatic conditions [17, 18].

Inadequate evaluation studies, inconsistent classification of wind resources in different places, and a lack of measurement data all hinder the development of wind energy in West Africa [19]. Because wind resources are highly site-specific, comprehensive national wind profiling requires multi-site evaluations. Nigerian wind energy evaluation has gone through several stages of growth as a result of policy measures that demonstrate the government's interest in harnessing wind resources for power generation [20, 21].

Although the Weibull distribution is still the most widely used model for wind speed analysis, studies have revealed that it may not always provide the best performance. For instance, the study [22, 23] used the Inverse Weibull (IW) distribution to analyze wind speed data in Turkey and showed that, for the majority of stations, the standard Weibull model yielded less accurate findings than parameter estimation using MLE and Modified Maximum Likelihood (MML) techniques [19].

Recent studies with an African focus further emphasise the need for region-specific modelling methodologies [19]. The application of the Weibull distribution to wind speed data from 2000 to 2023 across selected African stations revealed significant spatial variability in wind characteristics and power density, highlighting Africa's significant wind energy potential and the importance of tailored renewable energy policies [24]. In a similar vein, Ogunjo [25] employed Weibull and multifractal techniques to examine wind speed at heights of 50 and 100 meters in a tropical coastal setting, proving that land-sea breeze interactions greatly affect multi-fatality and validating the value of the Weibull distribution for wind characterization and energy-related applications.

In the development of wind speed modelling, flexible statistical frameworks that can capture the skewness, asymmetry, and heavy-tailed behaviour found in environmental datasets have grown more crucial [19, 26]. The generalized positive exponential family of distributions, which performs better in capturing non-normal features and wind speed variability, was proposed by the study [27, 28] as a dependable replacement for traditional models. Similar to this, the study [24, 29] assessed wind speed distributions outside of the conventional Weibull model and discovered that various heavy-tailed and skewed distributions can provide better fits in a range of wind regimes. Building on previous developments, the current work uses skewed statistical models to analyse wind speed data from Ikeja Station in an attempt to better capture non-normal behaviour and increase the accuracy and reliability of wind speed modelling.

This study used skewed probability distributions to statistically model and characterize the wind speed distribution over Abuja, a Sub-Saharan semi-arid station in northeastern Nigeria, in order to identify the optimal statistical model for accurate wind resource assessment and environmental applications [19].

Compared to many earlier studies, this work uses a long-term dataset that spans 46 years (1980–2025) and is generated from Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) reanalysis at a 10-m height. A thorough evaluation of Abuja's long-term wind speed characteristics is made possible by this expanded dataset. Furthermore, the study offers a more flexible framework for capturing non-normal atmospheric behaviour by looking at different skewed statistical distributions (Weibull, Gamma, and Lognormal) instead of depending only on the popular Weibull model.

2 Methodology

2.1 The Study Area

Abuja is located in the north-central area of Nigeria and is the capital city of the country in the Sub-Saharan climatic zone. The station's climate makes it suitable for statistical wind speed modelling and wind energy evaluation, particularly when employing skewed probability distributions that can faithfully capture asymmetric wind regimes common in dry and semi-arid regions. The station utilized for this study's map and climate conditions are displayed in Figure 1 and Table 1.

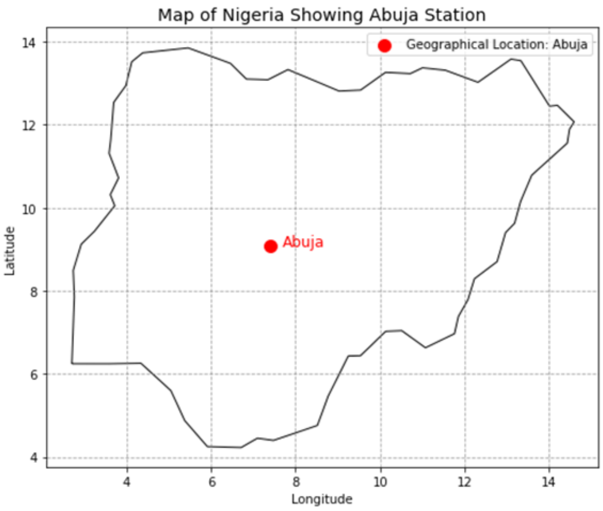

Figure 1. Map of Nigeria showing Abuja as the study location

Table 1. Abuja's coordinates, vegetation, height, and climate

Latitude (°N)	Longitude (°E)	Vegetation	Elevation (m)	Climate
9.0765	7.3986	Savanna	360	Tropical wet and dry

2.2 Utilisation and Distribution of Data

The monthly mean wind speed data utilised in this study came from the MERRA-2 reanalysis dataset, which was given by the National Aeronautics and Space Administration (NASA). By combining satellite observations with ground-based measurements using advanced data assimilation techniques, MERRA-2 guarantees great temporal consistency and dependability for long-term climatic investigations. The wind speed data for Abuja used in this study came from the MERRA-2 reanalysis archive, which provides gridded climatic fields at a monthly temporal resolution and a spatial resolution of 0.5° × 0.625°. The dataset spans 46 years, from January 1980 to December 2025, and contains monthly mean wind speed values at the standard near-surface level (10 m). The wide temporal coverage allows for a comprehensive capture of long-term trends, seasonal wind features, and inter-annual variability over Abuja. The information utilised in this study is similar to that of the reference [30], who employed meteorological data for analysis.

2.3 Preparing the Data

To ensure reliability and consistency, the data utilized in this study underwent data pre-processing. The wind speed data for the station was first subjected to quality control methods. The dataset was inspected for missing, negative, and physically implausible values before any anomalies were corrected using standard climatological interpolation and consistency tests. The original higher-resolution MERRA-2 data were temporally aggregated into monthly mean wind speed estimates in order to emphasize long-term climatological behaviour and reduce short-term variability. Descriptive statistical metrics like mean, standard deviation, skewness, and kurtosis were computed to assess the characteristics of the data distribution and facilitate the use of skewed statistical models. The processed data were further divided into monthly and seasonal subgroups to facilitate comprehensive variability and distributional studies prior to statistical modelling.

2.4 Statistical Modelling of the Data Used

The mean distribution of the statistical analysis used is shown in Eq. (1):

$$\bar{y} = \frac{1}{u}\sum_{j=1}^{u} y_j \tag{1}$$

where, $\bar{y}$ represents the arithmetic mean; u represents the total number of observations.

$$\sigma = \sqrt{\frac{1}{u-1}\sum_{j=1}^{u}\left(y_j - \bar{y}\right)^2} \tag{2}$$

where, σ represents the standard deviation of the data used; y represents the wind speed of the station considered, as shown in Eq. (2):

$$\mu = \frac{1}{u}\sum_{j=1}^{u}\frac{\left(y_j - \bar{y}\right)^3}{\sigma^3} \tag{3}$$

The coefficient of skewness, denoted by μ, measures the degree and direction of the data distribution's asymmetry with respect to its mean, as shown in Eq. (3):

$$f(x, \alpha, \beta) = \frac{\beta^2}{\Gamma(\alpha)}\chi^{\alpha-1}e^{-\beta x}, x > 0 \tag{4}$$

where, α and β denote the shape and rate (or scale) parameters of the gamma distribution, respectively; x represents the wind speed values.

With two parameters, α and β, the PDF of the Weibull distribution for wind speed x is defined as follows:

$$f(x, \alpha, \beta) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-(x/\beta)^{\alpha}}, x \geq 0 \tag{5}$$

where, x stands for the wind speed values; α and β are the shape and scale parameters of the Weibull distribution, respectively, as shown in Eq. (5).

With two parameters, μ and σ, the PDF of the log-normal distribution for wind speeds (x) is as follows:

$$f(x, \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left\{-\frac{(\ln x - \mu)^2}{2\sigma^2}\right\}, x > 0 \tag{6}$$

where, x represents the wind speed and σ and μ are the log-normal distribution's shape parameters represented in Eq. (6).

2.5 The Method of Moments and Maximum Likelihood Estimation

MOM and MLE were also used in this study, as shown in Eqs. (7) and (8), to generate the likelihood of wind speed results, and the moment of the wind speed values.

$$\mu'_k = \frac{1}{n}\sum_{i=1}^{n} x_i^k \tag{7}$$

Eq. (7) shows that μ_k^1 the wind speed value is the $k-th$ is sample moment. While the x_i variable is the observed wind speed value and n is the observation number.

$$L(\theta) = \prod_{i=1}^{n} f\left(x_i; \theta\right) \tag{8}$$

Eq. (8) provides the log-likelihood or something similar as shown in Eq. (9):

$$L(\theta) = \sum_{i=1}^{n} \ln f\left(x_i \theta\right) \tag{9}$$

where, $f\left(x_i; \theta\right)$ represents the collection of unknown parameters; θ is the PDF of the chosen distribution (Weibull, Gamma, or Lognormal) as revealed in Eq. (9). It should be made clear in the publication that parameter estimations are derived by solving Eq. (10):

$$\frac{\partial l(\theta)}{\partial \theta} = 0 \tag{10}$$

The Newton-Raphson algorithm, which is implemented in R through the fitdistrplus package, was used to numerically optimise all likelihood functions.

However, in order to increase the dependability of model fitting, the paper presents a rigorous methodological framework by merging two parameter estimation techniques: the Method of Moments (MOM) and MLE. Cullen–Frey skewness–kurtosis analysis, quantile–quantile (Q-Q) plots, Probability–Probability (P-P) plots, PDFs, cumulative distribution functions (CDFs), histograms, and many other graphical and statistical diagnostic tools are also used. Compared to earlier research that frequently relies on constrained GOF metrics, this thorough evaluation method offers a deeper understanding of each distribution's performance and applicability.

3 Results and Discussion

Figure 2 shows that the cube of skewness versus kurtosis yields the Cullen and Frey graph, a diagnostic tool for determining possible theoretical distributions for a set of data. The "Observation" point (shown by the blue star with a gold centre) in this representation is located close to 3.0 on the y-axis (kurtosis) and roughly 0.05 on the x-axis (square of skewness). This particular location is strikingly close to the logistic distribution marker (orange cross) and the normal distribution marker (black star), indicating that the Abuja wind speed data has "normal" tail thickness and is almost symmetrical.

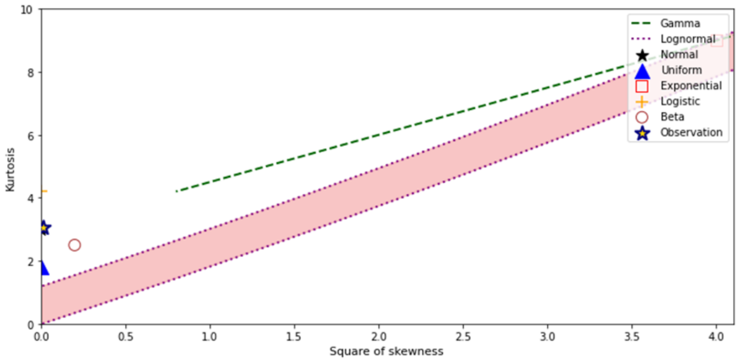

Figure 2. Cullen–Frey graph of skewness and kurtosis

The observation point is located close to the theoretical lines for Gamma and lognormal distributions and on the periphery of the Beta distribution zone (colored pink) beyond the key central markers, as revealed in Figure 2. There is a very small positive skew in the wind speeds since the square of skewness is non-zero (around 0.05). This closeness to various distribution types implies that skewed models, such as Gamma or Weibull, may provide a more nuanced match for the environmental variability found in Abuja, even though a normal distribution offers a strong baseline.

As revealed by Figure 3, the wind speed data is plotted against the Weibull, Gamma, and lognormal distributions in four diagnostic plots in this figure. The Weibull (orange) and Gamma (green) curves better capture the peak and the right-hand taper than the lognormal (red) curve in the histogram and theoretical densities (top-left), which displays the data peaks at a density of almost 0.8. This is further supported by the empirical and theoretical CDFs (bottom-left), which indicate that the lognormal curve deviates considerably within the 1.0 m/s and 2.5 m/s range, whereas the empirical blue line closely follows the Weibull and Gamma trajectories.

More thorough validation is offered throughout the distribution's range by the P-P plot (bottom-right) and Q-Q plot (top-right) as shown in Figure 3. Up to 3.0 m/s, the observed quantiles in the Q-Q plot roughly match the theoretical lines; after that, there are minor variations, especially for the lognormal model, which is unable to precisely track the higher wind speeds. The Weibull and Gamma distributions (orange and green dots) in the P-P plot remain nearly perfectly aligned with the 45-degree reference line, demonstrating their great reliability for estimating the likelihood of particular wind speed occurrences in Abuja.

Figure 4 shows the PDF overlay for Abuja, which is the main focus of this graphic; the real recorded wind speeds are represented by the red histogram. The data shows a clear "mode" or peak between 1.5 and 2.0 m/s, with a maximum density of about 0.75. The greatest visual match is provided by the Weibull_min (blue line) and Gamma (orange line) distributions, which faithfully capture the slow increase from 0.0 m/s and the comparatively smooth decrease following the peak.

The lognormal distribution (green line), on the other hand, seems unsuitable for this particular dataset; it overestimates the density at lower values and underestimates it in the 1.5–2.5 m/s range, and it peaks too early (around 1.1 m/s). Additionally, the histogram shows a "shoulder" or little secondary peak close to 1.0 m/s; this complexity is better handled by the Weibull distribution than by the others. This indicates that Abuja's wind regime is comparatively consistent, with most values centred in a narrow region about 1.7 m/s.

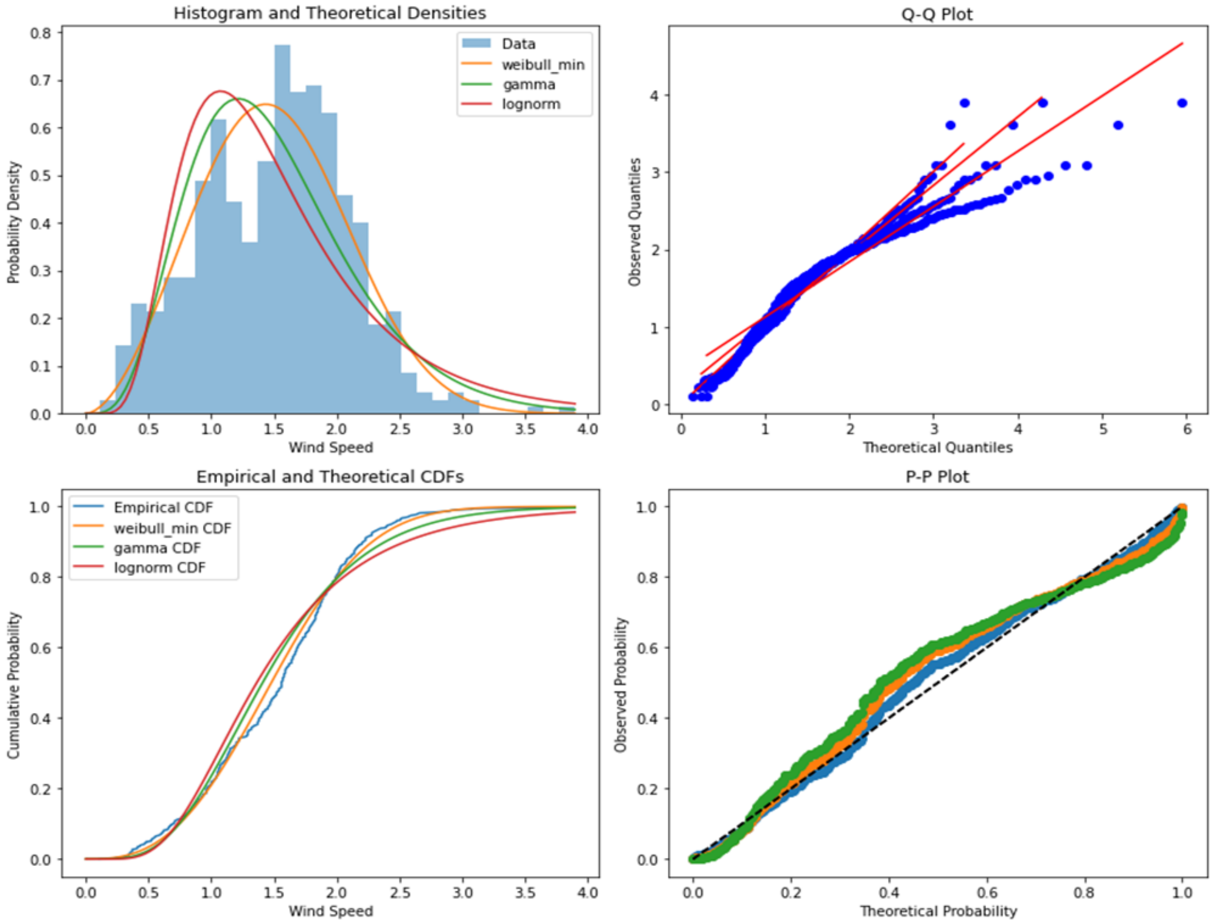

Figure 3. The goodness-of-fit (GOF) diagnostics for Weibull, Gamma, and Lognormal distributions

Note: CDF = cumulative distribution function; Q-Q = quantile–quantile; P-P = probability–probability.

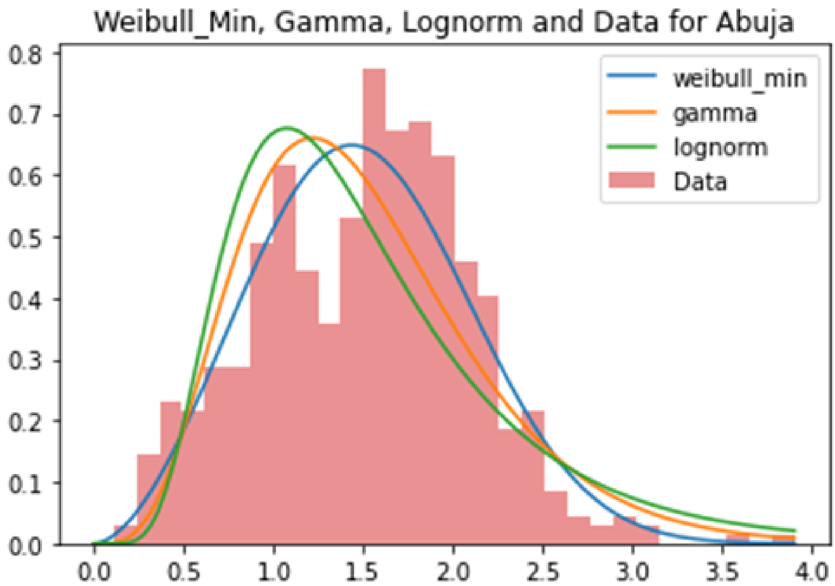

Figure 4. The probability distribution function (PDF) overlay for Abuja

Using a histogram, a Kernel Density Estimate (KDE), and a normal Q-Q Plot, Figure 5 offers a thorough examination of the data's structure. With a sample size of N = 552 and a bandwidth of 0.1671, the KDE (centre) displays a primary peak close to 2.0 m/s and a secondary lower-level peak close to 1.0 m/s. With more than 110 instances recorded in the 1.5 to 2.0 m/s bin, the histogram (left) demonstrates that this range has the highest frequency of observations.

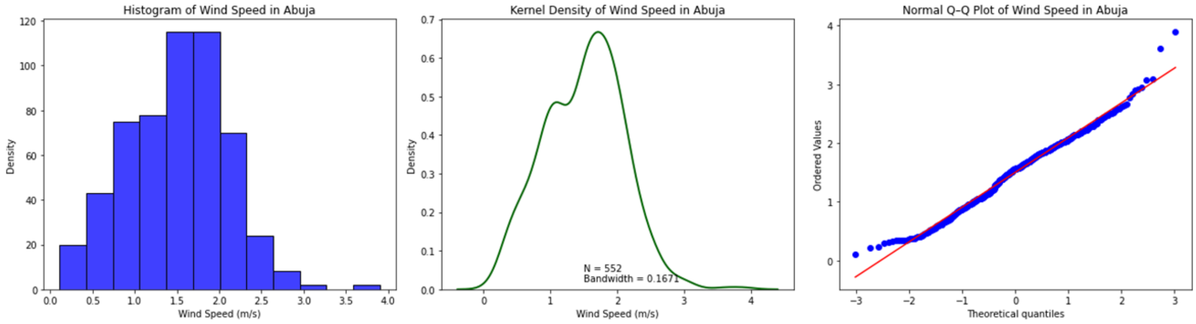

Figure 5. The histogram, kernel density estimate (KDE), and normal quantile–quantile (Q-Q) plot for Abuja.

The data's compliance with a perfect normal distribution is evaluated using the normal Q-Q plot (right). For most of the data between -1 and +2 theoretical quantiles, the points (blue dots) line up with the red reference line; nevertheless, they "curve" away at the extremes. In particular, the data points sit above the line at the lower end (below 0.5 m/s) and upper end (beyond 3.0 m/s), suggesting that Abuja's wind speed distribution has "shorter tails" than a typical normal distribution.

The graphical outputs in the findings section demonstrate that in order to improve scientific understanding, a thorough interpretation of the observed wind speed patterns is required. Specifically, regional meteorological and atmospheric phenomena typical of the tropical wet-and-dry (savanna) environment can be connected to the observed bimodal distribution of wind speeds across Abuja. Increased atmospheric stability, cloud cover, and moisture content lower surface wind speeds during the rainy season, which is when the initial peak (around 1.0 m/s) most likely refers to calmer conditions. On the other hand, the dry season, particularly during the Harmattan period, when higher pressure gradients and the effect of dry northeastern trade winds augment wind flow, may be responsible for the second and more prominent peak (around 1.5–2.0 m/s). The observed dual-peak behaviour is a result of wind regime variability caused by seasonal transitions between the Inter-Tropical Discontinuity (ITD) zones. Additionally, the comparatively "short-tailed" distribution indicates a low frequency of extreme wind episodes, which is consistent with Abuja's inland location and the lack of significant orographic or coastal wind acceleration processes. Because they show moderate but comparatively stable wind conditions controlled by seasonal atmospheric dynamics, these climatic interpretations not only explain the statistical characteristics shown but also offer crucial context for wind energy applications.

Figure 6 shows Abuja's cumulative distribution (bottom-right) and empirical density (bottom-left). The "bimodal" tendency with peaks at about 1.0 m/s and 1.8 m/s is readily seen in the density plot, which highlights the distribution's form with a smooth blue curve. With extremely few records surpassing 3.5 m/s, this indicates that Abuja encounters two typical wind speed states, probably driven by diurnal cycles or seasonal transitions.

The likelihood of experiencing wind speeds at or below a specific value is mapped in the bottom-right CDF graphic. The bulk of the 552 observations are focused between 0.5 and 2.5 m/s, where the curve is comparatively linear. At roughly 2.2 m/s, the CDF crosses the 0.8 (80%) probability barrier, indicating that 80% of Abuja's recorded wind speeds are 2.2 m/s or slower. This information is crucial for local wind energy or architectural considerations.

Table 2 shows that there are low Root Mean Square Error, Akaike Information Criterion, and Bayesian Information Criterion values, as well as their small Kolmogorov–Smirnov statistics, which show that the Weibull and Gamma distributions offer the most accurate depictions of the observed wind speed data. Graphical diagnostics, where both distributions exhibit excellent to very good alignment in Q-Q plots, P-P plots, and PDFs, effectively capture the central tendency and spread of the data, further confirming this quantitative performance. The lognormal distribution, on the other hand, shows considerably higher error metrics and a bigger Kolmogorov–Smirnov statistic, indicating a poorer GOF; this is also consistent with its discernible departure from the observed data, especially in the crucial wind speed range of 1.0–2.5 m/s. Overall, the findings show that the Weibull distribution provides the greatest match, closely followed by the Gamma distribution, and that the lognormal model is inappropriate for precisely characterizing the wind speed features in this investigation.

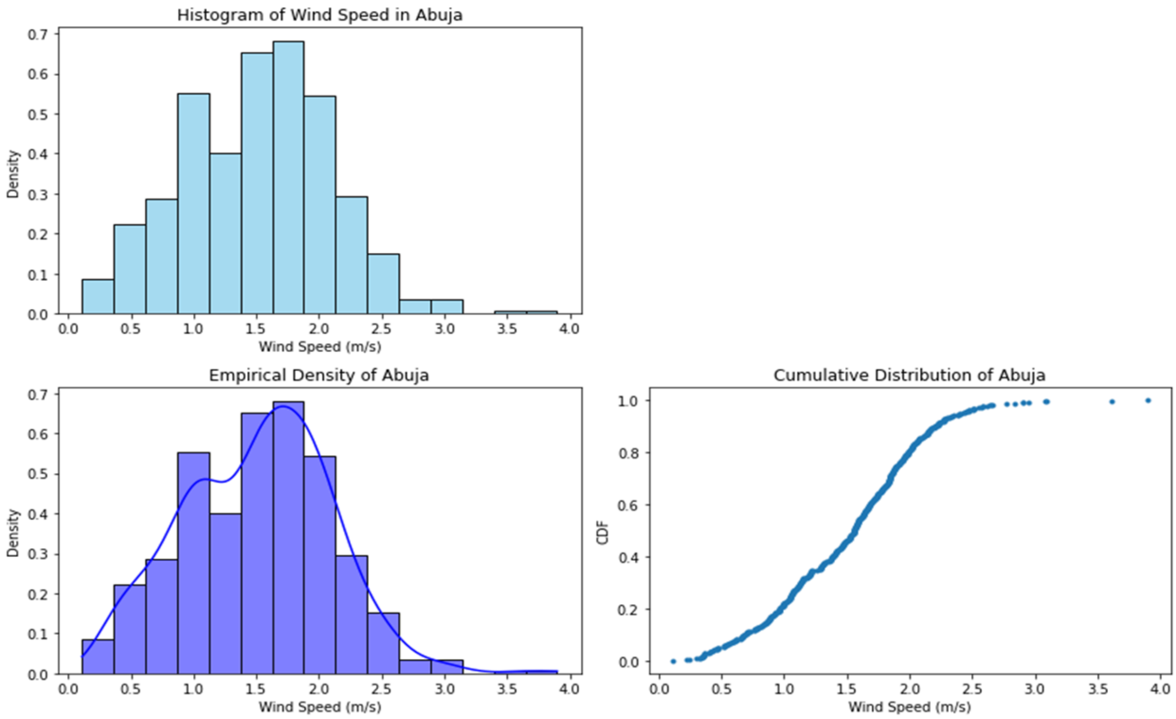

Figure 6. The empirical density and cumulative distribution function (CDF) for Abuja

Note: CDF = Cumulative Distribution Function.

Table 2. The goodness of fit as compared with the distribution of the parameters

Distribution	RMSE	AIC	BIC	K-S Statistic	Graphical Fit (Q-Q, P-P, PDF)	Overall Performance
Weibull	Low	Low	Low	Small	Excellent alignment with data	Excellent fit
Gamma	Low	Low	Low	Small	Good fit, close to Weibull	Good fit
Lognormal	High	High	High	Large	Noticeable deviation (especially 1.0–2.5 m/s range)	Inadequate fit

Note: Lower values of Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Kolmogorov–Smirnov (K-S) Statistic indicate better model fit. Q-Q = Quantile–Quantile; P-P = Probability–Probability; PDF = Probability Density Function.

4 Conclusions and Recommendations

The results of wind speed distributions in Abuja, Nigeria, highlight how crucial it is to choose high-fidelity statistical models in order to fully utilize the planet's vast potential for renewable energy. The study shows that although the conventional normal distribution offers a symmetrical baseline, it frequently fails to account for the asymmetric, skewed, and non-normal properties present in atmospheric data, using 46 years of MERRA-2 reanalysis data. This emphasises a change toward adaptable statistical frameworks that can precisely represent the distinct environmental diversity of certain places for academics and policymakers worldwide.

The Weibull and Gamma distributions are better at simulating Abuja's wind regime, according to thorough graphical diagnostics like Cullen and Frey skewness-kurtosis analysis and PDF overlays. These models accurately capture the frequency of wind speeds, especially in the 1.5 m/s to 2.0 m/s region, and manage well the observed bimodal tendencies and "shorter tails" of the data. On the other hand, the lognormal distribution consistently deviated from the real wind speed occurrences between 1.0 and 2.5 m/s, making it less dependable for this tropical station.

In the end, this study offers a crucial guide for the development of renewable energy in tropical and semi-arid areas, as 80% of observed wind speeds in Abuja are found to be 2.2 m/s or slower. It is crucial to comprehend these particular probability hurdles in order to design sustainable and site-specific wind energy regulations and infrastructure. The study supports international efforts to mitigate climate change and enhance energy security through data-driven, educated switches to wind power by enhancing wind profiling accuracy through these skewed statistical techniques.

Therefore, the study provides fresh perspectives and area-specific understanding of Abuja's wind speed characteristics. It reveals a bimodal distribution pattern and demonstrates that, especially in the dominant range of 1.5–2.0 m/s, the Weibull and Gamma distributions perform better than the lognormal model in describing the observed wind regime. These results promote more informed renewable energy planning and policy formulation in West Africa by improving site-specific wind energy assessment and modelling accuracy in semi-arid Sub-Saharan regions.

Finally, Abuja is impacted by the reported wind speed range (e.g., dominance around 1.5–2.0 m/s and the 80% threshold below 2.2 m/s). The work's practical usefulness and alignment with renewable energy applications would be greatly improved by even a simple quantitative evaluation or comparison with normal cut-in wind speeds of turbines. Therefore, the author wishes to recommend that the energy sector of the nation needs to invest in data-driven research for the purpose of generating data for energy generation.

Author Contributions

Conceptualization, F.O.A. and E.A.; methodology, F.O.A.; software, E.A.; validation, F.O.A., E.A., and A.Y.U.; formal analysis, F.O.A.; investigation, E.A.; resources, A.Y.U.; data curation, E.A.; writing original draft preparation, E.A.; writing review and editing, F.O.A. and K.O.O.; visualization, E.A.; supervision, F.O.A.; project administration, F.O.A.; funding acquisition, K.O.O. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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