SCOPUA Journal of Applied Statistical Research (JASR)

Vol.2, Issue 1, March 2026
DOI: https://doi.org/10.64060/JASR.v2i1.1

Modelling Wind Speed at Ikeja Station using Skewed Statistical Distributions

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Received: 06 October 2025 / Revised: 12 November 2025 / Accepted: 03 December 2025 / Published online: 10 December 2025

ABSTRACT

Wind speed, a key atmospheric parameter, results from the movement of air from high- to low-pressure regions driven primarily by temperature variations. This study modelled the wind speed (m/s) of Ikeja, Lagos State, using data from 2000 to 2020 through statistical techniques such as descriptive statistics, data visualization, and goodness-of-fit (GOF) tests, including chi-square, Kolmogorov-Smirnov, Anderson-Darling, and Cramer-von Mises analysis. Three positively skewed distributions, Gamma, Weibull, and Log-normal, were evaluated. Descriptive analysis indicated that the dataset was predominantly right-skewed (Skp > 0). The GOF results show that the Weibull distribution provides the best representation of the wind speed data (p=0.02), followed by the distributions of Log-normal and Gamma. The Weibull parameter ($\alpha > 1$) further confirmed its suitability for the data. The findings suggest that Ikeja may experience higher wind speeds in the future, emphasizing the need for precautionary measures to mitigate potential damage to infrastructure and property. This study provides valuable insights for meteorologists and urban planners in anticipating and managing climate-related risks in the city.

Keywords*:* Climate change; Data visualization; Meteorologists; Precautionary measures; Temperature variations

1. Introduction

Wind energy is a promising and abundant form of green energy available across many regions of the world. Its growing importance stems from factors like the decline in fossil fuel reserves, increasing global energy demand, and the urgent need to address climate change (Masseran, 2015). The negative impacts of climate change have prompted many nations to adopt sources of renewable energy, such as wind, resulting in the rapid global expansion of wind power generation (Chang et al., 2015). Among its key advantages are zero fuel costs, minimal price volatility, and enhanced energy security. However, its major drawback lies in the intermittent and unpredictable nature of wind (Afanasyeva et al., 2016). Excluding large hydropower, wind energy remains the most widely utilised renewable source for electricity generation, having grown nearly 300-fold since 1990. China, the United States, Germany, Spain, and India lead global developments in the sector (Abbasi & Abbasi, 2016).

A study was conducted by (Afolabi, 2020) on modelling water pollutants using Weibull and Lognormal distributions, analyzing thirteen pollutants from two major rivers in Oyo State in evaluating water safety. The findings revealed that not all pollutants exhibited right-skewed behaviour, and the distribution of Lognormal provided a better fit than the Weibull distribution based on the tests of GOF. Accurate wind distribution modelling requires multi-year data to capture variability and temporal patterns. To reduce the cost and time of processing long-term datasets, statistical distribution functions, notably probability density functions (PDFs), are widely applied to describe wind speed characteristics, with parameters commonly estimated using the Maximum Likelihood Estimation (MLE) method. Traditional models like Weibull, Lognormal, Gamma, and GEV distributions, along with mixture forms like Weibull-Lognormal and GEV-Lognormal, have proven effective in characterizing wind speed variability (Kollu et al., 2012). The integration of both wind speed and direction enhances modelling accuracy and adaptability under changing climatic conditions (Murphy et al., 2025).

The challenges encountered via wind energy development in West Africa are largely attributed to inadequate measurement data, limited assessment studies, and inconsistent wind resource classification across the region. Since wind resources are highly site-specific, accurate national wind profiling requires assessments across multiple locations. In Nigeria, wind resource evaluation has progressed through several developmental stages, with various policy initiatives reflecting the government's commitment to harnessing wind energy for electricity generation (Ajayi, 2013). Scholars such as (Akgül et al., 2016) emphasised that the Weibull distribution is widely used for modelling wind speed data, but it may not always yield accurate results. Their study applied the distribution of Inverse Weibull (IW) to wind speed modelling in Turkey and found that parameter estimation using MLE and Modified Maximum Likelihood (MML) methods produced more accurate results than the traditional Weibull model at most stations.

Weibull distribution is applied to wind speed data from 2000–2023 across selected African stations, revealing significant regional variability in wind characteristics and power density, and highlighting the continent's strong potential for wind energy development and the need for region-specific renewable energy policies (Aweda & Samson, 2024). The wind speed analysis at two altitudes ($50m$ and $100m$) in a tropical coastal location was carried out by (Ogunjo, 2025) using multifractal and Weibull statistical methods, revealing that multifractality is influenced by land-sea breezes and demonstrating the Weibull distribution's superior fit for characterizing wind behaviour essential for modelling and energy applications.

Recent studies have advanced the modelling of wind speed by introducing more flexible statistical frameworks capable of capturing asymmetry, skewness, and heavy-tailed behaviour in environmental data. (Chaturvedi et al., 2025) made a proposition of the generalized positive exponential family of distributions as a robust alternative to traditional models, demonstrating improved performance in representing the variability and non-normal characteristics of wind speed data. Similarly, (Lencastre et al., 2024) evaluated wind-speed distributions beyond the conventional Weibull model and showed that alternative skewed and heavy-tailed distributions can offer superior fit under diverse wind regimes. Building on these recent developments, the present study applies skewed statistical models to wind speed data from Ikeja Station, emphasizing their suitability for characterizing non-normality and enhancing the accuracy of wind-speed modelling.

2. Methodology

This section outlines the methodologies adopted to achieve the research objectives, focusing on Exploratory Data Analysis (EDA) and the application of skewed probability distributions for wind speed modelling. The EDA approach was employed to examine the structure and characteristics of the wind speed data, identify trends and patterns, and evaluate statistical properties such as central tendency, dispersion, and skewness.

2.1 Descriptive Statistics

Minimum

$$min(X) = min\{x_1, x_2 \dots, x_n\} \tag{1}$$

Maximum

$$min(X) = max\{x_1, x_2 \dots, x_n\} \tag{2}$$

Range

$$\text{Range} = \max(X) - \min(X) \tag{3}$$

Mean

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

Standard deviation

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{5}$$

Skewness

$$\gamma_1 = \frac{1}{n}\sum_{i=1}^{n} \frac{(X_i - \bar{X})^3}{s^3} \tag{6}$$

The arithmetic mean is the $\bar{x}$, the total number of observations is n, and the standard deviation raised to the third power is s^3, with X being the wind speed of interest. The histogram of wind speeds in Lagos State is presented to examine the data distribution. Additionally, the density plot and the Cullen and Frey plots are provided to assess the plausible distributions of the wind speed data.

2.2 Modelling the Distribution of Wind Speeds

The three distributions, which are Gamma, Weibull and Log-normal, considered in this study are presented below. The mathematical frameworks of each statistical distribution were provided to understand the computational aspect of each distribution.

Distribution of Gamma

The PDF - probability density function of the gamma distribution for wind speed (x), with two parameters α and β is expressed as:

$$f(x;\alpha,\beta)=\frac{\beta^\alpha}{\Gamma(\alpha)}x^{\alpha-1}e^{-\beta x}, x>0 \quad (7)$$

Where $\alpha,\ \beta, x$ are the parameters of the shape with rate or the scale of the gamma distribution, and the wind speed values, respectively.

Distribution of Weibull

The PDF – probability density function of the Weibull distribution for the wind speeds (x), with two parameters α and β is defined as:

$$f(x;\alpha,\beta)=\frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1}e^{-(x/\beta)^\alpha}, x>0 \quad (8)$$

Where α, β, and x are the parameters of the shape with the scale of the Weibull distribution, and wind speed values, respectively.

Distribution of Log-Normal

The PDF – probability density function of the log-normal distribution for wind speeds (x), with two parameters μ and σ is given by:

$$f(x;\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}\exp\left\{-\frac{(\ln x-\mu)^2}{2\sigma^2}\right\}, x>0 \quad (9)$$

Where σ, μ, and x are the parameters of the shape with the scale of the Log-normal distribution and wind speeds, respectively.

2.3 Parameter Estimation

For this study, both MLE – Maximum Likelihood Estimation and MOM – Method of Moment were employed.

2.3.1 Maximum Likelihood Estimation (MLE)

Likelihood Function of Gamma Distribution

$$L(\alpha,\beta \mid x_1,\dots,x_n)=\prod_{i=1}^{n}\frac{\beta^\alpha}{\Gamma(\alpha)}x_i^{\alpha-1}e^{-\beta x_i}$$
$$=\left(\frac{\beta^\alpha}{\Gamma(\alpha)}\right)^n\left(\prod_{i=1}^{n}x_i^{\alpha-1}\right)exp\left(-\beta\sum_{i=1}^{n}x_i\right)$$

The log-likelihood function is given thus;

$$\ell(\alpha,\beta)=n\alpha\ln\beta-n\ln\Gamma(\alpha)+(\alpha-1)\sum_{i=1}^{n}\ln x_i-\beta\sum_{i=1}^{n}x_i \quad (10)$$

Likelihood Function of Weibull Distribution

$$L(\alpha,\beta \mid x_1,\dots,x_n)=\prod_{i=1}^{n}\frac{\alpha}{\beta}\left(\frac{x_i}{\beta}\right)^{\alpha-1}exp\left[-\left(\frac{x_i}{\beta}\right)^\alpha\right]$$
$$=\left(\frac{\alpha}{\beta}\right)^n\left(\prod_{i=1}^{n}x_i^{\alpha-1}\right)\beta^{-n(\alpha-1)}exp\left(-\sum_{i=1}^{n}\left(\frac{x_i}{\beta}\right)^\alpha\right)$$

The function of log-likelihood is expressed as;

$$\ell(\alpha,\beta)=n(\ln\alpha-\ln\beta)+(\alpha-1)\sum_{i=1}^{n}\ln x_i-\alpha n\ln\beta-\sum_{i=1}^{n}\left(\frac{x_i}{\beta}\right)^\alpha \quad (11)$$

Likelihood Function of Lognormal Distribution

$$L(\mu,\sigma \mid x_1,\dots,x_n)=\prod_{i=1}^{n}\frac{1}{x_i\sigma\sqrt{2\pi}}exp\left[-\frac{(\ln x_i-\mu)^2}{2\sigma^2}\right]$$
$$=\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n\prod_{i=1}^{n}x_i^{-1}exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\ln x_i-\mu)^2\right]$$

The function of the log-likelihood is given as;

$$\ell(\mu,\sigma)=-n\ln(\sigma\sqrt{2\pi})-\sum_{i=1}^{n}\ln x_i-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\ln x_i-\mu)^2 \quad (12)$$

All likelihoods were optimized numerically using Newton–Raphson algorithms in R (fitdistrplus package).

2.3.2 Method of Moments (MOM)

Gamma MOM is expressed as:

$$\alpha=\frac{\bar{x}^2}{s^2}, \beta=\frac{\bar{x}}{s^2}. \quad (13)$$

Weibull MOM is solved numerically via:

$$\frac{s}{\bar{x}} = \sqrt{\frac{\Gamma(1+2/\alpha)}{\Gamma(1+1/\alpha)^2} - 1}. \tag{14}$$

Lognormal MOM is given as;

$$\hat{\mu} = \frac{1}{n}\sum \ln x_i, \hat{\sigma}^2 = \frac{1}{n}\sum(\ln x_i - \hat{\mu})^2. \tag{15}$$

Parameter estimation was performed in R programming using the **fitdistrplus** package, which applies numerical maximum-likelihood optimization.

2.4 Tests of Goodness of Fit (GOF)

The tests of GOF are used to assess whether it is rational to make an assumption that a given random sample was drawn or came from a specified distribution. They operate as a form of setting hypotheses, in which the hypotheses of null and alternative are defined as:

H_0: The sample data do not follow a specified distribution.

H_1: The sample data do follow a specified distribution.

2.4.1 Test of Hypothesis

With X represents the amount of wind speed, the hypothesis tests are formulated below;

$H_0: X \sim/\text{Gamma}(\alpha, \beta)\ vs. H_1: X \sim \text{Gamma}(\alpha, \beta)$.

$H_0: X \sim/\text{Weib}(\alpha, \beta)\ vs\ . H_1: X \sim \text{Weib}(\alpha, \beta)$.

$H_0: X \sim/\text{Lognorm}(\mu, \sigma)\ vs\ . H_1: X \sim \text{Lognorm}(\mu, \sigma)$.

2.4.2 Measures of Goodness of Fit

The following GOF measures were applied:

- Chi-square test.
- Kolmogorov-Sminorv (KS).
- Anderson-Darling (AD).
- Cramer-von Mises (CvMS)

Chi-square Test Statistic and P-value

Let O_i be the observed count and E_i be the expected count in the bin i:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{16}$$

Where k is the number of bins.

Degrees of freedom: $df = k - p - 1$**.** Where p is the number of parameters estimated.

P-value: Following the chi-square statistic above:

$$p\text{-value} = 1 - F_{\chi^2_{df}}(\chi^2) \tag{17}$$

Where the chi-square CDF - cumulative distribution function is $F_{\chi^2_{df}}$ with degrees of freedom as df.

Binning approach: Bins were constructed using Sturges' rule, $k = 1 + 3.3\log_{10}(n)$.

3. Empirical Results

A descriptive analysis of wind speed in Ikeja, Lagos, was conducted to examine its statistical characteristics. The results are summarized in Table 1. Wind speed in Ikeja is right-skewed (skewness = 0.818), with a mean of 9.062 m/s and a standard deviation of 3.127 m/s. The wind speeds spanned from 4.05 m/s to 18.15 m/s over the study period. The 21-year dataset reveals fluctuating patterns, suggesting that wind speeds in Ikeja display stochastic characteristics with a pronounced skewed distribution. Figure 1 presents the histogram and cumulative distribution of wind speed.

Table 1*: Descriptive Statistics of Wind Speeds (m/s) in Ikeja, Lagos*

Statistics	Wind Speeds (m/s)
Mean	9.062
Standard Deviation	3.127
Skewness	0.818
Minimum	4.05
Maximum	18.15

The histogram (Figure 2) shows a positively skewed distribution with a long, thin tail. Most wind speed observations in Ikeja, Lagos, fall between 4 m/s and 12 m/s, with fewer values ranging from 12.1 m/s to 18.15 m/s. Figure 2 also presents the kernel density estimate, the Normal Q-Q plot, and the Cullen and Frey plot for wind speed in Ikeja.

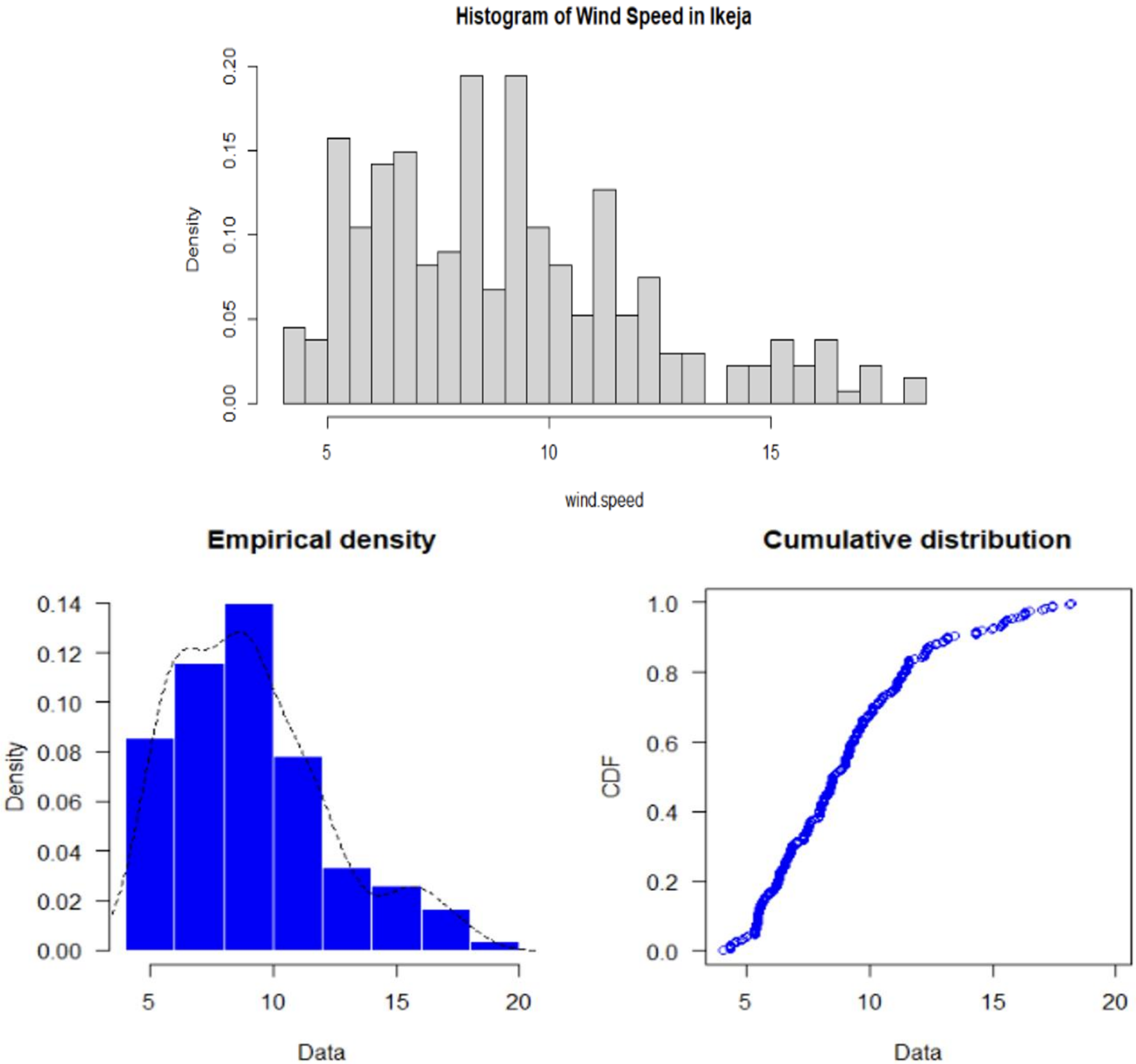

Figure 1: *Wind Speed Variation in Ikeja*

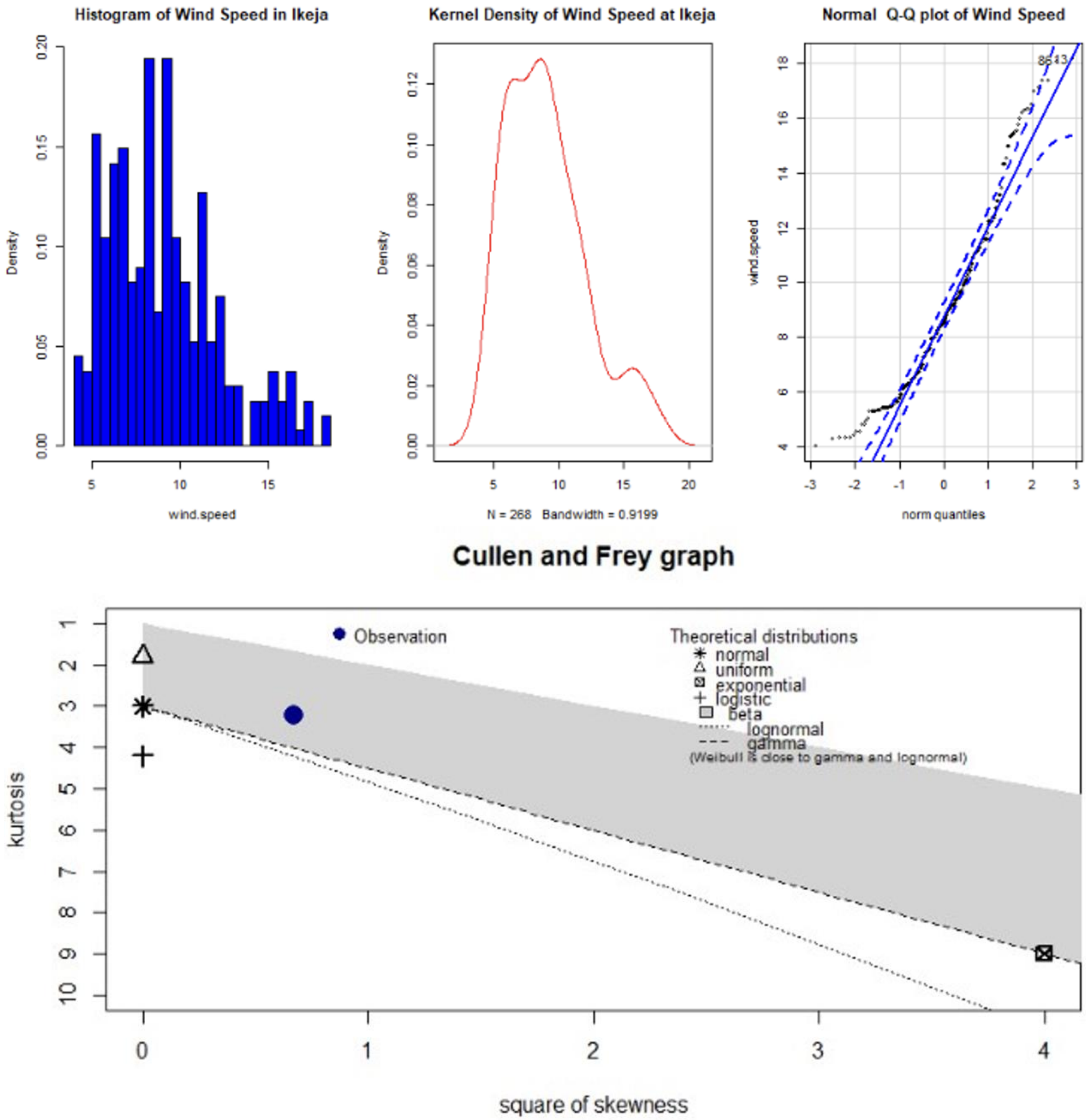

Figure 2: *Wind Speed Exploratory Data Analysis*

The plots established the appropriate suggestion of the data patterns in terms of skewness and suggest the likely fitted distributions as shown in the Cullen and Frey plot. The Normal Q-Q plot shows that the data deviated from normality, indicating that the distribution of normal is not suitable for consideration. It is then claimed that rightly skewed distributions should be adopted for modelling the data of wind speed. Having justified the selections of the distribution, the analysis proceeds with fitting the Weibull, gamma, and lognormal distributions.

3.1 Wind Speed Distribution Models

Three different continuous distribution models were fitted to the wind speed (m/s) data in Ikeja, Lagos, using two methods of estimation: Maximum Likelihood Estimation (MLE) and the Method of Moments (MOM). The estimated values of the distribution parameters for the Gamma, Weibull, and Lognormal distributions are presented in Table 2. Varying parameter values were obtained from the two estimation methods. Figure 3 compares the Weibull, Gamma, and Lognormal fits to the wind speed data using four diagnostic plots: density, Q–Q, CDF, and P–P. Together, they show how closely each distribution matches the observed data. Among the fitted models, the distribution of Weibull provides the best fit to the wind speed data compared to the Gamma and Lognormal distributions.

***Table 2**: Estimated Parameters of the Gamma, Weibull and Lognormal Distributions*

Methods	Parameters	Gamma	Weibull	Lognormal
MLE	Shape = α(S.E)	39.783 (12.231)	9.017 (1.657)	-
	Rate = β(S.E)	4.198 (1.298)	-	-
	Scale = β(S.E)	-	10.0524 (0.254)	-
	MeanLog = μ (S.E)	-		2.237 (0.00357)
	sdLog = σ (S.E)	-		0.164 (0.025)
MOM	Shape = α	44.566	9.012	-
	Rate = β	4.701	-	-
	Scale = β		10.044	-
	MeanLog = μ			2.238
	sdLog = σ			0.149

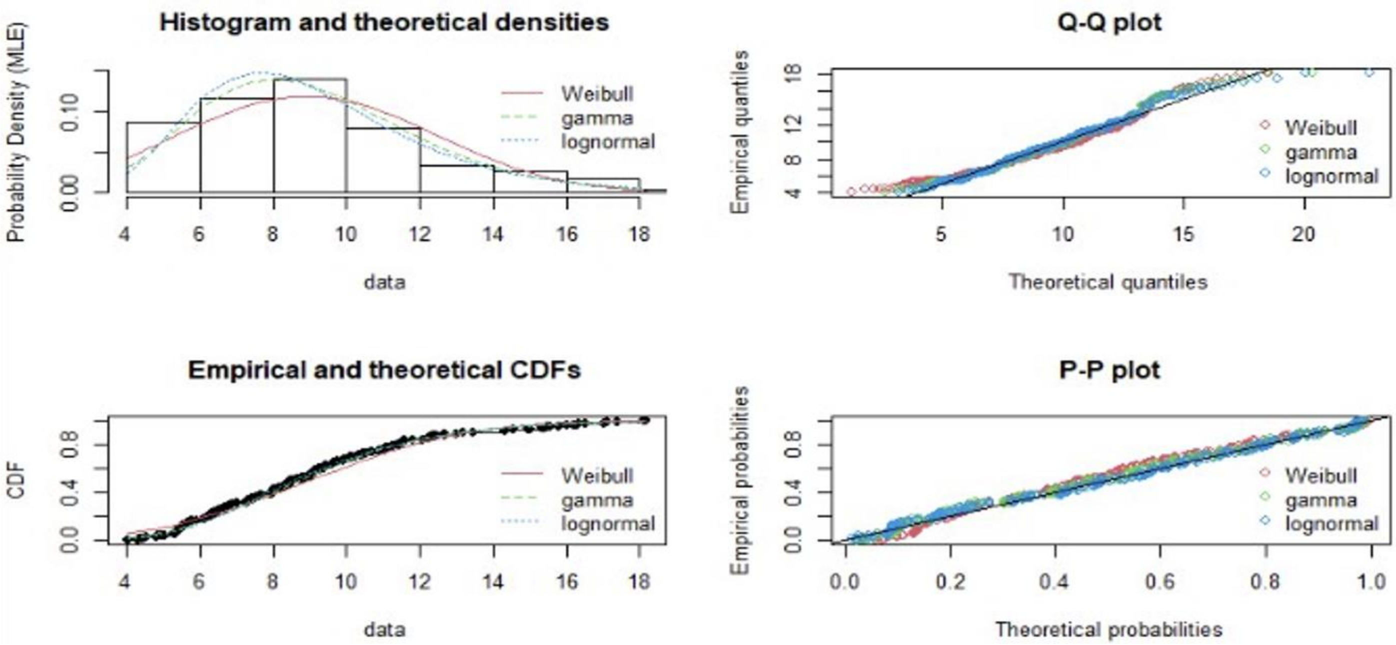

***Figure 3:** Model Diagnostics for Weibull, Gamma, and Lognormal Wind Speed Fits*

3.2 Efficiency of Estimates and Distributions

To obtain a better estimator of the MOM and MLE estimator for the wind speed (m/s) in Ikeja, Lagos, Nigeria, the following statistical tools were used based on the minimum value(s). Table 3 shows that the Weibull Distribution best described the Wind Speed (m/s) of Ikeja, Lagos State, followed by the Log-Normal Distribution, then the Gamma Distribution.

***Table 3**: Performance Comparison of MLE and MOM Estimation Methods*

Distribution	**Statistics**							**Remark**
Gamma	Log-likelihood	AIC	BIC	KS - value	CvMS	ADS	MSE	
MLE	-296.6432	**598.316**	**604.062**	0.0749	**0.1826**	**2.235**	3.724	**Good**
MOM	**-297.9629**	598.824	604.680	**0.0696**	0.1834	2.371	**3.491**	
$Gam(\alpha,\beta)$	-297.3031	598.570	604.371	**0.0723**	0.183	2.303	3.608	
Weibull								
MLE	-283.3128	**580.725**	**586.391**	0.0347	**0.0201**	0.1848	**3.628**	**BEST**
MOM	**-283.4161**	580.813	586.453	**0.2846**	0.0213	**0.10**	**3.628**	
$Weib(\alpha,\beta)$	-283.3645	**580.769**	**586.422**	0.160	**0.0207**	**0.1424**	3.628	
Log-Normal								
MLE	-302.1687	**605.347**	**612.141**	0.0943	0.311	**1.8214**	**3.421**	**Better**
MOM	**-302.705**	608.131	615.289	**0.0867**	**0.300**	2.153	3.331	
$Lnorm(\mu,\sigma)$	**-302.4369**	606.739	613.715	0.0905	0.3055	1.9872	**3.376**	

As revealed in Table 3, the distribution of Weibull offers the most accurate representation of wind speeds (m/s) in Ikeja, Lagos State, with the Log-Normal distribution next in performance, and the Gamma distribution performing the least.

3.3 Chi-square Goodness of Fit

Sequel to the results of the efficiency, it is also of interest to obtain a measure of goodness of fit to ascertain a better distributional pattern of the wind speed in Ikeja, Lagos, Nigeria. Table 4 provides the results obtained using the chi-square GOF for the Gamma, Weibull, and Lognormal distributions under both MLE - maximum likelihood and MOM - method of moments estimation. For each model, the chi-square statistics, degrees of freedom, and corresponding p-value are shown. Across all cases, the p-values are below the 0.05 significance level, indicating that the test of chi-square rejects the null hypothesis for each distribution. Although all models are rejected by this test, the Weibull distribution shows comparatively smaller chi-square values and higher p-values than the Gamma and Lognormal distributions, suggesting relatively better agreement with the observed wind-speed data.

***Table 4**: Chi-Square GOF Results for the Distribution*

Distributions	Methods	$\alpha - level$ = 0.05		
		χ^2 - value	df	p-value
Gamma	MLE	17.635	3	0.001
	MOM	17.937	3	0.0005
		17.786		0.00075
Weibull	MLE	16.867	3	0.0007
	MOM	15.020	3	0.002
		15.944		0.00135
Log-Normal	MLE	18.319	3	0.0004
	MOM	18.243	3	0.0004
		18.281		0.00007

The result in Table 4 establishes that among the three distributions applied to the fitness of the wind speed (m/s), the Weibull distribution is the best. In other words, the fitness of the wind speed in Ikeja, Lagos, might be arranged as $\boldsymbol{Weib}(\boldsymbol{x},\boldsymbol{\alpha},\boldsymbol{\beta}) \geq \boldsymbol{Lnorm}(\boldsymbol{x},\boldsymbol{\mu},\boldsymbol{\sigma}) \geq \boldsymbol{Gam}(\boldsymbol{x},\boldsymbol{\alpha},\boldsymbol{\beta})$, which is also consistent with Figure 4.

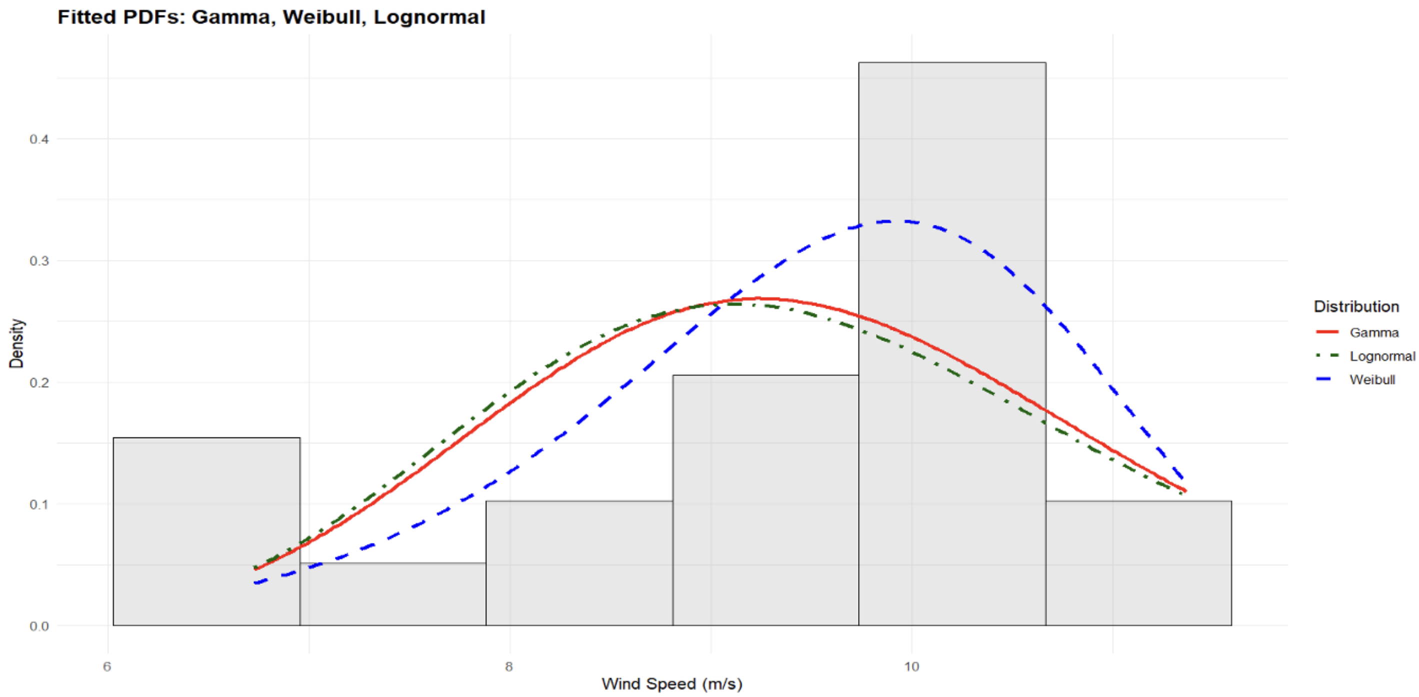

***Figure 4**: Fitted Distribution Curves*

The overlaid density plot in Figure 4 shows that the Weibull model (blue dashed curve) most closely follows the histogram of wind speeds, particularly around the modal region and in the upper tail, indicating that it is the most fitted distribution. The Lognormal model (green dot–dash) provides a moderate fit, while the Gamma model (red solid) shows the largest discrepancies, especially near the peak and at higher wind speeds.

4. Conclusion

In this study, distributions of Gamma, Weibull, and Lognormal were fitted to wind speed data at Ikeja, Lagos State. The results indicate that the Weibull distribution provides the best overall fit under both Maximum Likelihood Estimation – MLE and the Method of Moments - MOM, with both methods producing similar parameter estimates. The Lognormal distribution gives a reasonable fit under MLE, although MOM performs moderately for this model. For the Gamma distribution, MLE yields acceptable results, whereas MOM performs fairly. Overall, the Weibull distribution is recommended as the most suitable model for wind speed in Ikeja, outperforming both the Lognormal and Gamma distributions.

The distribution of the Weibull is widely utilized in wind engineering because its shape parameter $\boldsymbol{\alpha}$ describes wind variability, while the scale parameter $\boldsymbol{\beta}$ determines energy potential through wind power density. Therefore, the Weibull model adopted in this study provides a practical basis for wind resource assessment and turbine selection in urban environments like Ikeja. This study is restricted to just fitting three models, Gamma, Weibull, and Lognormal, to the wind speed in Ikeja, Lagos State. However, looking at the display of the Cullen and Frey graph in Figure 2, it was observed that the Beta distribution could be considered in comparison with the Weibull distribution. Future study could consider fitting a Beta distribution for further justification of this study's findings.

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Declaration

Conflict of Study: The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution Statement: Olalude, G.A., Olaleye, O. A., and Folorunso, S. A. conceived the idea and designed the research; then Afolabi S. A. analyzed and interpreted the data and wrote the paper.

Funding Statement: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of Data and Material: Data will be made available by the corresponding author on reasonable request.

Consent to Publish: All authors have agreed to publish this Journal.

Ethical Approval: Not Applicable

Consent to Participate: All participants were made aware that their responses would be kept anonymous and confidential and that the data would only be utilized for the study.

Acknowledgement: The author is thankful to the editor and reviewers for their valuable suggestions to improve the quality and presentation of the paper.

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Appendix

Calculation of the p-value of a Chi-square Distribution

A. Manual Approach:

Computing the **p-value (p)** for a chi-square statistic, one of the approaches is to use the survival function of the distribution of chi-square.

$$p = 1 - F_{\chi_v^2}(x)$$

Scenario

- $x = 15.020$ is the chi-square value,
- $df = 3$ is the degree of freedom,
- $F_{\chi_v^2}(x)$ is the cumulative distribution function (CDF).

Step-by-Step Mathematical Computation

$$p = 1 - F_{\chi_3^2}(15.020)$$

The chi-square CDF expression for $df = 3$ is given thus:

$$F_{\chi_3^2}(x) = \frac{\gamma\left(\frac{3}{2}, \frac{x}{2}\right)}{\Gamma\left(\frac{3}{2}\right)}$$

Where $\gamma(s, t)$ is the lower incomplete gamma function, and $\Gamma(s)$ is the gamma function.
Computing the intermediate values,

- $\Gamma\left(\frac{3}{2}\right) = \frac{\sqrt{\pi}}{2} \approx 0.88623.$
- $x/2 = 15.020/2 = 7.510$

Computing the lower incomplete gamma function,

- $\gamma\left(\frac{3}{2}, 7.510\right) \approx 0.88533$

Note: This value is taken from standard mathematical tables/computer evaluation.
Computing the CDF, we have

$$F_{\chi_3^2}(15.020) = \frac{0.88533}{0.88623} \approx 0.99899$$

Compute the p-value, we have:

$$p = 1 - 0.99899$$
$$p \approx 0.00101$$

B. Technical Approach with R-software:

R-programming Code

```
p_value <- 1 - pchisq(15.020, df = 3)
```

R-programming Result

```
> p_value <- 1 - pchisq(15.020, df = 3)
> p_value
[1] 0.001799637
```

≈ 0.002.