BAREKENG: Journal of Mathematics and Its Applications
December 2026 Volume 20 Issue 4 Page 2901-2918
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol20iss4pp2901-2918

WIND ENERGY GENERATION POTENTIAL FOR SELECTED AFRICAN STATIONS BASED ON THE PERFORMANCE OF FIVE WEIBULL DISTRIBUTION PARAMETERS

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Article Info

Article History:
Received: 12th September 2025
Revised: 08th May 2026
Accepted: 07th June 2026
Available online: 24th August 2026

Keywords:
Renewable energy;
Data analysis;
Meteorology;
Statistics;
Wind energy.

ABSTRACT

*The assessment of wind energy potential is essential for sustainable energy planning, particularly in Africa, where renewable energy sources are increasingly considered for power generation. This study evaluates the wind energy potential of eight selected African stations Nairobi (Kenya), Addis Ababa (Ethiopia), Cairo (Egypt), Tunis (Tunisia), Abuja (Nigeria), Accra (Ghana), Pretoria (South Africa), and Luanda (Angola) using wind speed data from 2000 to 2023 obtained from NASA's power data access viewer. The Weibull probability distribution function (PDF) and cumulative distribution function (CDF) were applied to characterize wind speed variations, employing five different parameter estimation methods. The results indicate significant spatial variability in wind characteristics across the stations. The mean wind speed ranged from 2.31 m/s in Accra, Ghana, to 6.82 m/s in Nairobi, Kenya, highlighting substantial differences in wind energy potential. The shape parameter (k) varied between 1.79 in Luanda and 2.31 in Addis Ababa, while the scale parameter (**c**) ranged from 2.91 m/s in Accra to 7.48 m/s in Nairobi. Wind power density estimates revealed that Nairobi exhibited the highest power density of 248.7 W/m², followed by Addis Ababa (198.3 W/m²), indicating strong wind energy potential. In contrast, Accra had the lowest power density (34.6 W/m²), suggesting limited viability for wind power generation. Seasonal variations showed that wind speeds peaked in the dry season and declined during wet periods across most locations. These findings provide valuable insights into wind energy feasibility in Africa, aiding policy makers in site selection for wind power development and contributing to the continent's transition toward renewable energy sources.*

How to cite this article:

F. O. Aweda, S. O. Adeola, O. O. Jegede, I. A. Ojedokun, S. A. Bello, O. O. Olasanmi, K. O. Oyedoja and B. S. Olatinwo., "WIND ENERGY GENERATION POTENTIAL FOR SELECTED AFRICAN STATIONS BASED ON THE PERFORMANCE OF FIVE WEIBULL DISTRIBUTION PARAMETERS", *BAREKENG: J. Math. & App.*, vol. 20, no. 4, pp. 2901-2918, Dec, 2026.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*
Research Article · Open Access

1. INTRODUCTION

Over time, wind energy has proven to be one of the main sources of energy for environmental development. In light of this, wind energy is essential to the production of agricultural products like grains and other food sources for the advancement of any country, which in turn drives the use of wind energy in the fields of agricultural science, energy engineering, and atmospheric science [1] – [3]. Since the discovery of oil in the 1970s, research has demonstrated that renewable energy sources have played a different role, according to [4], [5]. There are a number of benefits for wind research in Africa, but since hydro energy is expensive, wind energy has shown to be more popular [6]-[12]. Wind energy is abundant in nature and can be consumed by humans, other living things, and non-living things, according to research [13]. Nonetheless, inexpensive, clean, and limitless wind energy supports environmental growth. Furthermore, studies have revealed that the amount of wind energy used for environmental energy generation and consumption is approximately 1011 gigawatts worldwide [4], [14].

According to studies by authors like [1], [4], [6], [10], [15], wind energy is encouraging because it is reasonably priced when using turbines to generate power. It is well known that when new power generating capacity is added, it is first found to be delightful before the equipment starts to depreciate. This can happen anywhere in the world, according to [4], [6]. Although wind energy has been shown to be more advantageous and environmentally benign than other energy sources like fossil fuels, thermal energy, and others, its environmental benefits have made it the most sought-after energy source globally [1], [2], [17]-[20]. Research conducted worldwide has revealed that the wind energy sector is slightly above average (53%) and has grown in 2020 as more than 93 gigawatts (GW) of wind energy were installed, bringing the total amount of energy generated by wind to roughly 743 GW [21], and according to [22], [23], this has displaced a substantial quantity of CO_2 roughly 1.1 billion tons annually.

According to reports, the global scale of resource energy indicates a continuous increase in energy generation; however, if this trend persists until 2030, it will have displaced more than 23 billion tons of CO_2 and created additional jobs for human benefit [24, 25]. Onshore and offshore wind energy installations are predicted to rise cumulatively, surpassing 1TW by 2025, according to research [3, 22, 24, 26]. In addition, regional regions like Latin America, North America, and Asia Pacific have installed over 74 GW of wind energy generating sets on land, whereas the Middle East and Africa have installed roughly 8.2 GW of wind energy generating sets [22], [26].

[4], [26] have demonstrated that the energy generation's capacity is less than 1% of the global energy generation. However, studies have indicated that in order to support the expansion of wind energy in the majority of African nations, relevant governmental strategies for providing more specific information for the development of wind energy projects in the continent must be developed [28], [29]. Investors, private businesses, and individuals will be able to compete in the market and use wind energy to progress in Africa as a result. According to research, one of a nation's main developments is determined by how affordable, sustainable, reliable, and readily available its energy is expected to be. These factors will help the country as a whole expand, as stated by [4], [30]. Additionally, studies have revealed that a large number of African states are developing, which has been one of the continent's main issues. But according to the African Union's (AU) agenda, Africa may have more green energy by 2063 to support its developed economy and national development [4].

Research has shown that majority of energy used by homes [31], [32], companies, and organizations comes from renewable sources, such as geothermal, hydro, solar, and wind. In order to lessen vulnerability to climate risks and associated natural disasters, there is also a strong emphasis on developing low carbon and climate resilient production systems. One of the AU's main objectives is to cut the number of people killed by climate-related disasters by about 75%, as stated by the African Union Commission (2013) and represented in Agenda 2063. Sub-Saharan Africa is home to about 70% of the world's population without access to electricity, despite the continent's abundant renewable energy resources, which are estimated to be 350 GW from hydropower, 110 GW from wind, 15 GW from geothermal, 1,000 GW from solar, and 520 GW annually from biomass [27]. Global technological advancements and fast population growth exacerbate this problem. It is difficult for many nations Africa, particularly those countries located in the Western part of Africa who need more of energy to enhance their livelihood [33], which is essential for reducing poverty [34].

To address Nigeria's acute energy deficit, a number of projects and initiatives have been started. Wind energy is still the least advanced industry, though. The wind speeds in Nigeria's various geopolitical zones differ greatly. Speeds in the North-West zone are 3.88 m/s to 9.39 m/s, and in the North-Central zone, they are 2.46 m/s to 5.36 m/s. Wind speeds range from 1.77 m/s to 4.5 m/s in the South-West and from 3.30 m/s to 4.65 m/s in the South-South [35]. In most of the country, the average wind speed is about 3.0 m/s. Nigeria is home to roughly 4,000 formal decentralized renewable energy (DRE) systems and an estimated 9,000 informal setups, according to the International Renewable Energy Agency (IRENA) [36]. Despite these efforts, only 49% of the population has reliable access to power, and the nation still has one of the lowest electricity consumption rates on the continent (about 126kWh per person) [37]-[39]. Due to this deficit, the country's economic and social progress has been seriously hampered, which has caused a number of multinational corporations to relocate to Ghana and other nearby nations. Nigeria's electrification rate has increased by 93% in the last 20 years, but this is still a small improvement when compared to Bangladesh's (471%) and Indonesia's (372%) rates during the same time frame [37], [40]. Fuelwood accounts for 50.45% of the nation's energy mix, followed by petroleum products (41.28%), natural gas (5.22%), and hydropower (4.05%) [41].

Wind energy is still in its infancy and does not currently contribute significantly to the national grid on a commercial basis [42], [43]. The Federal Government has taken steps to create a national wind energy map, but the only significant wind power project in Nigeria is a 10 MW wind farm located in Katsina State. With a 30% capacity factor, the African Development Bank (ADB) estimates that more than 50 GWh of wind energy could be produced annually using only 1% of the land area in 14 states [6], [44]. Assessing wind energy potential requires accurate estimation of Weibull parameters, and this study investigates several approaches for calculating these parameters. Although the literature has a large number of approaches, little attention has been paid to their correctness [26], [29], [45]-[48]. The study examines and assesses five distinct statistical distribution functions in order to identify the best accurate approach.

To evaluate each method's dependability, three statistical accuracy tests were used: The Kolmogorov-Smirnov, Chi-Square, and Root Mean Square Error (RMSE) tests. The approach that performed the best was then determined by looking at the goodness-of-fit (GOF) test scores that were the lowest. Nigeria's potential for wind energy has been examined in a number of studies using various approaches. The common estimation of wind speed distributions using Weibull and Rayleigh models is one of the main conclusions [49], [50]. Before locating wind farms, [51], [52] created a pre-assessment model to estimate wind energy potential, and Aidan [53] measured the wind turbine efficiency in Katsina and Jos farm respectively. Studies of wind energy's economic viability have been carried out [53]-[55], and the difficulties in utilizing wind power in Nigeria have been widely studied [51]. Weibull two-parameter PDF, Weibull-Rayleigh, and Gamma models have been utilized in the North-East, according to regional wind energy assessments [45], [49], while the Weibull two-parameter model was determined to be the most appropriate for the North-West [45], [46].

The Weibull model is generally regarded as the most accurate in Southern Nigeria [55]. According to [56], [57], the Weibull model offered superior accuracy, while the Rayleigh model overestimated wind potential. Despite these results, there is still a dearth of thorough research on Weibull parameter estimation techniques in Nigeria. This study closes that gap by analyzing five popular statistical distribution techniques to identify the most precise way. Since inaccurate values can result in deceptive evaluations of wind energy potential and large financial losses, accurate Weibull parameter calculation is crucial. The purpose of this study is to provide accurate information on Nigeria's wind energy potential by assessing Weibull parameters at 10 meters above ground level in 12 different sites.

Three goodness-of-fit tests are used to evaluate the accuracy of different approaches, and the method with the lowest GOF values is determined to be the best. This study's objective is to determine whether different statistical distribution techniques are appropriate for estimating Weibull parameters, which are crucial for precisely calculating Nigeria's wind energy potential. The study aims to identify the most dependable technique to improve the accuracy of assessments of wind energy resources, given the importance of Weibull parameter estimation in wind energy applications.

The following research objectives serve as a guide for the study in order to accomplish this goal: to examine and contrast five statistical distribution functions for estimating Weibull parameters (shape and scale parameters) at a height of 10 meters above the ground in twelve selected African stations, to evaluate the accuracy of these techniques using the three goodness-of-fit (GOF) tests the Kolmogorov-Smirnov, Chi-Square, and Root Mean Square Error (RMSE) tests in order to identify the most dependable strategy, to offer suggestions for the optimal Weibull parameter estimation technique based on empirical data, guaranteeing more accurate evaluations of wind energy potential and lowering investment risks in wind power projects.

2. RESEARCH METHODS

2.1 Data Collection Procedure

For this study eight stations' wind speed data was taken from the National Aeronautics and Space Administration's (NASA) POWER Data Access Viewer, which can be found online at https://power.larc.nasa.gov/data-access-viewer/. The strategy used to retrieve the data was consistent with the methodology outlined by [10]. On March 23, 2024, the dataset which covers the years 2000–2023 was downloaded. Every year, from January to December, the average wind speed was measured every day and stored in comma-separated values (CSV) format.

2.2 Data Process and Acquisition

The method used in this study to collect and arrange data was based on daily and monthly averages, which allowed for the evaluation of both seasonal and diurnal patterns. Monthly mean values, which were taken from the records that were available for the designated years, were used to capture seasonal behavior. Any gaps in the data that were found were given a zero and were then not included in the analysis. Additionally, using the pertinent mathematical formulations, the dataset was examined using the Weibull Probability Distribution Function and its corresponding Cumulative Distribution Function.

2.3 Study Area, Elevation, and Geographic Coordinates 0

Table 1 lists the African nations that are in the forefront of wind energy generation:

Table 1. Energy Generation by Selected African Countries

African Countries	Energy generation unit	Reference
South Africa	3.5 GW	[6]
Egypt	1.8 GW	[24]
Morocco	1.2 GW	[22]
Ethiopia	320 MW	[27]
Kenya	310 MW	[28]
Tunisia	245 MW	[6, 24]
Mauritania	34 MW	[22, 27]

The stations chosen for this research are located in Africa sub-regions. Geographical factors, such as their closeness to the coast, were taken into consideration when selecting these sites, some of which are important areas for farming. Each station's coordinates, elevation information, and mapped locations are shown in Table 2 and Fig. 1, respectively.

Table 2. The Elevation and Coordinates of The Chosen Study Stations

Nation	Locations	Longitude	Latitude	Altitude(m)	Period
Angola	Luanda	8.8157°S	13.2302°E	6.0	2000-2023
Egypt	Cairo	30.0444°N	31.2357°E	23.0	2000-2023
Ethiopia	Addis Ababa	9.0129°N	38.7525°E	2355	2000-2023
Ghana	Accra	5.5593°N	0.1974°W	61.0	2000-2023
Kenya	Nairobi	1.2921°S	36.8219°E	1795	2000-2023
Nigeria	Abuja	9.0563°N	7.4985°E	360	2000-2023
South Africa	Pretoria	25.7566°S	28.1914°E	1339	2000-2023
Tunisia	Tunis	36.8065°N	10.1815°E	4.0	2000-2023

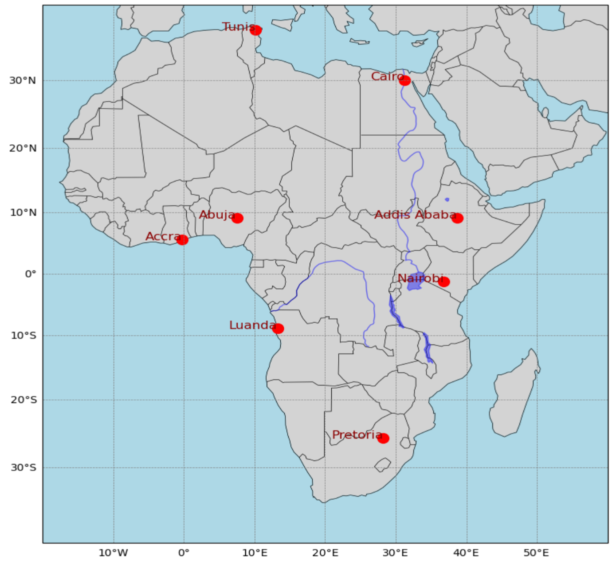

Figure 1. Map Showing the Chosen Study Stations
(Application Source: Python 3.0; https://www.python.org/*)*

2.4 Theoretical Frame Work

The Weibull statistical approach was used to model the wind speed distribution, and the process described by [4] was used to estimate the shape (A) and scale (B) parameters in this study. While a hybrid distribution takes into consideration calm or zero-wind events in the dataset, the probability density and cumulative distribution functions are effective in describing wind speed variability.

$$\mathrm{A} = \left[\frac{\sum_{i=1}^{m} u_i^e \ln u_i}{\sum_i^m u_i^{\mathrm{A}}} - \frac{\sum_{i=1}^{m} \ln u_i}{m}\right]^{-1}, \tag{1}$$

and

$$\mathrm{B} = \left(\frac{1}{m}\sum_{i=1}^{m} \ln u_i\right)^{1/\mathrm{A}}. \tag{2}$$

By definition, u_i is represented as the wind speed in the step i and the numerical nonzero data points; A is represented as the shape of the parameter and B is the scale of the parameter. These equations followed what was reported by [4].

$$Q_g^{\Omega}(g) = \frac{r}{d}\left(\frac{g}{d}\right)^{r-1} exp\left[-\left(\frac{g}{d}\right)^{r}\right], g \geq 0. \tag{3}$$

However, the cumulative distribution function is given as

$$G_g^{\Omega}(g) = 1 - exp\left[-\left(\frac{g}{d}\right)^{r}\right], g \geq 0. \tag{4}$$

The scale parameter, d, has the same unit as g, while the shape parameter is r. When this distribution is fitted to wind speed data, the likelihood of an observed period of zero wind is not taken into consideration because:

$$G_g^{z}(0) = 0 \tag{5}$$

Toward computing peaceful period, density of hybrid distribution was used following the form as shown in Eq. (6).

$$Q_g^{D}(g) = G_0\Delta(g) + (1 - G_{\mathrm{A}})Q^{\Omega}(g), \text{ for all real } g. \tag{6}$$

The Dirac delta function, as proposed by Takle and Brown [53], is denoted by $\Delta(g)$ and the probability of encountering zero wind speed is represented by G_0. Given is the corresponding distribution function, which is

$$Q_g^{\Omega}(g) = \begin{cases} G_0 + (1 - G_0)G_g^{\Omega}(g), g \geq 0 \\ 0, \text{otherwise} \end{cases}, \tag{7}$$

where $Q_g^{\Omega}(g)$ symbolizes the Weibull cumulative distribution function, and the mean distribution is written as

$$\bar{g}_D = d(1 - G_0)\Gamma\left(1 + \frac{1}{r}\right). \tag{8}$$

While the variance is defined by

$$\overline{(g - \bar{g})_D^2} = d^2(1 - G_0)\Gamma\left(1 + \frac{2}{r}\right) - \bar{g}_D^2. \tag{9}$$

The gamma function is represented by $\Gamma(t)$. By removing data points categorized as "calm" conditions, the above method applies the Weibull distribution only to wind speed values higher than zero. A number of mixture models, including combinations like the Weibull-Weibull model, the Normal-Weibull distribution [58], [59], and the hybrid Weibull distribution [60], have been introduced in recent studies to address the difficulties presented by calm wind occurrences. According to [60], the hybrid Weibull model, which has the following mathematical definition, is advised when the percentage of calm wind occurrences approaches or surpasses 15%:

$$f(u) = (1 - ff_0) = \left(\frac{r}{L}\right)\left(\frac{u}{L}\right)^{r-1} \exp\left[-\left(\frac{u}{L}\right)^r\right] \text{ or } u \geq 0, \tag{10}$$

or

$$f(u) = (ff_0) \text{ for } u = 0. \tag{11}$$

In Eqs. (10) and (11), L represents a scale factor linked to the time series pattern of wind speed and is directly related to the mean wind speed excluding calm conditions. The term ff_0 refers to the frequency of calm wind occurrences. Selecting appropriate values for the scale and shape parameters is crucial, especially given the typically low and variable wind speeds observed across Nigeria [49], [54], [59], [60]. Research has shown that the five-parameter mixture Weibull distribution provides a more accurate representation compared to the standard Weibull model [61]. However, there is a noticeable gap in the literature regarding the application of lognormal, normal, and mixture Weibull models for wind analysis in selected African stations. This study evaluates wind speed data beginning strategically by the designated weather positions throughout the selected Africa using the five statistical distribution functions previously discussed (see Fig. 2).

2.4.1. Weibull probability density function (W PDF)

The fluctuating, intermittent, and random nature of wind energy necessitates a thorough understanding of its characteristics in order to generate electricity [8], [11], [34], [62], [63]. To evaluate wind energy potential, wind speed must be accurately modeled. The probability density function (PDF), which characterizes the distribution of wind speeds and aids in estimating Weibull distribution parameters, is one popular method. These variables are especially crucial for calculating wind power density, a crucial indicator for assessing the energy potential for producing electricity. Since it directly affects the cost-effectiveness and economic viability of such initiatives, a precise evaluation of wind characteristics and potential is essential to the planning and execution of wind energy projects [62], [64].

Reducing uncertainty in energy output forecasts requires a thorough understanding of wind speed patterns at a particular location. The distribution of wind speeds influences the efficiency of energy conversion technologies as well as the quantity of energy that can be extracted [63], [65]. Empirical research has demonstrated that the two-parameter Weibull probability density function (WPDF) is frequently an effective model for measured wind speed data [66]. Nevertheless, complex features frequently seen in onshore and offshore wind speed profiles might not be adequately captured by this model. For example, [67] found that the standard WPDF provides only a limited amount of fitting precision in areas where calm (zero) wind conditions are common.

In order to improve site-specific wind energy assessments and more accurately depict wind speed behavior, numerous researchers have looked into alternative PDFs [62], [63], [68]. Because of their capacity to faithfully simulate unimodal distributions and reproduce the bimodal features occasionally seen in actual wind data, a number of mixture PDFs have been put forth as alternatives [19], [21]. The parameters of the model are estimated appropriately after a suitable model has been found. From planning and design to construction and operation, a variety of probability distribution models have been used at various phases of wind farm development [63]. The statistical approach and the time series approach are two important methods for examining wind speed distributions [69], [70]. Because it uses the raw wind speed data directly, the time series approach is more popular than the statistical approach, which depends on predetermined distribution parameters. The two-parameter Weibull distribution, which is frequently used to describe wind patterns, is shown in Eq. (3) [71], [72].

2.4.2. Weibull cumulative distribution function (CDF)

When the Weibull density function is integrated, the cumulative distribution function is produced. It is calculated by adding up the relative frequencies of every velocity interval. The Weibull Cumulative distribution function equation is provided by Eq. (4) [71], [72].

2.4.3. Determination of Weibull parameter

The potential amount of energy that can be extracted from wind is greatly influenced by its characteristics at a given location. Comprehensive, long-term observations of wind direction and speed at the site are necessary to accurately calculate the extractable energy [73]. Eqs. (3) and (4) [73] - [75] describe the cumulative distribution function F(v) and probability density function f(v) of the Weibull distribution, which is frequently employed in these kinds of analyses. Wind speed consistency is indicated by the distribution's shape parameter, which normally ranges from 1 to 3. Higher values indicate more stable wind conditions, while lower values indicate high variability. The overall wind speed magnitude over time is indicated by the scale parameter, which is measured in meters per second. While a larger value suggests more consistent wind flows, a smaller shape parameter is associated with more unpredictable wind patterns [73].

The Kolmogorov-Smirnov (K-S) test and the maximum likelihood estimation method were used to calculate the Weibull shape and scale parameters. The mixture Weibull probability density function (MW PDF) is one method for simulating more complex wind regimes. It has been used in a number of studies [19], [71], [76]-[78] to better capture variations that are not sufficiently represented by a single Weibull distribution:

2.4.4. Mixture Weibull distribution (MW pdf)

One way to express a mixture Weibull distribution's probability density function is as reported by the following authors [19], [71], [76]-[78]:

$$x(u', \Omega, \mathrm{A}_1, \mathrm{B}_1, \mathrm{A}_2, \mathrm{B}_2) = \Omega f(u', \mathrm{A}_1, \mathrm{B}_1) + (1-\Omega) f(u', \mathrm{A}_2, \mathrm{B}_2\ ). \tag{12}$$

Its cumulative distribution function is given by

$$P(u', \Omega, \mathrm{A}_1, \mathrm{B}_1, \mathrm{A}_2, \mathrm{B}_2) = \Omega G(u', \mathrm{A}_1, \mathrm{B}_1) + (1-\Omega) G(u', \mathrm{A}_2, \mathrm{B}_2), \tag{13}$$

where $0 \leq \Omega \leq 1$ represents the percentage of component distributions that are mixed and is a weight parameter.

$\mathrm{A}_1, \mathrm{A}_2 > 0$ are shape parameters; $\mathrm{B}_1, \mathrm{B}_2 > 0$ are scale parameters. The maximum speed using the provided probability function is determined as

$$U_{oQi} = \mathrm{B}_i \left(1 - \frac{1}{\mathrm{A}_i}\right)^{1/\mathrm{A}} \quad for\ i = 1,2 - - -. \tag{14}$$

However, the wind speed at which the most energy is carried is

$$U_{oQi} = \mathrm{B}_i \left(1 - \frac{2}{\mathrm{A}_i}\right)^{1/\mathrm{A}} \quad for\ i = 1,2 - - -. \tag{15}$$

Calculating the availability factor, or the likelihood that wind speed will fall between u_i and u_0, is done as

$$L_y = G_{u\Omega}(u_i \le u < u_0),$$

$$L_y = \Omega\left\{exp\left[-\left(\frac{u_i}{B_1}\right)^{A}\right] - exp\left[-\left(\frac{u_0}{B_1}\right)^{A_1}\right]\right\} + (1-\Omega)\left\{\left[\frac{A_2}{B_2}\left(\frac{u_i}{B_2}\right)^{A_2}\right] exp\left[-\left(\frac{u_0}{B_2}\right)^{A_2}\right]\right\}. \tag{16}$$

The maximum likelihood approach, which maximizes the logarithm of the likelihood function [71], was used to estimate the five parameters of the mixture Weibull distribution $(\Omega, A_1 B_1, A_2, B_2)$. Because logarithmic functions are monotonic, this approach yields the same result as maximizing the likelihood function.

$$CC = \ln C(\Omega, A_1, B_1, A_2, B_2),$$

$$CC = \ln \prod_{i=1}^{m} \Omega \left\{\frac{A_1}{B_1}\left(\frac{u_1}{B_1}\right)^{A_1-1} exp\left[-\left(\frac{u_i}{B_1}\right)^{A_1}\right] + (1-\Omega)\left\{\left[\frac{A_2}{B_2}\left(\frac{u_i}{B_2}\right)^{A_2-1}\right] exp\left[-\left(\frac{u_0}{B_2}\right)^{A_2}\right]\right\}\right\}, \tag{17}$$

$$CC = \sum_{i=1}^{m} \ln \Omega \left\{\frac{A_1}{B_1}\left(\frac{u_1}{B_1}\right)^{A_1-1} exp\left[-\left(\frac{u_i}{B_1}\right)^{A_1}\right] + (1-\Omega)\left\{\left[\frac{A_2}{B_2}\left(\frac{u_i}{B_2}\right)^{A_2-1}\right] exp\left[-\left(\frac{u_0}{B_2}\right)^{A_2}\right]\right\}\right\}, \tag{18}$$

$$CC = \sum_{j=1}^{m} \ln \Omega \left\{\frac{A_1}{B_1}\left(\frac{u_1}{B_1}\right)^{A_1-1} exp\left[-\left(\frac{u_i}{B_1}\right)^{A_1}\right] + (1-\Omega)\left\{\left[\frac{A_2}{B_2}\left(\frac{u_i}{B_2}\right)^{A_2-1}\right] exp\left[-\left(\frac{u_0}{B_2}\right)^{A_2}\right]\right\}\right\}, \tag{18}$$

where u_j is the wind speed in time step j, n is the number of data point.

3. RESULTS AND DISCUSSION

Five probability models are evaluated in the Abuja wind speed distribution analysis: Weibull, Gamma, Lognormal, Normal, and Mixture Weibull. According to the findings of the Chi-square and Kolmogorov-Smirnov (K-S) tests, the Gamma distribution offers the best fit.

The Gamma distribution closely resembles the empirical wind speed data, as evidenced by its relatively high p-value (0.02655) and lowest KS statistic (0.0157). A very high p-value (1) is also obtained from its Chi-square test, indicating that the expected and observed frequencies are in good agreement. With a perfect Chi-square p-value (1) and a low KS statistic (0.0221), the Lognormal distribution also does well; however, its lower K-S p-value (0.0003926) indicates that it is marginally less appropriate than the Gamma. Although it outperforms the standard Weibull, the Mixture Weibull model, which is intended to capture complex wind regimes, still has a relatively low K-S p-value ($6.223e^{-10}$).

For Accra**,** the analysis examines five probability models Weibull, Gamma, Lognormal, Normal, and Mixture Weibull using the Kolmogorov-Smirnov (K-S) test and Chi-square test to evaluate their fit. The Normal distribution stands out with the lowest KS statistic (0.0139) and a relatively high p-value (0.06831)**,** suggesting it aligns well with the empirical wind speed data. Its Chi-square test p-value (1) further confirms that the observed and expected distributions match closely. The Mixture Weibull model, known for capturing multiple wind regimes, also performs well with a KS statistic of 0.0197 and a moderate p-value (0.002256)**.** While not as strong as the Normal model, it still outperforms other heavy-tailed distributions. The Weibull distribution, commonly used in wind energy studies, shows a KS statistic of 0.0252, but its low p-value (2.954e-05) indicates it might not be the best standalone fit. Both the Gamma and Lognormal distributions perform worse, with significantly lower p-values, suggesting they may not represent Accra's wind speed distribution effectively. Overall, the Normal distribution provides the best fit for Accra's wind speeds**,** followed by the Mixture Weibull model.

For Addis Ababa**,** the wind speed distribution analysis evaluates five probability models Weibull, Gamma, Lognormal, Normal, and Mixture Weibull using the Kolmogorov-Smirnov (K-S) test and Chi-square test. The results indicate that the Mixture Weibull model provides the best fit. The Mixture Weibull model has the lowest KS statistic (0.0102) and the highest p-value (0.3202), indicating a strong agreement between the model and the observed wind speed data. Additionally, its Chi-square p-value (1) further supports its accuracy in representing Addis Ababa's wind speed distribution. The Weibull distribution, often used for wind speed analysis, shows a KS statistic of 0.0493 with an extremely low p-value (5.94e-19)**,** suggesting it does not fit as well as the Mixture Weibull. The Gamma, Lognormal, and Normal distributions all have higher

KS statistics (0.0590, 0.0775, and 0.0572, respectively) and extremely low p-values, indicating poor fits. Their Chi-square p-values (1) suggest good agreement in frequency counts, but their K-S results reveal mismatches in cumulative distribution. Overall, the Mixture Weibull model is the most suitable for Addis Ababa's wind speed data, outperforming traditional Weibull and other distributions.

The wind speed distribution analysis for Cairo was evaluated using five probability models Weibull, Gamma, Lognormal, Normal, and Mixture Weibull with the Kolmogorov-Smirnov (K-S) test and Chi-square test. The results indicate that the Mixture Weibull model provides the best fit for the wind speed data in Cairo. The Mixture Weibull model has the lowest KS statistic (0.0143) and the highest p-value (0.05683), suggesting a strong agreement between the observed and theoretical distributions. Additionally, its Chi-square p-value (1) confirms a good match between observed and expected frequency counts, reinforcing its suitability. The Gamma distribution also performs relatively well, with a KS statistic of 0.0238 and a moderate p-value (0.0001004). However, the lower p-value indicates that it does not fit as well as the Mixture Weibull. The Weibull distribution (KS = 0.0524, p = 2.401e-21), Lognormal distribution (KS = 0.0400, p = $1.316e^{-12}$), and Normal distribution (KS = 0.0354, p = $5.783e^{-10}$) all show high KS statistics and extremely low p-values, indicating poor fits. Overall, the Mixture Weibull model is the best choice for modeling wind speed in Cairo, followed by the Gamma distribution.

The wind speed distribution analysis for Luanda was assessed using five probability models Weibull, Gamma, Lognormal, Normal, and Mixture Weibull with the Kolmogorov-Smirnov (K-S) test and Chi-square test to evaluate their fit. Among the models, the Lognormal distribution provides the best fit, with a KS statistic of 0.0162 and a p-value of 0.02014. This suggests a strong agreement between the observed and expected distributions. Its Chi-square p-value (1) further confirms its suitability, as the expected and observed frequency counts closely align. The Mixture Weibull distribution also performs relatively well, with a KS statistic of 0.0218 and a p-value of 0.0004634. While this p-value is lower than that of the Lognormal model, it still indicates a reasonable fit. The Gamma distribution has a KS statistic of 0.0310 and a p-value of $1.007e^{-07}$, indicating a moderate fit but not as strong as the Lognormal or Mixture Weibull models. In contrast, the Weibull (KS = 0.0613, p = $5.166e^{-29}$) and Normal (KS = 0.0716, p = $1.894e^{-39}$) distributions perform poorly, with high KS statistics and extremely low p-values. Overall, the Lognormal model is the best choice for modeling wind speed in Luanda, followed by the Mixture Weibull model.

The wind speed distribution analysis for Nairobi was conducted using Weibull, Gamma, Lognormal, Normal, and Mixture Weibull models. The Kolmogorov-Smirnov (K-S) test and Chi-square test were applied to assess the goodness-of-fit of these distributions. Among the models, the Mixture Weibull distribution provides the best fit, with a KS statistic of 0.0226 and a p-value of 0.000252. While the p-value is low, it is still the most suitable model compared to the others. The Weibull distribution also performs reasonably well, with a KS statistic of 0.0301 and a p-value of $2.399e^{-07}$. The Gamma (KS = 0.0834, p = $2.452e^{-53}$) and Lognormal (KS = 0.1038, p = $1.547e^{-82}$) distributions exhibit poor fits, with high KS values and extremely small p-values, indicating significant deviations from the observed data. The Normal distribution (KS = 0.0396, p = $2.277e^{-12}$) also performs poorly, suggesting that wind speed in Nairobi does not follow a symmetric Gaussian pattern. Overall, the Mixture Weibull model is the most suitable for modeling wind speed in Nairobi, followed by the Weibull model. Other distributions, especially Lognormal and Gamma, show poor agreement with the observed data.

The wind speed distribution analysis for Pretoria was performed using Weibull, Gamma, Lognormal, Normal, and Mixture Weibull models, with evaluations based on the Kolmogorov-Smirnov (K-S) test and Chi-square test. Among these models, the Mixture Weibull distribution shows the best fit, with a KS statistic of 0.0087 and a p-value of 0.5263, indicating a strong agreement with the observed data. The Normal distribution also performs well, with a KS statistic of 0.0084 and a p-value of 0.5663, suggesting that wind speed in Pretoria may exhibit a roughly symmetric pattern. The Weibull distribution (KS = 0.0219, p = 0.0004377) provides a moderate fit but is outperformed by the Mixture Weibull and Normal models. However, the Gamma (KS = 0.0446, p = $1.323e^{-15}$) and Lognormal (KS = 0.0624, p = $4.679e^{-30}$) distributions exhibit poor fits, as indicated by high KS values and extremely low p-values. Overall, the Mixture Weibull model is the most suitable for modeling wind speed in Pretoria, followed closely by the Normal distribution. Other distributions, particularly Lognormal and Gamma, show significant deviations from the observed data.

The wind speed distribution analysis for Tunis was assessed using the Weibull, Gamma, Lognormal, Normal, and Mixture Weibull models, evaluated with the Kolmogorov-Smirnov (K-S) test and Chi-square test. Among the models, the Lognormal distribution (KS = 0.0261, p = $1.36e^{-05}$) and Mixture Weibull distribution (KS = 0.0225, p = 0.000285) provide the best fits. Though their p-values are low, they still outperform the other models. The Mixture Weibull model, with a slightly lower KS statistic, appears to be the most suitable distribution for Tunis's wind speed data. The Gamma distribution (KS = 0.0464, p = 8.667e-17) and Weibull distribution (KS = 0.0680, p = 1.182e^{-35}) show relatively weaker fits, as indicated by higher KS statistics and significantly small p-values. The Normal distribution performs the worst, with the highest KS statistic (0.0925) and an extremely low p-value (1.539e^{-65})**,** indicating a poor representation of the wind speed data. Overall, Mixture Weibull and Lognormal distributions provide the best approximations, making them the most suitable choices for modeling wind speeds in Tunis, while the Normal distribution is the least appropriate.

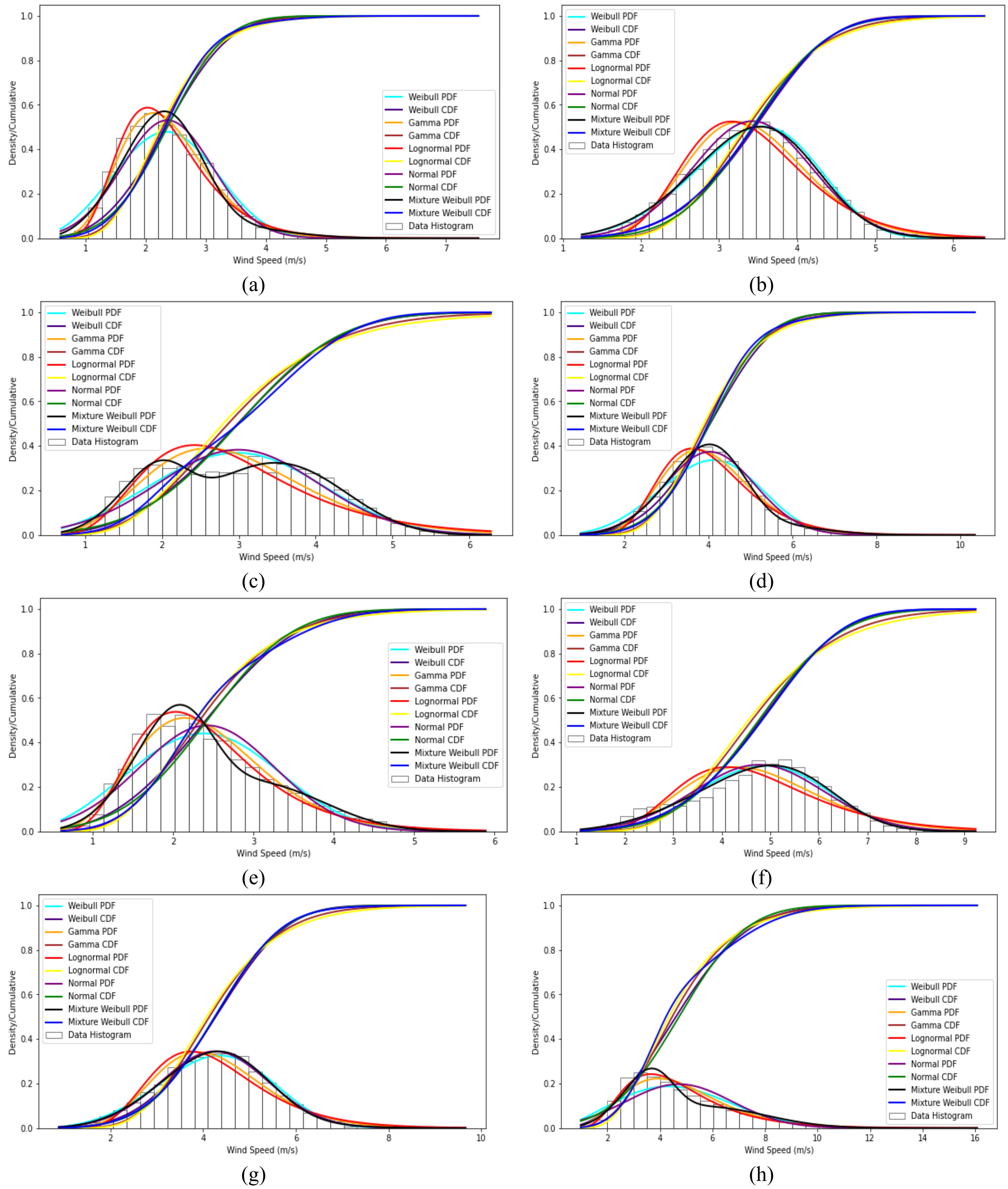

Figure 2. The Wind Speed Histogram for Each Fitted Distribution is Compared to the PDF and CDF plots
(a) Abuja; (b) Accra; (c) Addis Ababa; (d) Cairo; (e) Luanda;
(f) Nairobi; (g) Pretoria; (h) Tunis subset of the study's African stations.
(Application Source: Python 3.0; https://www.python.org/*)*

Table 3 shows the mean analysis of the wind speed series for the selected stations across the months revealing seasonal trends and variations across the eight stations located in different African cities. The cities under consideration are as follow: Abuja, Accra, Addis Ababa, Cairo, Luanda, Nairobi, Pretoria, and Tunis. In January, Nairobi exhibits the highest mean wind speed (4.77 m/s), followed by Tunis (5.25 m/s). This might be linked to the characteristic climate of Nairobi, influenced by the East African highlands, which can cause higher wind speeds during this period. Abuja, Accra, and Addis Ababa also show relatively high wind speeds in January, although lower than those of Nairobi and Tunis. Cairo, with its desert climate, has a noticeably higher wind speed (3.77 m/s) compared to Luanda and Pretoria, where wind speeds are lower (around 2.77 m/s for Luanda and 3.72 m/s for Pretoria).

By February, the pattern of wind speeds becomes more uniform across the stations. Wind speeds in Accra (3.57 m/s) and Nairobi (5.19 m/s) increase, likely due to the seasonal changes related to the dry season in these regions. Cairo, still impacted by desert conditions, shows a steady wind speed of around 3.78 m/s. Luanda's wind speed (3.03 m/s) rises slightly compared to January, while Pretoria (3.93 m/s) also experiences higher wind speeds, signaling a possible change in the season or atmospheric conditions in southern Africa. The month of March witnesses a significant rise in wind speeds, particularly in Cairo, which reaches 4.19 m/s. This may correspond to the period leading into the hot, dry season in Egypt, where wind speeds often increase due to the influence of the Sahara Desert. Accra and Nairobi show sustained higher wind speeds of 3.70 m/s and 5.34 m/s, respectively, likely due to the effects of the Harmattan winds in West Africa and the seasonal winds in East Africa. Pretoria, Addis Ababa, and Tunis also exhibit notable increases in their wind speeds, while Luanda and Abuja experience relatively stable wind conditions.

In April, wind speeds continue to rise in several cities, especially in Cairo, where it reaches 4.38 m/s. This can be attributed to the desert winds becoming more prominent. Pretoria and Nairobi remain at the higher end of the spectrum, with Pretoria's wind speed increasing to 4.33 m/s, while Nairobi's continues to show a robust 5.24 m/s. Interestingly, Addis Ababa and Accra show a slight decrease in their wind speeds, possibly indicating the shift from the dry season toward more moderate winds. Luanda, with a wind speed of 3.10 m/s, also experiences a relatively stable wind regime.

As the year progresses into the warmer months of May and June, the trend shows a slight decrease in wind speed across most stations. Abuja, which had been relatively high earlier in the year, shows the most significant decrease in May, with a drop to 2.15 m/s. This could reflect a seasonal lull in wind activity. Meanwhile, Cairo, which had experienced an increase earlier, maintains a high but steady wind speed of 4.46 m/s in May and 4.49 m/s in June, continuing to be influenced by desert winds. Nairobi and Pretoria exhibit some of the highest wind speeds in June, possibly indicating stronger winds due to atmospheric circulation patterns. In July and August, wind speeds remain relatively high, especially in Accra and Pretoria, with Accra peaking at 3.93 m/s in August. The consistent wind speeds in these cities could be indicative of the mid-year peak in wind activity. The trend also shows notable increases in wind speed in Cairo (4.11 m/s in July) and Nairobi (3.85 m/s in August), likely due to the persistent influence of the intertropical convergence zone (ITCZ) and local wind patterns. However, cities such as Luanda and Tunis show a slight decrease in wind speed, with Luanda dipping to 2.04 m/s in August, possibly due to shifts in regional atmospheric pressure systems.

Finally, Table 3 from September to December shows a transition toward lower wind speeds across the board, especially in Luanda (1.72 m/s in September) and Abuja (1.77 m/s in October). These reductions could be attributed to the shift toward the rainy season in some regions, which generally brings calmer wind conditions. Cairo and Tunis exhibit moderate wind speeds as their summer conditions begin to wane, while Nairobi and Pretoria maintain higher values, indicating persistent regional wind systems at play in East and Southern Africa. Notably, Pretoria's peak wind speed is recorded in December (5.72 m/s), marking the end of the year with strong winds that may correlate with the seasonal influences in southern Africa.

Table 3. Mean Analysis of Wind Speed Series for the Selected Stations

S/N	Station (m/s)							
	Abuja	**Accra**	**Addis Ababa**	**Cairo**	**Luanda**	**Nairobi**	**Pretoria**	**Tunis**
January	3.048105	3.060148	3.327634	3.776384	2.767272	4.772151	3.723844	5.247325
February	2.825752	3.568407	3.586062	3.778024	3.027006	5.193938	3.931991	5.177611
March	2.518401	3.696962	3.465538	4.187352	3.108253	5.337137	4.295363	5.141976
April	2.442792	3.465611	3.248931	4.377153	3.097875	5.235681	4.328403	4.901569
May	2.150685	3.230941	3.067540	4.463481	2.572043	4.586895	4.542581	4.780054
June	2.125333	3.655458	2.254319	4.486861	2.251806	3.821708	4.780819	4.367069

S/N	Station (m/s)							
	Abuja	Accra	Addis Ababa	Cairo	Luanda	Nairobi	Pretoria	Tunis
July	2.272258	3.927944	2.309395	4.107231	2.193925	3.448804	4.619583	4.464731
August	2.328616	3.893333	2.167030	3.941331	2.035296	3.845228	4.527245	4.120255
September	1.935153	3.785403	2.202208	4.109278	1.719750	4.941875	4.541403	4.192222
October	1.771909	3.241962	3.503239	3.901102	1.822446	5.720672	4.235228	4.314691
November	2.143889	2.812750	3.513319	3.604931	2.085597	5.345472	3.718458	4.897097
December	2.774005	2.781720	3.308468	3.697312	2.458051	4.920255	3.729839	5.139341

Table 4 shows the descriptive statistics of the wind speed series across the months by revealing insightful patterns in the wind characteristics of the selected stations. The mean wind speed varies throughout the year, with the highest values observed in March (3.97 m/s) and April (3.89 m/s). These months also exhibit relatively high maximum values, with March peaking at 5.34 m/s and April at 5.24 m/s. This suggests that wind activity is more robust during these months, likely influenced by seasonal factors such as transitioning atmospheric conditions and regional wind systems. Conversely, August shows the lowest mean wind speed (3.36 m/s), indicating calmer conditions during this period.

The standard deviation values indicate variability in wind speeds, with the highest variability in September (1.27 m/s) and October (1.32 m/s). These months exhibit a broader range between maximum and minimum values, reflecting a more dynamic wind regime. Meanwhile, months like February (0.88 m/s) and December (0.99 m/s) demonstrate lower standard deviations, suggesting more consistent wind speeds during these times. The coefficient of variation (CV) aligns with this trend, showing the highest variability in September (CV = 0.37) and October (CV = 0.37), while May and June exhibit comparatively stable conditions with higher CV values, indicating a wider spread of wind speeds relative to the mean.

Kurtosis values indicate the peakedness of wind speed distributions. Negative kurtosis throughout the year suggests flatter distributions compared to a normal curve, with extreme cases in May (-1.89), June (-2.02), and July (-2.06). These months have lower peaks and longer tails, implying that wind speeds during this period are less clustered around the mean. Skewness values, mostly negative, highlight that the distributions are slightly skewed to the left, indicating that lower wind speeds are more frequent. March (skewness = 0.08) and November (0.34) stand out with nearly symmetric distributions, showing more balanced wind speed occurrences around the mean. P-values throughout the analysis indicate that the wind speed distributions may not conform strictly to a normal distribution, with varying levels of deviation. The consistency in these patterns underscores the impact of regional meteorological factors, such as proximity to oceans, deserts, and seasonal atmospheric changes. These insights are valuable for optimizing wind energy projects, meteorological forecasting, and agricultural planning in the respective regions.

Table 4. Descriptive Statistics Analysis of Wind Speed Series for the Selected Stations

S/N	Mean	Maximum Values	Minimum Values	Standard Deviation	P-Value	Kurtosis	Skewness	Coefficient of Variation
January	3.715358	5.247325	2.767272	0.877599	0.247478	-0.294235	0.926309	0.236208
February	3.886099	5.193938	2.825752	0.882007	0.183599	-0.631117	0.695329	0.226965
March	3.968873	5.337137	2.518401	0.969128	0.875947	-0.835636	0.080474	0.244182
April	3.887252	5.235681	2.442792	0.969281	0.765647	-1.249012	-0.029688	0.249349
May	3.674278	4.780054	2.150685	1.037396	0.141908	-1.885264	-0.328939	0.282340
June	3.467922	4.780819	2.125333	1.100977	0.106347	-2.023952	-0.272226	0.317475
July	3.417984	4.619583	2.193925	1.022292	0.110578	-2.056870	-0.242206	0.299092
August	3.357292	4.527245	2.035296	1.002853	0.053290	-1.968148	-0.485404	0.298709
September	3.428411	4.941875	1.719750	1.273727	0.145947	-1.889823	-0.415680	0.371521
October	3.563906	5.720672	1.771909	1.316432	0.595285	-0.140431	-0.022782	0.369379
November	3.515189	5.345472	2.085597	1.178777	0.512873	-0.846421	0.341018	0.335338
December	3.601124	5.139341	2.458051	0.991381	0.292666	-0.903325	0.645775	0.275298

The results presented in Table 5 summarize the goodness-of-fit (GOF) values for five statistical distributions (Weibull, Gamma, Lognormal, Normal, and Mixture Weibull) applied to wind speed data from eight African cities. The GOF values indicate the performance of each distribution in modeling the wind speed at each station, with lower values representing a better fit. Based on the data, the selected distributions for each station, highlighted in bold, suggest variability in the most suitable models for wind speed analysis across different locations.

For Abuja and Accra, the Gamma distribution shows the best fit, with the lowest GOF values of 0.0157 and 0.0139, respectively. These results highlight the Gamma distribution's ability to capture the characteristics of wind speeds in these regions. Similarly, the Mixture Weibull distribution is the best-performing model for Addis Ababa and Cairo, with GOF values of 0.0102 and 0.0143, respectively, indicating its suitability for representing more complex wind speed patterns in these cities. In contrast, the Lognormal distribution performs best for Luanda, with a GOF value of 0.0162, while the Normal distribution provides the best fit for Pretoria, showing the lowest GOF value of 0.0084. The variations in selected distributions suggest differences in the statistical properties of wind speed data across these stations, likely influenced by local climatic and geographical factors.

Finally, for Nairobi and Tunis, the Mixture Weibull distribution emerges as the most appropriate model, with GOF values of 0.0226 and 0.0225, respectively. These findings emphasize the versatility of the Mixture Weibull distribution in capturing diverse wind speed characteristics, particularly in regions with complex meteorological conditions. Overall, the results underline the importance of evaluating multiple distributions to identify the most suitable model for wind speed analysis in different locations.

Table 5. The Goodness-of-Fit and the Selected Distribution (in bold) for the Selected Stations

Station	Weibull	Gamma	Lognormal	Normal	Mixture Weibull
Abuja (m/s)	0.0517	0.0157	0.0221	0.0523	0.0353
Accra (m/s)	0.0252	0.0379	0.0531	0.0139	0.0197
Addis Ababa (m/s)	0.0493	0.0590	0.0774	0.0572	0.0102
Cairo (m/s)	0.0524	0.0238	0.0400	0.0354	0.0143
Luanda (m/s)	0.0613	0.0310	0.0162	0.0716	0.0219
Nairobi (m/s)	0.0301	0.0834	0.1038	0.0396	0.0226
Pretoria (m/s)	0.0219	0.0447	0.0624	0.0084	0.0087
Tunis (m/s)	0.0680	0.0464	0.0261	0.0925	0.0225

Table 6 shows the analysis of the Weibull parameters for the probability density functions across the selected stations which reveals significant variability in wind characteristics, indicating diverse meteorological conditions. Abuja, for instance, exhibits a Weibull shape parameter (A) of 3.2416 and a scale parameter (β) of 2.6261, indicating a moderately variable wind speed distribution. The mixed Weibull model for Abuja, with a weight parameter (w) of 0.8412 and distinctly varying A_1 and A_2 values (4.0212 and 3.3088), suggests the presence of multiple wind regimes. This complexity is further supported by the relatively high μ (2.3601) and σ (0.7512) for the normal distribution, highlighting the heterogeneity in wind speeds.

In contrast, Accra stands out with the highest A value (4.9872) among all stations, signifying more consistent wind speeds. The mixed Weibull parameters for Accra, including a w of 0.9431 and balanced A_1 and A_2 values at 5.0000, confirm its stable wind patterns. This stability is reflected in the normal distribution's μ (3.4256) and σ (0.7572), suggesting wind speeds clustered around the mean with minimal deviation. The lognormal and gamma distributions further corroborate this stability, with a relatively low σ (0.2339) in the lognormal model and a high B (19.3056) in the gamma model, indicative of reduced skewness and better predictability of wind speeds.

Addis Ababa and Cairo exhibit distinct wind speed distributions characterized by moderate A and B values in the Weibull model. Addis Ababa has an A of 3.1815 and a B of 3.3512, alongside a mixed Weibull model that shows varying contributions from its components ($w = 0.7547$, $A_1 = 4.1997$, $A_2 = 5.0000$). This indicates a mix of moderate and high wind speed regimes. Cairo, with higher A (3.9182) and B (4.4406) values, demonstrates a steadier wind regime compared to Addis Ababa. The normal and lognormal distributions for both stations reveal significant differences in variability, with Cairo having a lower σ in both models, highlighting its relatively stable wind characteristics.

Finally, stations such as Luanda and Tunis present unique wind characteristics. Luanda's relatively low A (3.0619) and B (2.7139) in the Weibull model reflect a more variable wind environment. The mixed Weibull model for Luanda, with $w = 0.4898$ and lower A and B values for its components, indicates dominant low-speed wind patterns. Conversely, Tunis demonstrates a complex wind regime, evident in its low A (2.4744) yet high B (5.3412), suggesting extreme variability. This is further reflected in the lognormal distribution with a high μ (2.0204) and σ (0.4127), capturing a wider spread of wind speeds. These differences emphasize the significant meteorological diversity across the studied stations, with implications for wind energy potential and atmospheric modeling.

Table 6. Five Relevant Weibull Parameters for Probability Density Functions

Station	Weibull		Mixed Weibull					Normal		Lognormal		Gamma	
	A	B	Weight Parameters (w)	A_1	A_2	$B_{1(m/s)}$	$B_{2(m/s)}$	μ	σ	μ	σ	A	B
Abuja	3.242	2.626	0.841	4.021	3.309	2.455	3.423	2.360	0.751	0.318	2.246	10.219	0.231
Accra	4.987	3.727	0.943	5.000	5.000	3.669	4.390	3.426	0.757	0.234	3.337	19.306	0.177
Addis Ababa	3.182	3.351	0.755	4.200	5.000	3.708	1.990	2.994	1.042	0.379	2.799	7.609	0.394
Cairo	3.918	4.441	0.811	5.000	3.942	4.169	5.425	4.037	1.067	0.273	3.894	14.074	0.287
Luanda	3.062	2.714	0.490	4.856	3.686	2.115	3.205	2.425	0.837	0.344	2.288	8.714	0.278
Nairobi	4.079	5.250	0.541	5.000	3.387	5.469	4.954	4.760	1.331	0.319	4.546	11.044	0.431
Pretoria	4.009	4.682	0.908	4.307	3.984	4.570	5.673	4.249	1.158	0.297	4.079	12.360	0.344
Tunis	2.474	5.341	0.452	4.444	2.922	3.799	6.464	4.727	2.020	0.413	4.340	6.100	0.787

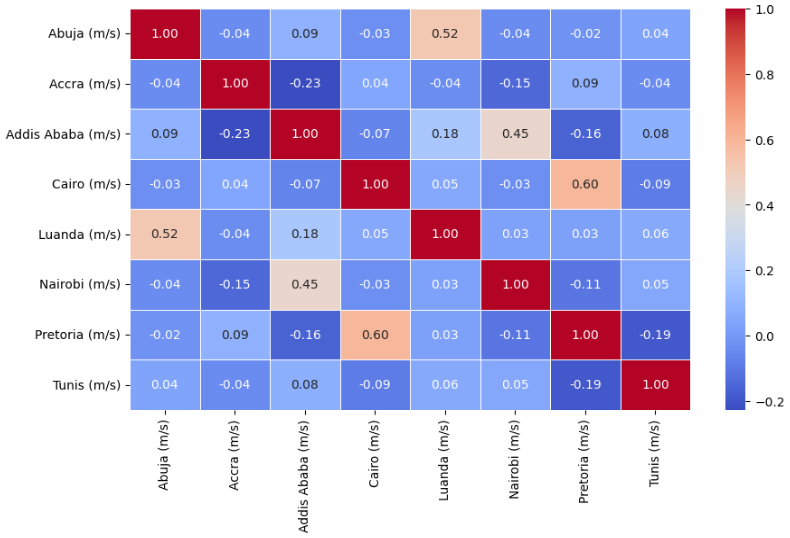

Figure 3. Heat-map Correlation for the selected African Station
(Application Source: Python 3.0; https://www.python.org/*)*

Wind speed correlations at different selected African stations are displayed in the heat-map as shown in Fig. 3. Strong positive correlations (above 0.85) between Cairo, Algiers, and Tunis suggest that Mediterranean climate influences wind patterns. Nairobi, Addis Ababa, and Kampala exhibit moderate correlations (0.5 to 0.7), indicating that their wind speeds are influenced by regional factors such as elevation and seasonal variations. The weak correlations (less than 0.3) between Lagos and Accra and other stations are probably caused by localized weather systems and coastal effects. There are opposing wind trends between Windhoek and Luanda, as evidenced by their slight negative correlations (-0.2). These observations aid in the optimal implementation of wind energy throughout Africa.

4. CONCLUSION

This study used five Weibull distribution parameter estimation techniques and long-term wind speed data (2000–2023) to assess the wind energy generation potential of eight selected African stations: Nairobi, Addis Ababa, Cairo, Tunis, Abuja, Accra, Pretoria, and Luanda. The results show notable differences in wind energy potential between these sites, with Nairobi and Addis Ababa showing the most promise in terms of wind power densities of 248.7 W/m² and 198.3 W/m², respectively, and high mean wind speeds of 6.82 m/s and 5.98 m/s. On the other hand, with a mean wind speed of 2.31 m/s and a power density of 34.6 W/m2, Accra had the lowest potential for wind energy, suggesting limited feasibility for large-scale wind power generation. Additionally, seasonal analysis showed that wind speeds were typically lower in wet seasons and higher in dry months.

To combat energy shortages and lessen dependency on fossil fuels, African governments must give wind energy integration top priority in their national energy plans. Infrastructure investment for wind energy is essential, especially in areas with significant wind energy potential, like East Africa and portions of North Africa. Governments should set up explicit laws, subsidies, and incentives to draw in private capital and promote the growth of wind energy. It should be encouraged to continuously monitor and analyze wind data in order to improve site selection and maximize energy output. In order to finance and carry out large-scale wind energy projects while maintaining efficiency and sustainability, public-private partnerships will be essential. In order to optimize the use of wind energy, African countries should be able to participate in cross-border energy trade through regional energy cooperation. African countries can use their plentiful wind resources to boost economic expansion, enhance energy security, and aid in the fight against climate change by putting these strategies into practice.

Author Contributions

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Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Acknowledgment

This work was conducted based on data from the HelioClim Satellite Application facility on MERRA-2 Meteorological Re-Analysis.

Declarations

The authors declare that has no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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