Evaluation and Improvement of the Accuracy of Reanalysis and Analysis Datasets for Wind Resource Assessment in Sudan

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ABSTRACT

Wind speed datasets are used to evaluate wind resources and energy production of wind farms. In locations where measured data are not available, reanalysis and analysis datasets can be used as an alternative to assess wind resources. This study evaluated the accuracy of wind speed data collected from reanalysis and analysis datasets against mast-measured data between 1975 and 1985 in Sudan, using monthly statistical analyses. Three bias correction methods, based on Measure-Correlate-Predict (MCP) and Linear Adaptation (LA1 and LA2), were applied to determine the original wind speed. The results indicate that LA1 outperformed MCP and LA2. Furthermore, the Weibull distribution function was employed to analyze the wind speed characteristics. In addition, wind power density was calculated using data from different sources. The findings show that although the wind power potential of the chosen locations is not suitable for large wind turbines, wind power can still be exploited with small wind turbines. Consequently, this study introduces a wind energy roadmap to attract investors in clean energy for sustainable development in Sudan, address energy problems, and meet domestic demands. The study also identifies the most important grid datasets for assessing the country's wind potential, enhancing the accuracy of assessments for investors and policymakers.

Keywords-Sudan; bias correction methods; mast measurement; reanalysis and analysis datasets; wind energy potential

I. INTRODUCTION

Energy plays a crucial role in driving economic growth, whereas its scarcity can negatively affect developing countries such as Sudan [1-2]. Increasing energy demands, consumption of fossil fuels, global warming, and climate change necessitate the transition from conventional to renewable energy sources [3]. Not only does the use of renewable energy improve energy security, but it also fosters sustainable development [4]. Renewable energy, a vital component of the energy mix, offers cost-effective and environmentally friendly solutions, reducing dependence on fossil fuels [5]. This shift towards clean energy addresses environmental concerns and supports sustainable development for future generations [6]. Wind energy is the second largest source of renewable energy worldwide and plays a crucial role in sustainable and economic energy generation [7-8]. Wind speed data are significant to assess the potential of wind energy and optimize the design and layout of wind farms for maximum energy production [9]. Therefore, accurate and consistent wind speed data is essential for informed decision-making, ensuring the economic viability and efficiency of wind energy projects.

A. Literature Review on Reanalysis and Analysis of Datasets

In developing countries such as Sudan, the scarcity of wind speed data requires alternative sources for conducting preliminary wind resource evaluations. One of the primary issues in determining wind potential at a site or region is the long-term availability of accurate and uniform datasets [10-11]. This is not necessarily true for meteorological measurement stations, which may show discontinuities in data records due to equipment inefficiencies and performance, particularly in extreme climate conditions. Therefore, satellite data, including reanalysis or analysis data, become vital for the assessment of the wind energy potential [10]. Despite their value, it is important to recognize that satellite data may contain errors in estimations [10-11]. Meteorological prediction departments around the world offer satellite datasets as an alternative form of meteorological data. An assimilation scheme and a numerical weather prediction model are part of the data integration system that processes satellite data. Numerous sources, including satellites, buoys, aircraft, and ground surface stations, have provided historical weather data that this system integrates.

Reanalysis and analysis of datasets on a broad scale have gained attention as a competitive substitute for measured data obtained at meteorological stations in the field of wind resource evaluation, due to its ability to cover huge regions at many timescales. Numerous studies have used satellite databases to evaluate the wind energy potential in different places [10-30]. For example, in [10], the wind energy potential in Libya's coastal agricultural regions was assessed using TerraClimate, ERA5, ERA5-Land, MERRA-2, and CFSR. In [11], measured data from 2009 to 2018 were utilized to examine the reliability of the ERA5 dataset at three windy locations in the southwest of the Algerian Sahara. In [12], the accuracies of ERA-Interim, JRA-55, CFS, and MERRA-2 were assessed in the northern hemisphere employing measured wind speed. In [13], a NASA dataset was put into service to assess the wind energy potential of three coastal cities in Cameroon. As a result, the review of previous studies highlights the importance of carefully considering the accuracy of the data when deploying satellite-based wind speed datasets for wind energy evaluations.

B. Literature Review on Wind Resource Assessment in Sudan

Sudan is one of the largest countries in Africa. Fossil fuels currently supply 92% of Sudan's energy production, while hydropower provides the remaining 8% of the country's power needs. Sudan has six dams that use the waters of the Nile to produce energy. In addition, there are three thermal power plants, Umm Dabakir in the south and Garria and Bahri in the north. In general, the total power generation capacity of the whole country is estimated to be 4,000 MW. However, with a capacity of approximately 1,820 MW, the power generation ability falls short of this potential. The mean amount of electricity consumed in Sudan is 4,500MW, which meets all the needs of industrial and residential customers. Additionally, population expansion and the ongoing need for a variety of new appliances contribute to increasing electricity usage, according to the International Energy Agency (IEA). Sudan has been suffering from an electricity crisis for many years. According to [2], about 60% of people do not have access to electricity. The country is increasingly requiring more power and the available supply has difficulty keeping up with this demand [31]. The country's outdated electrical infrastructure is deteriorating, there is a lack of investment in the electricity industry, and climate change negatively affects hydropower generation, exacerbating the problem [31]. The country's dependence on the expensive maintenance and operation of diesel generators is a direct effect of the power crisis [32]. Many Sudanese homes and businesses cannot purchase electricity due to its high cost.

The Sudanese government has recognized the value of renewable energy in addressing the country's electrical issues [33]. Wind energy is an alternative energy source that has gained popularity in recent years. Sudan has significant wind resources that could be used to generate electricity, especially in the northeast and eastern parts of the country [34]. The Global Wind Atlas published by the World Bank indicates that the typical wind power density at a 50-meter altitude ranges between 75-830 W/m^2. In Sudan, there have been recent attempts to increase wind energy usage. According to a government goal, by 2023, the country's electrical mix should contain 20% more renewable energy [35]. Furthermore, wind power systems can act as a substitute to supply electrical power needs and reduce CO_2 emissions [36]. In [37], it was stated that more than half of Sudan's land offers favorable conditions for the installation of wind farms. According to [38], most of Sudan is not suitable for small-scale wind-solar hybrid systems. In [39], it was concluded that wind energy could be an alternative option to reduce Sudan's energy production from fossil fuels. In [40], the mean wind speed in more than 50% of Sudan was reported to vary between 4.5 and 6 m/s, which is an appropriate speed range for wind power generation. Furthermore, several studies have proposed that wind energy can help solve the electricity crisis in the country [41-50]. In [41], it was shown that a small-scale wind power system would be more financialy beneficial for remote rural areas.

C. Importance of the Study

Sudan suffers from an electricity crisis characterized by chronic electricity shortages and a weakening power sector, which has adverse effects on businesses, healthcare facilities, and households, affecting daily life and hindering development efforts. To address the electricity crisis, Sudan needs significant investments to promote renewable energy sources, such as wind energy, and implement energy efficiency measures to ensure a reliable and sustainable electricity supply. Most of the previous studies on wind energy evaluation in Sudan used data from the NASA database. However, only the studies in [42-45] and [50] employed measured data to determine the country's wind energy potential. This study aims to improve and evaluate the accuracy and reliability of four satellite-based wind energy sources by comparing them with measured data collected from eight locations in Sudan. Bias correction methods are adopted to reduce the bias of satellite-derived wind energy products. This evaluation is critical before deploying these data sources for wind potential evaluations and wind farm development. The measured data were collected from [42]. Additionally, statistical analysis of observed data and satellite-based wind energy outputs is performed implementing the two-parameter

Weibull distribution function, both before and after applying bias correction approaches. Moreover, an assessment of the Wind Power Density (WPD) is performed to evaluate the wind power potential of the country. Engaging data from several sources, this study offers a novel approach to decision-making in Sudan's first stages of wind farm development. This all-inclusive strategy closes a significant research gap and offers insightful information to potential wind farm investors in the country.

II. MATERIALS

A. Study Area

This study focuses on the eight sites listed in Table I, which were chosen due to the availability of measured data for the period 1975–1985.

B. Mast-Measured Data

The mean monthly wind speed data used in this analysis were taken from [42]. These wind data were obtained from the Meteorological Department of Khartoum, Sudan. These wind speed data were gathered between 1975 and 1985 at a height of 10 m.

TABLE I. INFORMATION OF THE SELECTED LOCATIONS

Location number	Location name	Latitude [°N]	Longitude [°E]	Elevation [m]
L#1	Atbara	17.70	34.01	358
L#2	Shendi	16.67	33.45	364
L#3	Aroma	15.81	36.14	443
L#4	Khartoum	15.50	32.56	387
L#5	Kassla	15.46	36.40	505
L#6	El Showak	14.40	35.87	516
L#7	Wad Madani	14.39	33.54	412
L#8	E1 Gadarif	14.02	35.37	598

C. Reanalysis and Analysis of Dataset

Reanalysis and analysis of datasets include large-scale meteorological data produced by sophisticated data assimilation methods [51]. These datasets are produced by combining many observational sources utilizing advanced mathematical models, including observations from weather stations, satellite data, and other relevant inputs [2, 8, 10]. This study chose four datasets, ERA5, AgERA5, TerraClimate, and NASA, based on their high spatial resolution, coverage domain, and periods of availability, as observed in Table II.

TABLE II. MAIN CHARACTERISTICS OF THE SELECTED SATELLITE DATABASE USED IN THE STUDY

Sources	Description/Full name of the dataset	Resolution	Period	Spatial extent
ERA5	Fifth-generation reanalysis product of the European Centre for Medium-Range Weather Forecasts	0.05°/1 d	1979–present	Global
AgERA5	Daily surface meteorological data for 1979-present is input for agriculture and agro-ecological studies. It is based on the hourly ECMWF ERA5 data at the surface level.	0.1° × 0.1°	1979–present	Global
TerraClimate	Global gridded dataset of meteorological and water balance for global terrestrial surfaces	0.500°×0.625°	1958- present	Global
NASA	NASA/Forecasting of World Energy Resources (NASA/POWER)	0.05° × 0.05°	1981–present	Global

III. METHODS

A. Bias Correction Methods

The estimated wind speed values from datasets may contain errors due to inadequate parameterization techniques, leading to either overestimation or underestimation depending on data assimilation. This discrepancy, known as bias, often arises from locally dominant atmospheric components. To improve accuracy, bias correction methods can be applied deploying on-site measured wind speed data. These methods help mitigate bias impact, enhancing the overall reliability of wind speed estimates. Based on [51-52], Measure-Correlate-Predict (MCP) and Linear Adaptation (LA) are commonly employed to reduce the bias of model-derived data.

1) Measure-Correlate-Predict (MCP)

The bias in the estimated v, using measured v, can be reduced by finding a correction or scaling factor adopting the MCP method. The method utilized for bias correction, known as ratio bias correction [24], is mathematically represented in (1). The scaling factor is calculated by dividing the mean of measured v ($\overline{v_m}$) by the mean of estimated v ($\overline{v_e}$), and the scaling factor is multiplied by the estimated v data to get corrected v data (v_{ec}).

$$v_{ec,i} = \frac{\overline{v_m}}{\overline{v_e}} \times v_{e,i} \quad (1)$$

2) Linear-Adaptation (LA)

The bias correction by LA is another method to correct the estimated value of wind speed. The line of best fit between measured and estimated v is developed using (2) and then subtracted from the $v_e = v_m$ line to get (3). It should be noted that v_{en} represents the new estimated v with negligible bias.

$$v_{e,i} = m_1 v_{m,i} + c_1 \quad (2)$$

$$v_{en,i} = V_{e,i} - \left[(m_1 - 1)v_{m,i} + c_1\right] \quad (3)$$

Furthermore, the correction performed based on mast measurements can be extended to non-overlapping years by developing a linear fit between new estimated v data (v_{en}) and estimated v (v_e) as in (5) to get the slope and intercept. Equation (6) is employed to find a time series of corrected v data. This bias correction method is referred to as LA1.

$$v_{en,i} = m_2 v_{e,i} + c_2 \quad (4)$$

$$v_{ec,i} = m_2 v_{e,i} + c_2 \quad (5)$$

Moreover, bias correction based on on-site mast measurements can be accomplished by establishing a linear relationship between the measured and estimated wind speed, represented in (6). The slope and gradient of the best-fit line from this relationship are then deployed to derive the corrected time series using (7). This specific approach of bias correction utilizing linear adaptation is denoted as LA2.

$$v_{m,i} = mv_{e,i} + c \tag{6}$$

$$v_{ec,i} = mv_{e,i} + c \tag{7}$$

B. Statistical Indices

The performance of these datasets is assessed using statistical metrics like Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), as outlined in (8-10).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(a_{a,i}-a_{p,i})^2}{\sum_{i=1}^{n}(a_{p,i}-a_{a,ave})^2} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|a_{a,i} - a_{p,i}\right| \tag{10}$$

where n is the number of data, $a_{p,i}$ is the predicted value, $a_{a,i}$ is the actual value, $a_{a,ave}$ is the average actual value and i is the number of input variables.

C. Weibull Distribution Function and Wind Power Density

The Weibull distribution is the most common among the probability distributions employed in wind energy. This statistical model represents the pattern of wind speed data well and is adaptable and flexible. The probability density function $f(v)$ and cumulative distribution function $F(v)$, which are given in (11) and (12), respectively, are characteristics of the Weibull distribution [53]. The curve is defined by two parameters: the scale parameter c affects the mean wind speed, which indicates the typical wind speed at the site, and the form parameter k determines the curve's peak or spread.

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right], v > 0, k > 0, c > 0 \tag{11}$$

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right], v > 0, k > 0, c > 0 \tag{12}$$

In this study, the Maximum Likelihood Method (MLM) was selected due to its widely acknowledged efficiency. Using MLM, the parameters k and c of the Weibull distribution are estimated as follows [54]:

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{1}{n}\sum_{i=1}^{n} \ln v_i\right] \tag{13}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right) \tag{14}$$

Equation (12) involves numerical solving for the parameter k, and in this study, the bisection method was employed for solving (14).

D. Wind Power Density (WPD)

WPD is a crucial metric to assess the potential of wind resources and estimate the amount of wind energy that is accessible at particular locations [55]. This parameter is essential for evaluating wind turbine power and identifying the best kind of turbine for a particular location [56]. Equation (15) is used to calculate the WPD in W/m^2 based on wind speed data. Equation (16) can also be utilized to calculate WPD based on the Weibull distribution [55, 57].

$$\frac{\bar{P}}{A} = \frac{1}{2}\rho\bar{v}^3 \tag{15}$$

$$\frac{P}{A} = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) \tag{16}$$

where v_i is the measured/observed wind speed (m/s), n is the sample size of the wind speed data, and ρ denotes the air density (kg/m^3). The standard air density is taken to be $\rho = 1.225$ kg/m^3.

IV. RESULTS AND DISCUSSION

A. Descriptive Statistics of Mast Measurement and Estimated Data before using Bias Correction Methods

Figure 1 presents the descriptive statistics of wind speed data, including the mean, standard deviation, minimum, and maximum for all regions.

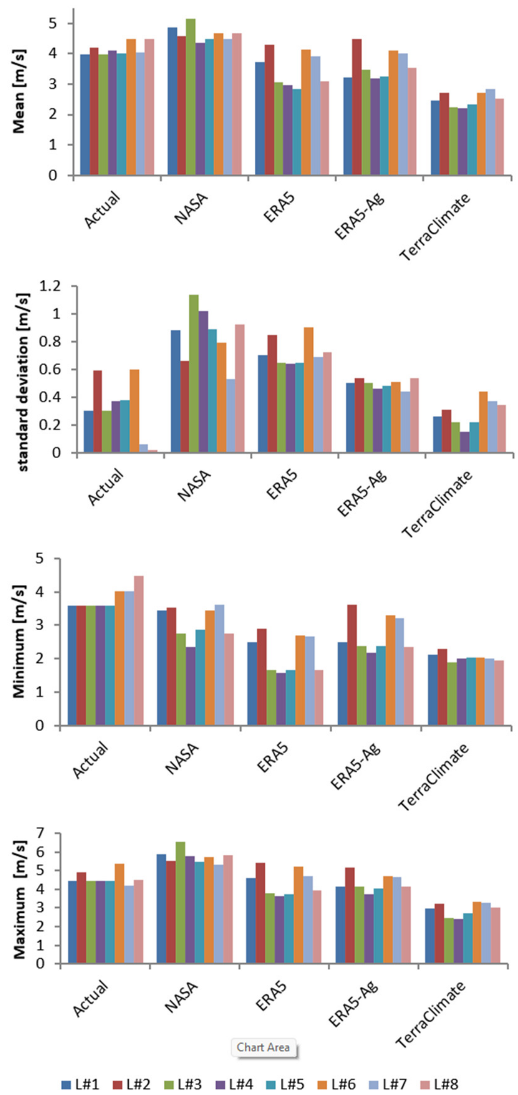

Fig. 1. Descriptive statistics of wind speed data for all locations before using bias correction methods.

Focusing on the mast-measured data, the mean wind speed ranged from 3.99 to 4.48 m/s. The maximum value of the mean monthly wind speed was recorded in Wad Madani, while the minimum value was found in Aroma and El Gadarif. Moreover, *CV* is a statistical measure that represents the relative variability or dispersion of a dataset compared to its mean. *CV* was found to be moderately low, ranging from 0.39 to 13.09%, which means that the wind speed data for all regions demonstrate relatively low variability compared to their respective mean values. On the other hand, when considering the satellite database, the mean wind speed ranges between 2.47 and 4.78 m/s for Aroma, 2.72 and 4.59 m/s for Atbara, 2.25 and 5.16 m/s for El Gadarif, 2.22 and 4.36 m/s for El Showak, 2.33 and 4.49 m/s for Kassala, 2.71 and 4.66 m/s for Khartoum, 2.83 and 4.50 m/s for Shendi, and 2.53 and 4.66 m/s for Wad Madani. Notably, the maximum and minimum wind speed values were obtained from NASA and TerraClimate datasets, respectively. The mean values collected from ERA5, NASA, and EAR5-Ag were found to be close to the mast-measured data.

B. *Statistical Analysis before using Bias Correction Methods*

Figure 2 depicts the R^2, MAE, and RMSE statistical parameters for the wind data, by comparing estimated datasets with the measured data for all locations.

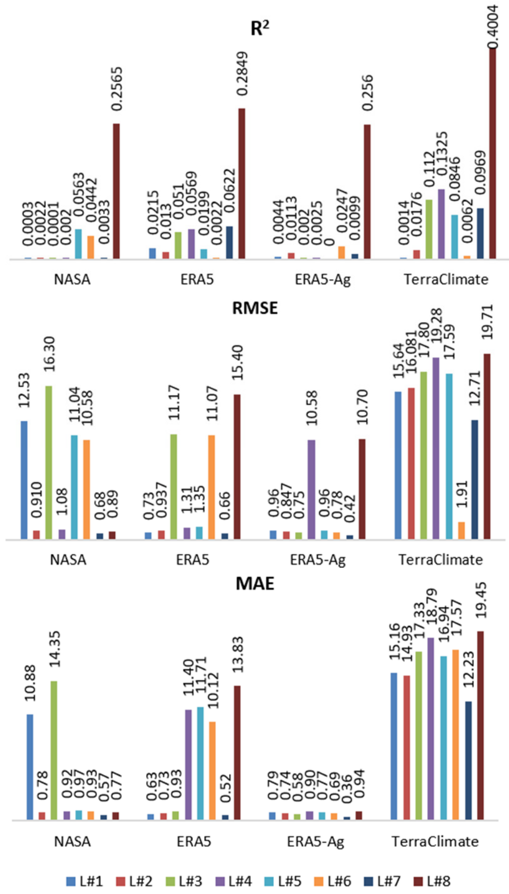

Fig. 2. Statistical parameters for wind speed using monthly mean wind speed.

R^2 ranges from 0 to 1, and as reported in [58], an acceptable R^2 value is typically considered to be higher than 0.5. Figure 2 exhibits that R^2 is within the range of 0.00-0.400, suggesting that the dataset does not fit the data well and that there is a significant amount of unexplained variability or error in the estimation of wind speed data. Furthermore, RMSE is employed to measure the level of agreement between observed and estimated data. An RMSE value of 0 indicates a perfect match between the observed and estimated values, and increasing RMSE values indicate a progressively poorer match. The analysis reveals that the RMSE varied between 0.4242 and 1.9707 m/s. The minimum RMSE value was observed when using the EAR5-Ag dataset at Shendi. The maximum RMSE value was obtained when utilizing the TerraClimate dataset at Wad Madani. MSE is a statistical measure that quantifies the average squared difference between the actual and the estimated data. A lower MAE indicates better accuracy, as it represents smaller differences between the observed and estimated values. MAE ranged between 0.3593 and 1.9449m/s. and the lowest and highest values were recorded at Shendi and Wad Madani, respectively.

C. *Determination of Weibull Parameters and Wind Power Density before using Bias Correction Methods*

Figure 3 presents the Weibull distribution parameters for the chosen locations.

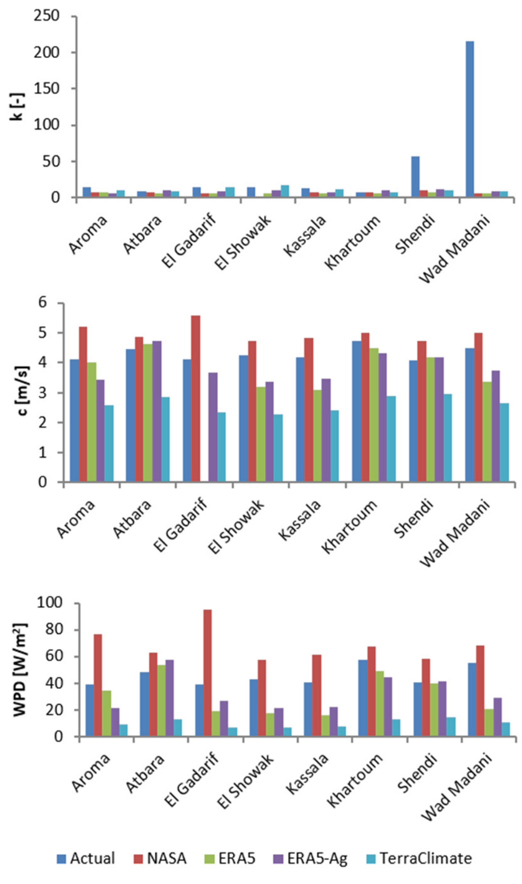

Fig. 3. Weibull parameters and wind power density for all locations.

These parameters were determined implementing the maximum likelihood approach based on the mean monthly wind speed data collected from different datasets. The k values were within the range of 7.9-216.00, 5.56-10.34, 5.73-7.81, 6.86-12.18, and 7.32-17.36 for the mast-measured, NASA, EAR5, EAR5-Ag, and TerraClimate data, respectively. The c value was found to range from 4.08 to 4.74 m/s for the mast-measured dataset. In contrast, c ranged from 2.29 to 5.59 m/s for all datasets. The maximum value of 5.59 m/s was obtained in El Gadarif, while the minimum value was recorded in El Showak. k varied between 7.9 and 216.00 for the mast-measured data, 5.56 and 10.34 for NASA data, 5.73 and 7.81 for EAR5 data, 6.86 and 12.18 for EAR5-Ag data, and 7.32 and 17.36 for TerraClimate data. WPD was calculated to evaluate the wind potential at the selected locations. In the measured dataset, WPD ranged from 39.31 to 57.83W/m^2 with an average value of 45.56 W/m^2. Based on wind power classification at 10 m height [10], the selected locations can be considered fair (WPD < 100W/m^2). As a result, in the designated zones, small-scale wind turbines are appropriate for utilizing the wind energy potential. Moreover, it can be deduced that wind energy potential in the designated sites can be collected by high-capacity wind turbines (MWs) that are 90 m or higher. Concentrating on NASA, ERA5, EAR5-Ag, and TerraClimate datasets, it was found that WPD varied between 6.77 W/m^2 (El Showak, TerreClimate dataset) and 94.77 W/m^2 (El Gadarif, NASA dataset). In this case, the wind energy potential in the selected locations is also categorized as fair. Therefore, small wind turbines are suitable for use in areas selected to exploit the potential of available wind energy.

D. Descriptive Statistics of Mast Measurement and Estimated Data after using Bias Correction Methods

The reduction in error in the reanalysis and analysis datasets was checked employing the bias correction methods MCP, LA1, and LA2. Using a variety of statistical indices, including R^2, RMSE, and MAE, the performance of the corrective reanalysis and analysis datasets was compared with the measured data to determine the optimal bias correction methods. The R^2 values were within the range of 0.00-0.400 deploying the MCP and LA2 methods, indicating that the data do not fit well and there is a significant amount of unexplained variability or error in the estimation of the wind speed data. When utilizing the LA1 method, the R^2 values were within the range of 0.0033-0.8792. Based on these findings, some of the R^2 values acquired from the LA1 method could fall below the acceptable range. Therefore, it can be concluded that the corrected data gathered from the TerraClimate dataset is the best option compared to the other datasets, especially for the regions of Aroma, Atbara, El Gadarif, El Showak, Kassala, and Khartoum. The TerraClimate dataset yielded higher R^2 values, indicating a better fit of the model to the observed wind speed data in these regions compared to the other datasets and methods applied. The LA1 method produced the lowest RMSE and MAE values compared to other methods. RMSE and MAE varied from 0.0129 to 1.512 m/s and from 0.0112 to 1.3829 m/s, accordingly. In this case, the ranges of RMSE and MAE values suggest that some datasets have a better fit, with smaller differences between the observed and predicted wind speed values, while others may exhibit larger discrepancies, resulting in higher RMSE values. Overall, the corrected data from TerraClimate is the best option compared to the other datasets.

Figure 4 portrays the R^2, RMSE, and MAE values for the optimum bias correction method, LA1. Figure 5 illustrates the descriptive statistics for wind speed data in all regions. Based on the mast-measured data, the mean wind speed ranged between 3.99 and 4.48 m/s. The maximum mean monthly wind speed was recorded in Wad Madani, while the minimum was found in Aroma and El Gadarif. Regarding the corrected satellite database, it was found that the mean wind speed was within the range of 3.99 and 4.48 m/s, indicating that the mean value of the corrected satellite database is close to the measured value for all selected locations. Additionally, the findings demonstrated that the standard deviation, minimum, and maximum values of the corrected wind speed satellite database are close to the measured value for all the selected locations. This agreement between the corrected satellite data and the measured values demonstrates that the correction process was effective in producing reliable and accurate wind speed estimates for all the selected locations, boosting confidence in using them for further analysis and decision-making related to wind energy projects and other applications.

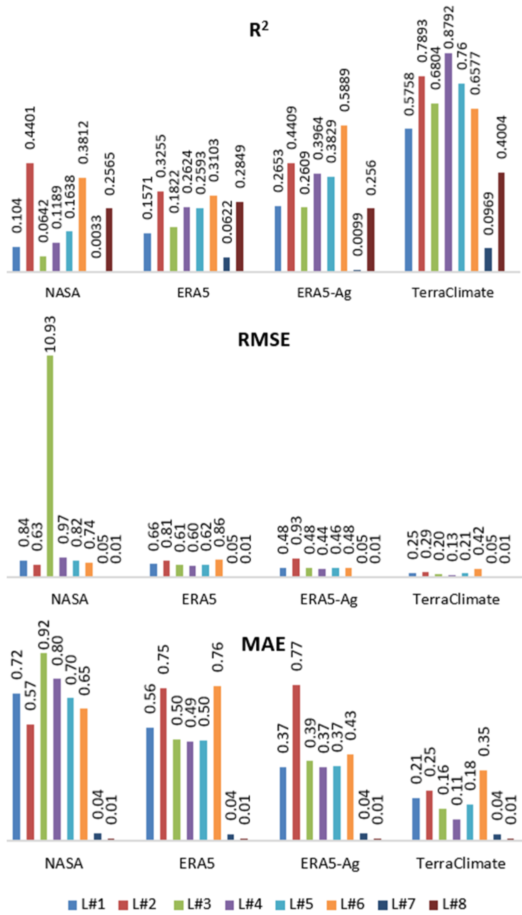

Fig. 4. Statistical parameters for wind speed using monthly mean wind speed.

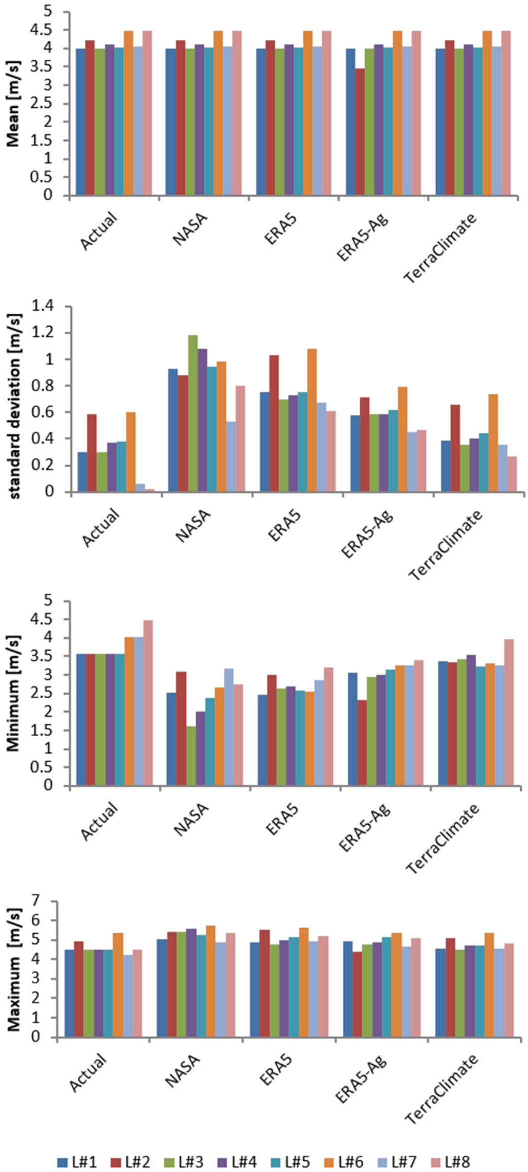

Fig. 5. Descriptive statistics of wind speed data for all locations after using bias correction methods.

E. Determination of Weibull Parameters and Wind Power Density after Using Bias Correction Methods

Figure 6 displays the Weibull distribution parameters for all locations, calculated implementing the maximum likelihood approach. WPD values were determined based on these parameters. The k values were found to fall within the following ranges: 7.99-216.00 for mast-measured data, 4.31-9.34 for NASA data, 4.85-10.07 for EAR5 data, 5.76-13.77 for EAR5-Ag data, and 4.14-4.77 for TerraClimate data. Additionally, for the mast-measured dataset, c ranged from 4.08 to 4.74 m/s. However, for all datasets utilized, c ranged from 3.72 to 4.86 m/s. The maximum c value of 4.86 m/s was obtained in Khartoum, while the minimum value was recorded in Atbara. In the mast-measured dataset, WPD ranged from 39.31 to 57.83W/m^2, with an average value of 45.56 W/m^2. The wind energy generation potential of the sites is classified according to the average WPD values. Based on the classification of wind power at 10 m height, the selected locations can be considered poor (WPD < 100 W/m^2). Therefore, small-scale wind turbines are suitable to be used in selected regions to exploit the available wind energy potential. Furthermore, it can be concluded that high-capacity wind turbines with a height of 90 m and higher can be suitable for gathering the wind energy potential in the selected locations. This is investigated employing the power-law model, i.e., the collected data at 10 m height is synthesized to the 90 m height, which is the height of most 1 MW or above wind turbines. Based on NASA, ERA5, EAR5-Ag, and TerraClimate datasets, WPD was found to vary between 6.77 W/m^2 (El Showak, TerreClimate dataset) and 94.77W/m^2 (El Gadarif, NASA dataset). In this case, the wind energy potential in the selected locations is also classified as fair. Therefore, small wind turbines are suitable for use in selected areas to exploit the potential of available wind energy.

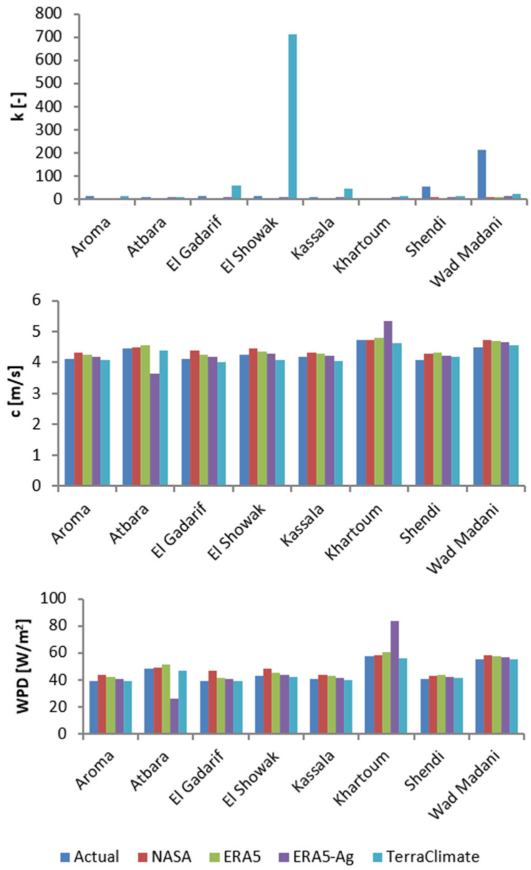

Fig. 6. Weibull parameters and wind power density for all locations.

V. CONCLUSIONS

Due to the unavailability of historically measured wind data in the country, assessing and forecasting next-generation wind resources becomes more important when using data from satellite observations and different reanalyses. These alternate data sources are essential resources for assessing wind energy potential and financial viability in certain areas. However, it is important to validate the suitability of these datasets for specific regions by comparing them with the available mast-measured data. Therefore, the reanalysis and analysis estimates of wind speed data were evaluated and compared to the mean monthly measured data collected from eight locations in Sudan. In general, ERA5-Ag performs better than other datasets. The original wind speed was modified employing three bias correction techniques, MCP, LA1, and LA2. According to the statistical criteria applied, LA1 performed better than MCP and LA2.

Especially in developing countries, such as Sudan, corrected wind speed data from reanalysis and analysis datasets can be utilized in the early assessment of wind resources. Wind speed characteristics were analyzed deploying the two-parameter Weibull distribution, whose parameters were used to determine the annual WPD values at the chosen places. The results revealed that the selected locations can be categorized as fair based on wind power at a height of 10 m. Therefore, small-scale wind turbines are suitable for harnessing the wind energy potential at the selected locations. Furthermore, it can be concluded that high-capacity wind turbines of 90 m or more height can exploit the wind energy potential. This study presents a wind energy road map with the aim of attracting investors interested in clean energy technology to mitigate the impact of global warming and achieve sustainable technological development in the country. In the future, onshore wind farms should be the focus of technical and economic analysis based on a variety of data sources, focusing on the investment payback period, the selection of the most suitable turbines, and the present value of the electricity production cost.

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