# Wind Resource Evaluation in Libya: A Comparative Study of Ten Numerical Methods for the Estimation of Weibull Parameters using Multiple Datasets

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**ABSTRACT**

**This study examines Libya's pursuit of sustainable wind energy solutions, using nine sites with mast measurements before the 2011 civil war and six gridded datasets, including CFSR, ERA5, EAR5-Ag, MERRA2, EAR5-Land, and TerraClimate. Employing the Weibull distribution function with ten methods, the empirical method of Justus proved to be optimal for calculating Weibull parameters across datasets. Al Bayda and Darnah exhibit substantial wind power potential (116.80-123.00 W/m²) based on MERRA2 data, making them ideal for large-scale wind turbine deployment. Furthermore, the results showed that wind power density was estimated below 100 W/m² for all selected locations according to CFSR, ERA5, EAR5-Ag, EAR5-Land, and TerraClimate. This study emphasizes the need for new mast measurements to refine dataset selection, which is crucial for accurate assessments and large wind farm planning. Consequently, this study provides key insights into optimizing wind energy utilization in diverse Libyan regions, addressing both the potential and the challenges in sustainable energy development.**

***Keywords-Libya; wind energy potential; Weibull distribution; numerical estimation method; measured data; gridded datasets***

## I. INTRODUCTION

Energy is an essential catalyst for promoting economic growth and facilitating industrialization [1]. The global energy supply chain mainly relies on fossil fuels and plays an indispensable role in meeting global energy needs [2]. Therefore, renewable energy can be considered as an alternative solution to the energy crisis due to the limited fossil fuel reserves and their environmental consequences [3]. Renewable sources such as wind energy are rapidly developing and becoming more economically competitive [4]. Wind energy is a promising alternative that has enormous global capacity and is poised to transform the energy landscape, offering abundant and sustainable power for the future [5-6]. Wind energy's first advantage is its global availability. Certain countries with favorable geography have higher wind capabilities [7]. The second advantage is the high energy output achievable with commercial wind turbines, now reaching multi-megawatt capacities [8]. In general, understanding local wind characteristics is crucial for efficient planning and construction of wind power plants [9]. Therefore, the initial stage of assessing wind power potential includes utilizing an anemometer to measure wind speed data at the specific location of the intended wind power plant [10-11]. However, in certain cases, direct wind speed measurement may be challenging due to factors, namely budget constraints, logistical difficulties, or lack of available monitoring infrastructure. In such cases, gridded datasets emerge as an alternative data source to evaluate wind speed [12]. Gridded datasets are spatial datasets that provide information on various meteorological parameters across a grid of geographic points [13]. These datasets are often generated by integrating observational data, satellite imagery, and numerical models [12-13]. Moreover, choosing suitable gridded datasets for wind speed assessments is a challenge. Accuracy depends on input data quality, spatial resolution, and interpolation methods. Inaccuracies can compromise the success of wind power projects, highlighting the need for careful consideration and validation. Several studies have investigated the challenges and opportunities associated with the use of gridded datasets to assess wind power prospects [14-19]. For example, in [14], it was demonstrated that the ERA5 wind speed data were closely aligned with ground measurements, indicating higher accuracy and reliability than MERRA. In [16], the ERA wind data were validated as valuable for accurately estimating the wind potential. In [17], the importance of higher-resolution wind speed data was emphasized for local and global site prioritization. In [18], the ERA5 data were proved to be reliable for offshore and onshore locations. In [19], a stronger agreement was observed for the ERA5 data with onshore sites, compared to MERRA2.

As a continuation of [20-25], this study aimed to identify a suitable gridded dataset, from CFSR, ERA5, EAR5-Ag, MERRA2, EAR5-Land, and TerraClimate, for evaluating the wind energy potential in Libya and to find the best numerical method (Least Squares Regression Method (LSRM), Energy Pattern Factor Method (EPFM), Empirical Method of Lysen (EML), Empirical Method of Justus (EMJ), Method of Moments (MM), Maximum Likelihood Method (MLM), Modified Maximum Likelihood Method (MMLM), Mean Standard Deviation Method (MSDM), Moment Iteration Method (MIM), and Empirical Method of Mabchour (EMM)) to determine the parameters of the Weibull distribution function, which is used to estimate the wind energy potential at a given location. A review of previous studies [22], NASA datasets, and wind speed measurements collected before 2011 were employed for the evaluation of wind energy in Libya. As far as is known, this is the first study to establish a methodology for the decision-making process in the initial stages of a wind farm investment in Libya engaging data collected from multiple sources.

## II. METHODS

The main objective of this study is to estimate the wind energy potential of nine selected sites in Libya using various datasets. Figure 1 illustrates a flowchart of the overall research methodology adopted.

### A. Measured Wind Speed Data

The most reliable wind resource data are collected from weather station masts, utilizing an anemometer to measure the wind speed. For this study, mean monthly wind data from nine stations were collected for the period 1990-2010. In recent years, the Civil War in Libya resulted in a scarcity of the instruments required for wind speed measurement. Detailed geographic information for these selected stations can be found in Table I.

TABLE I. DETAILS OF THE SELECTED LOCATIONS

| Location | Latitude [°N] | Longitude [°E] | Altitude [m] | Period |
|---|---|---|---|---|
| Tripoli | 32.892 | 13.173 | 81 | 1981-2010 |
| Nalut | 31.874 | 10.979 | 568 | 1981-2010 |
| Espiaa | 32.537 | 13.177 | 73 | 1993-2009 |
| Al bayda | 32.754 | 21.757 | 626 | 2000-2009 |
| Benghazi | 32.129 | 20.082 | 2 | 2000-2009 |
| Al-kufrah | 24.199 | 23.293 | 394 | 2000-2009 |
| Misratah | 32.375 | 15.090 | 8 | 1996-2010 |
| Sabha | 27.033 | 14.432 | 426 | 1995-2010 |
| Darnah | 32.766 | 22.624 | 48 | 2000-2009 |

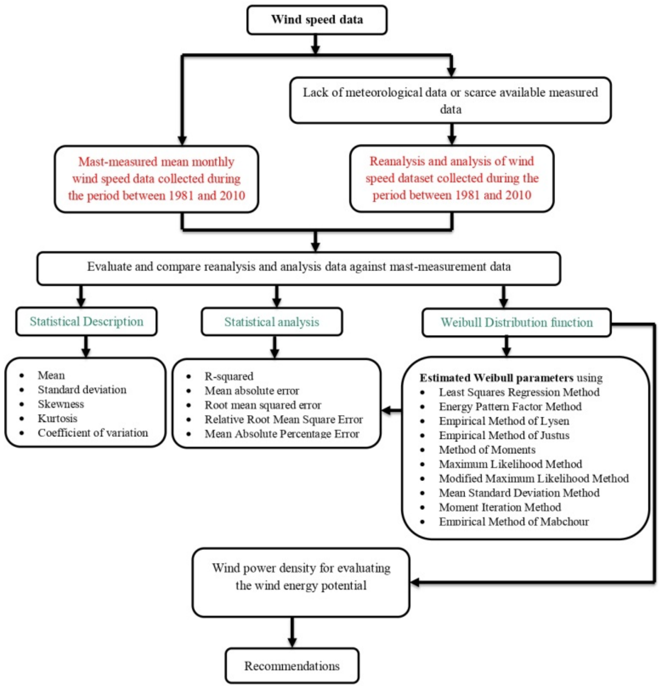


Fig. 1. Research methodology.

### B. Reanalysis and Analysis of Wind Speed Dataset

In regions lacking measurement tools, it is vital to assess Satellite Products (SPs) thoroughly before using them for meteorological data [22]. This ensures the reliability and accuracy of service providers in specific areas. Dataset analysis and reanalysis involve creating comprehensive meteorological datasets, applying advanced data assimilation techniques, and combining various data sources, such as weather stations and satellite data [26-27]. These datasets are critical for assessing wind energy potential [12, 22]. This study chose six SPs based on high spatial resolution, coverage range, and availability periods (Table II). The performance of these datasets was evaluated using statistical metrics, like the coefficient of determination ($R^2$), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Relative Root Mean Square Error (RRMSE), and Mean Absolute Percentage Error (MAPE), as outlined in (1)-(5).

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

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|a_{a,i} - a_{p,i}\right| \tag{3}$$

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}\left(a_{p,i}\right)^2} \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{a_{a,i} - a_{p,i}}{a_{a,i}}\right| \times 100 \tag{5}$$

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.

TABLE II. INFORMATION OF USED SATELLITE PRODUCTS

| Product | Description | Resolution | Period |
|---|---|---|---|
| TerraClimate | Global gridded dataset of meteorological and water balance for global terrestrial surfaces | 0.042°× 0.042° | 1958-present |
| ERA5 | Fifth-generation reanalysis product of the European Centre for Medium-Range Weather Forecasts | 0.05°/1 d | 1979–present |
| ERA5-Land | ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis | 0.125°× 0.125° | 1963-present |
| ERA5-Ag | Agriculture-specific dataset of the ECMWF ERA5 | 0.1°× 0.1° | 1979–present |
| MERRA-2 | Second-generation Modern-ERA Retrospective Analysis for Research and Applications | 0.5°× 0.625° | 1981-present |
| CFSR | NCEP (NOAA NWS National Centers for Environmental Prediction) Climate Forecast System Reanalysis dataset | 1/5° | 1979-present |

## C. *Wind Speed Distribution*

Wind speed analysis is vital for designing and operating wind energy systems. The two-parameter Weibull (2p-W) distribution function is widely utilized to assess wind speed data, wind potential, and energy generation in a specific area [28]. It describes wind speed variation through the probability density function $f(v)$ and cumulative distribution function $F(v)$ [28-29].

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{6}$$

$$F(v) = 1 - exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{7}$$

where $v$ represents the wind speed, and $c$ and $k$ are the scale and shape parameters of the Weibull distribution function.

## D. *Estimation of Weibull Parameters*

Various methods have been proposed to estimate the $c$ and $k$ Weibull parameters [30-33]. In [30], energy pattern factor, mean standard deviation, and maximum likelihood were used to estimate the Weibull parameters by analyzing wind speed data in Iran. In [31], the empirical approach and wasp algorithm were employed for data in Pakistan, noting limited effectiveness in certain locations. In [32], the maximum likelihood and the modified maximum likelihood methods were found suitable to determine the Weibull parameters in Brazilian stations. In [33], the modified maximum likelihood method was the best for representing wind data in Northern Pakistan. This study utilized 10 numerical methods to estimate the Weibull distribution parameters, displayed in Table III.

TABLE III. METHODS USED FOR CALCULATING THE PARAMETERS OF 2P-W

| Method | Weibull distribution parameters |
|---|---|
| LSRM | $k = \frac{n\sum_1^n ln(v) \times ln[-ln\{1-F(v)\}]\sum_1^n ln(v)\sum_1^n ln[-ln\{1-F(v)\}]}{n\sum_1^n ln(v^2) - \{\sum_1^n ln(v)\}^2}$ ; $c = \left(\frac{1}{n}\sum_1^n v_i^k\right)^{1/k}$ |
| EPFM | $k = 1 + \frac{3.69}{EPF^2}$ ; $EPF = \frac{1}{\bar{v}^3}\left(\sum_{i=1}^{n}\frac{v_i^3}{N}\right)$ ; $c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)}$ ; $\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i$ |
| EML | $k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086}$ ; $c = \bar{v}\left(0.568 + \frac{0.433}{k}\right)$; $\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i$ |
| EMJ | $k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086}$ ; $c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)}$ ; $\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i$ |
| MM | $k = \left(\frac{0.9874\bar{v}}{\sigma}\right)^{1.0983}$ ; $c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)}$; $\sigma = c\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{1}{k}\right)\right]^{0.5}$ ; $\frac{\bar{v}^2}{\sigma^2} = \frac{\left\{\Gamma\left(1+\frac{1}{k}\right)\right\}^2}{\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{1}{k}\right)\right]^{0.5}}$ |
| MLM | $k = \left(\frac{\sum_1^n v_i^k ln(v_i)}{\sum_1^n v_i^k} - \frac{\sum_1^n ln(v_i)}{n}\right)^{-1}$ ; $c = \left(\frac{1}{n}\sum_1^n v_i^k\right)^{1/k}$ |
| MMLM | $k = \left(\frac{\sum_1^n v_i^k ln(v_i) f(v_i)}{\sum_1^n v_i^k f(v_i)} - \frac{\sum_1^n ln(v_i) f(v_i)}{f(v \geq 0)}\right)^{-1}$ ; $c = \left(\frac{1}{f(v \geq 0)}\sum_1^n v_i^k\right)^{1/k}$ |
| MSDM | $k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.806}$ ; $c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)}$ |
| MIM | $\frac{\bar{v}^2}{\sigma^2} = \frac{\left\{\Gamma\left(1+\frac{1}{k}\right)\right\}^2}{\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{1}{k}\right)\right]^{0.5}}$; $\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i$ ; $\sigma = c\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{1}{k}\right)\right]^{0.5}$ |
| EMM | $k = 1 + [0.483 \times (v_i - 2)]^{0.51}$ ; $c = \frac{\bar{v}}{\Gamma\left(1+\frac{1}{k}\right)}$ |

*E. Wind Potential Estimation*

Wind Power Density (WPD) is one of the most important indicators for designing a wind farm. WPD is used to assess the potential of wind resources at a particular location and can be determined by the Weibull two-parameter method [34]:

$$\frac{P}{A} = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right) \quad (8)$$

where $P$ represents the wind power, $p$ is air density ($p$ = 1.23 kg/m$^3$), $\bar{v}$ is the mean wind speed in m/s, $c$ is the scale parameter of the Weibull distribution function in m/s, and $k$ is the shape parameter of the Weibull distribution function. The wind energy potential is categorized according to the average WPD as exhibited in Table IV.

TABLE IV. WIND ENERGY POTENTIAL CLASSIFICATION

| Number | Power class | P (W/m$^2$) at 10 m | P (W/m$^2$) at 30 m |
|---|---|---|---|
| 1 | Poor | ≤100 | ≤160 |
| 2 | Marginal | ≤150 | ≤240 |
| 3 | Moderate | ≤200 | ≤320 |
| 4 | Good | ≤250 | ≤400 |
| 5 | Excellent | ≤300 | ≤480 |
| 6 | Excellent | ≤400 | ≤640 |
| 7 | Excellent | ≤1000 | ≤1600 |

## III. RESULTS

*A. Statistical Description of the Wind Speed Data Based on the Period of Mast Measurement Data*

Figure 2 summarizes the statistical details of the average monthly wind speed for all locations. It includes mean, Standard Deviation (*SD*), Coefficient of Variation (*CV*), Minimum (*Min.*), Maximum (*Max.*), Kurtosis (*K*), and Skewness (*S*).

*1) Mast Measurements*

The average monthly wind speeds range from 2.12 m/s (Espiaa) to 6.13 m/s (Benghazi). In general, the mean and *SD* values indicate consistent wind behavior. *CV* values range from 6.75% to 15.36%. A *CV* of 6.75% suggests a low variation around the mean, while 15.36% implies a slightly higher variation. The minimum wind speeds were 5.14 m/s in Darnah and 1.75 m/s in Espiaa, while the maximum was 6.91 m/s in Benghazi. Most locations showcase negatively skewed distributions, implying left-skewed data. *K* values range from -1.83 to 2.82, indicating differences in data flatness. A negative *K* suggests a slightly flatter distribution, while a positive *K* indicates heavier tails than normal distribution. Wind speeds vary between locations, but they demonstrate consistency with relatively low variation, left-skewed distributions, and varying degrees of flatness in their data distributions.

*2) CFSR*

The mean wind speed varied between 2.48 m/s in Al Bayda and 4.63 m/s in Misratah, indicating consistency in wind patterns. *CV* values ranged from 7.82% to 11.94%, showing relatively low to moderate variation around the mean. The dataset exhibited a minimum monthly wind speed of 2.08 m/s in Darnah and a maximum of 6.91 m/s in Misratah. The *S* values for Benghazi, Darnah, Espiaa, Misratah, and Nalut were negative, implying left-skewed distributions. Al Bayda, Al-Kufrah, Sabha, and Tripoli had right-skewed distributions. *K* values, ranging from -1.96 to 0.21, indicated varying degrees of flatness in the data distributions.

*3) EAR5*

The mean wind speed varied from 2.161 m/s (Espiaa) to 4.69 m/s (Benghazi). In general, the mean and *SD* values disclose consistent wind behavior. *CV* values ranged from 7.79% to 19.68%. The minimum monthly wind speed was recorded in Al Bayda (2.02 m/s) while the maximum was 5.78m/s in Benghazi. The *S* values were positive for all locations except Nalut, indicating right-skewed distributions. The *K* values, ranging from -1.95 to 1.14, revealed differences in the flatness of the data distributions.

*4) EAR5-Land*

The mean wind speed varied between 2.68 m/s (Al Bayda) and 4.47m/s (Misratah). In general, the mean and *SD* values suggest a high level of consistency in wind behavior. *CV* values, ranging from 9.47% to 19.89%, indicate moderate variability around the mean. A *CV* of 9.47% suggests relatively low variation, while 19.89% indicates slightly higher variability. Remarkably, minimum monthly wind speeds of 2.10 m/s and 3.68 m/s were observed in Al Bayda and Misratah, respectively, while the maximum monthly wind speed of 5.40 m/s was also recorded in Misratah. *S* values for most locations are positive, demonstrating right-skewed distributions. Additionally, *K* values ranged from -1.76 to 0.74.

*5) EAR5-Ag*

The mean wind speeds ranged from 3.73 m/s in Al-Kufrah to 4.60m/s in Benghazi. *CV* values ranged from 9.40% to 12.80%. Furthermore, Al-Kufrah had a minimum monthly wind speed of 3.044 m/s. On the other hand, Benghazi recorded the highest monthly wind speed of 5.20 m/s. The *S* values for most locations were negative, indicating left-skewed distributions. *K* values ranged from -2.11 to 0.50.

*6) MERRA2*

The MERRA2 dataset shows wind speeds ranging from 3.96 m/s (Al-Kufrah) to 5.75 m/s (Darnah), indicating consistent wind behavior. The *CV* values, ranging from 6.20 to 17.31%, suggest moderate variability around the mean. Al-Kufrah recorded a minimum monthly wind speed of 3.30 m/s, while Darnah had the highest monthly wind speed of 7.10 m/s. Most locations display right-skewed distributions based on positive *S* values. *K* values ranging from -1.42 to -0.07 indicate varying degrees of distribution flatness, with negative values suggesting slightly flatter distributions.

*7) TerraClimate*

The TerraClimate dataset illustrates wind speeds ranging from 3.23 m/s (Espiaa) to 5.15 m/s (Darnah). The mean and *SD* values indicate consistent wind behavior. *CV* values, ranging from 6.60% to 12.06%, suggest moderately low variability around the mean. Darnah and Espiaa had the minimum and maximum monthly wind speeds. Most locations exhibited right-skewed distributions with positive *S* values. *K* values, from -1.59 to -0.07, represent the data's flatness.

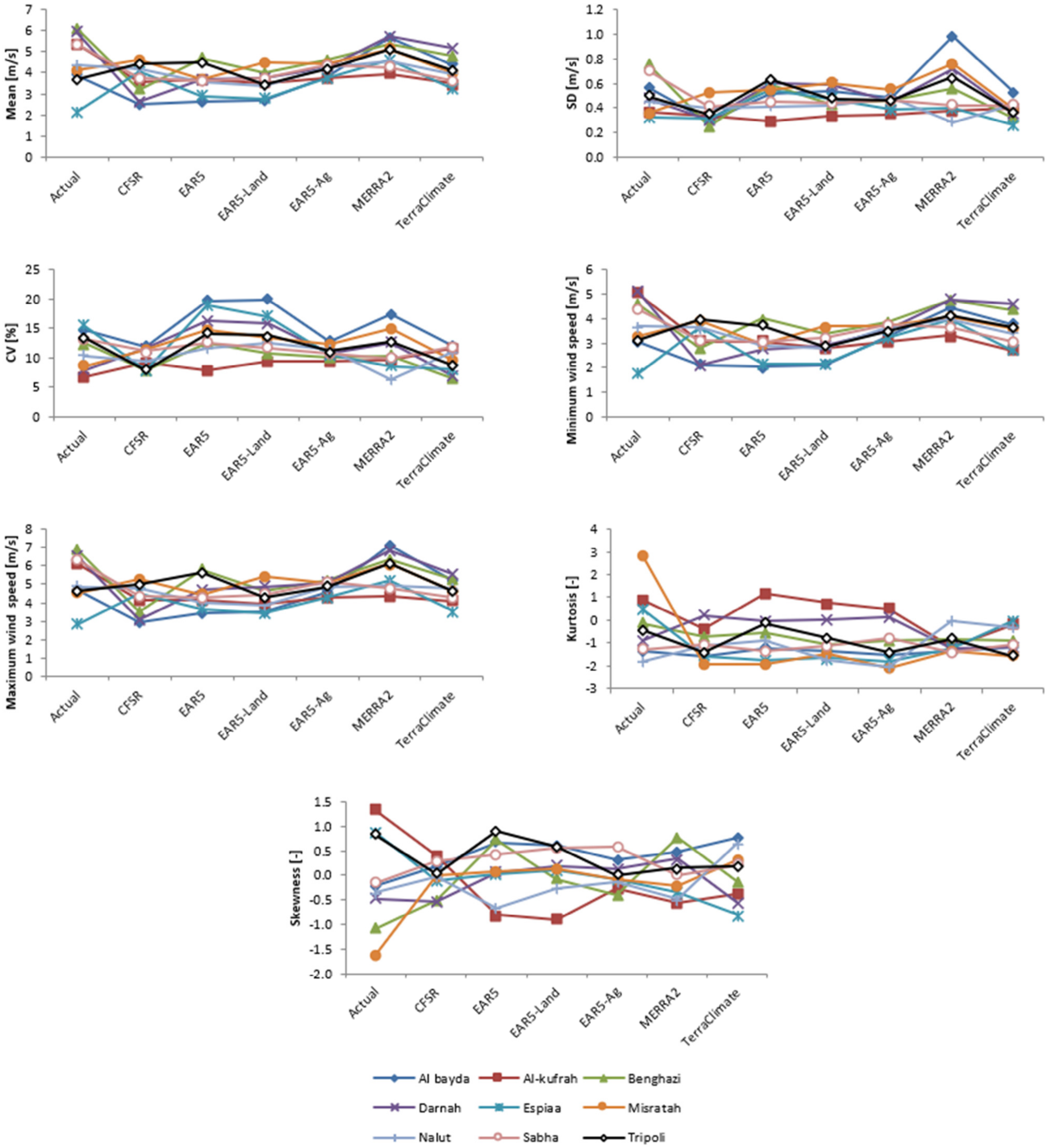


Fig. 2. Statistical description of average monthly wind speed values. Mean, SD, max. speed, curtosis, and skewness.

### B. *Best Satellite Products Based on the Period of Mast Measurement Data*

Figure 3 compares the measured and estimated data collected from SPs. This study used various statistical metrics to find the best SP for evaluating wind energy potential. The evaluation of the SPs' performance was based on $R^2$, which measures the degree of the linear relationship between observed and modeled values. The highest value of $R^2$ was found to be 0.9344 for the EAR5-Ag dataset in Nalut, while the minimum value of 0.00016 was obtained for the TerraClimate dataset in Misratah. Generally, $R^2$ is a statistical measure that falls within the 0 to 1 range and signifies the proportion of variance in observed data explained by a model. It is important to understand that higher $R^2$ values do not automatically indicate the superiority of one dataset over another.

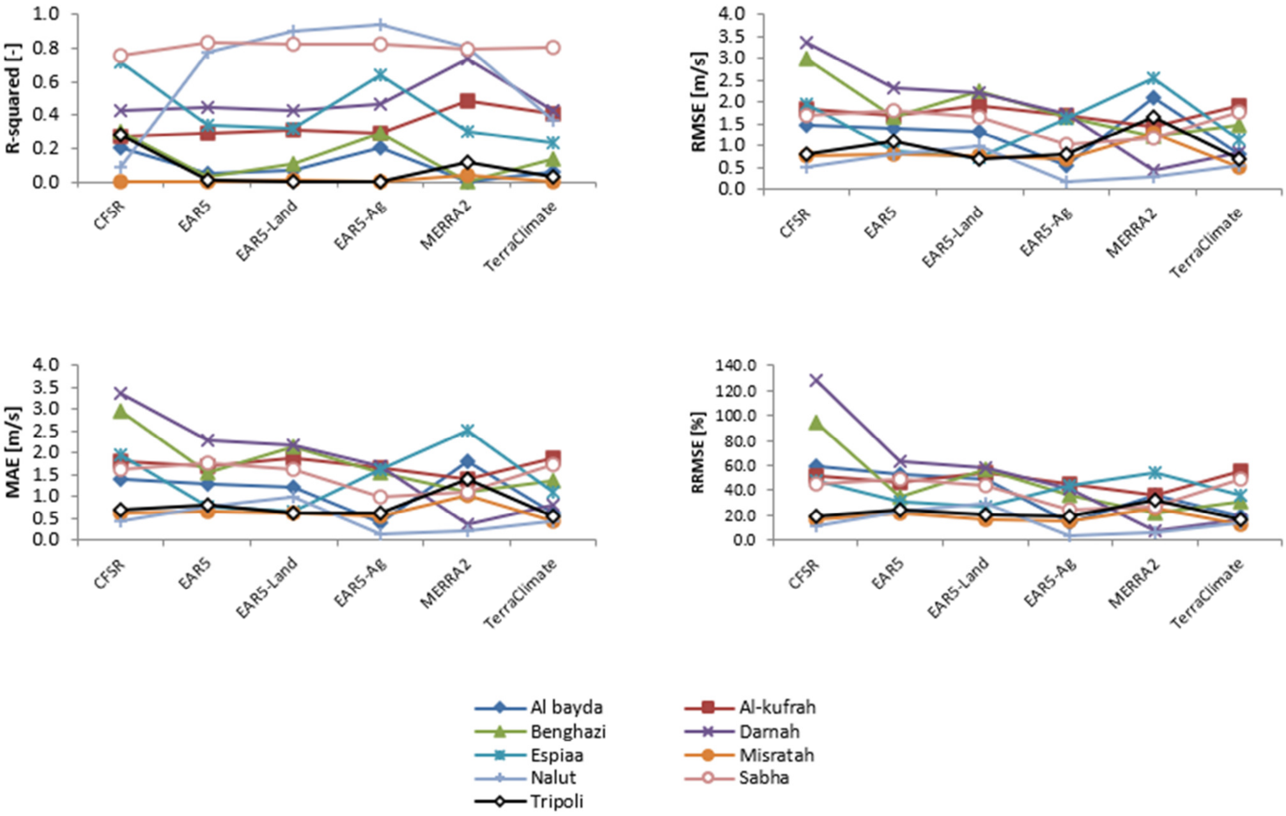


Fig. 3. Statistical description of average monthly wind speed values. $R^2$, RMSE, MAE, and RMSE (%).

Table V presents the SP ranking for evaluating the wind potential in the selected regions based on *RMSE*, *MAE*, and *RRMSE*. In general, *RMSE* is used to evaluate the accuracy of the estimated data, as it measures the average magnitude of the differences between the observed and estimated values. A zero *RMSE* signifies a perfect match between the observed and predicted data, signifying that the model predictions are precise. However, as *RMSE* increases, it denotes a progressively poorer match between the observed and predicted values, implying that the model's accuracy decreases. EAR5-Ag exhibited superior performance compared to other datasets for Al Bayda, Nalut, and Sabha. Furthermore, MERRA2 showed better performance compared to other datasets in Al-Kufrah, Benghazi, Darnah, Misratah, and Tripoli. EAR5-Land exhibitedf better performance compared to other datasets in Espiaa. In addition, *RRMSE* and *MAPE* were used to evaluate the SPs' performance. All SPs ranged above 30%, particularly for Al-Kufrah and Espiaa, implying that their performance can be considered poor. Based on *MAPE*, CFSR has a high *MAPE* compared to other SPs in Darnah, showing that the performance can be considered inaccurate. In Espiaa, the *MAPE* for TerraClimate, EAR5-Ag, CFSR, and MERRA2 was notably higher than 50% compared to other SPs. According to the performance rate of these products, the latter can be characterized as inaccurate estimates.

### *C. Weibull Distribution Function and Wind Power Density*

The parameters of the Weibull distribution were calculated using ten methods. Additionally, the WPD was computed to evaluate the wind potential for each selected location. Table VI lists the ranking of methods employed to estimate the WPD for evaluating the wind potential based on the percentage absolute error. Figure 3 depicts the WPD value for each location depending on the best approach. Based on the actual data, Benghazi and Darnah recorded the highest WPD values (141.52-148.26 W/m$^2$ and 129.09-131.15 W/m$^2$, respectively). It can be concluded that the wind power potential in both Benghazi and Darnah is quite promising, making these locations suitable for harnessing wind energy through large-scale wind turbines. Focusing on the MERRA2 dataset, the highest WPD values were observed in Al Bayda and Darnah, with WPD from 122.22 to 120.58 W/m$^2$ and from 116.80 to 123.00 W/m$^2$, respectively. These findings strongly suggest that both Al Bayda and Darnah possess significant wind power potential, making them excellent candidates for utilizing large-scale wind turbines to harness wind energy effectively. In contrast to the previously mentioned data, other datasets reveal that the WPD values in the region are less than 100 W/m$^2$, which can be categorized as poor. These low values signify that wind resources may not be suitable for the deployment of high-capacity wind turbines. However, there is still potential for utilizing wind energy in the regions using small-scale wind turbines.

TABLE V. SP RANKING PER AREA AND METRIC

| Location | The rank of SPs based on RMSE and MAE | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Al Bayda | EAR5-Ag | TerraClimate | EAR5-Land | EAR5 | CFSR | MERRA2 |
| Al-Kufrah | MERRA2 | EAR5-Ag | EAR5 | CFSR | EAR5-Land | TerraClimate |
| Benghazi | MERRA2 | TerraClimate | EAR5-Ag | EAR5 | EAR5-Land | CFSR |
| Darnah | MERRA2 | TerraClimate | EAR5-Ag | EAR5-Land | EAR5 | CFSR |
| Espiaa | EAR5-Land | EAR5 | TerraClimate | EAR5-Ag | CFSR | MERRA2 |
| Misratah | TerraClimate | EAR5-Ag | CFSR | EAR5-Land | EAR5 | MERRA2 |
| Nalut | EAR5-Ag | MERRA2 | CFSR | TerraClimate | EAR5 | EAR5-Land |
| Sabha | EAR5-Ag | MERRA2 | EAR5-Land | CFSR | TerraClimate | EAR5 |
| Tripoli | TerraClimate | EAR5-Ag | EAR5-Land | CFSR | EAR5 | MERRA2 |
| **Location** | **Rank of SPs based on RRMSE** | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Al bayda | EAR5-Ag | TerraClimate | EAR5-Land | EAR5 | CFSR | MERRA2 |
| Al-kufrah | MERRA2 | EAR5-Ag | EAR5 | CFSR | EAR5-Land | TerraClimate |
| Benghazi | MERRA2 | TerraClimate | EAR5-Ag | EAR5 | EAR5-Land | CFSR |
| Darnah | MERRA2 | TerraClimate | EAR5-Ag | EAR5-Land | EAR5 | CFSR |
| Espiaa | EAR5-Land | EAR5 | TerraClimate | EAR5-Ag | CFSR | MERRA2 |
| Misratah | TerraClimate | EAR5-Ag | CFSR | EAR5-Land | EAR5 | MERRA2 |
| Nalut | EAR5-Ag | MERRA2 | CFSR | TerraClimate | EAR5 | EAR5-Land |
| Sabha | EAR5-Ag | MERRA2 | EAR5-Land | CFSR | TerraClimate | EAR5 |
| Tripoli | TerraClimate | CFSR | EAR5-Ag | EAR5-Land | EAR5 | MERRA2 |
| **Location** | **Rank of SPs based on MAPE** | | | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Al bayda | EAR5-Ag | TerraClimate | EAR5-Land | EAR5 | CFSR | MERRA2 |
| Al-kufrah | MERRA2 | EAR5-Ag | EAR5 | CFSR | EAR5-Land | TerraClimate |
| Benghazi | MERRA2 | TerraClimate | EAR5-Ag | EAR5 | EAR5-Land | CFSR |
| Darnah | MERRA2 | TerraClimate | EAR5-Ag | EAR5-Land | EAR5 | CFSR |
| Espiaa | EAR5-Land | EAR5 | TerraClimate | EAR5-Ag | CFSR | MERRA2 |
| Misratah | TerraClimate | EAR5-Ag | CFSR | EAR5-Land | EAR5 | MERRA2 |
| Nalut | EAR5-Ag | MERRA2 | CFSR | TerraClimate | EAR5 | EAR5-Land |
| Sabha | EAR5-Ag | MERRA2 | CFSR | TerraClimate | EAR5 | EAR5-Land |
| Tripoli | TerraClimate | EAR5-Land | EAR5-Ag | CFSR | EAR5 | MERRA2 |

TABLE VI. THE RANK OF THE METHODS USED FOR ESTIMATING WPD

| Location | Dataset | Rank | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Al Bayda | Measured and SPs | EMJ | EPFM | LSRM | MMLM | MM | MLM | EML | EMM | MSDM | MIM |
| Al-kufrah | Measured and SPs | EMJ | EPFM | LSRM | MM | MMLM | EMM | MSDM | MLM | EML | MIM |
| Benghazi | Measured and SPs | EMJ | EPFM | MMLM | LSRM | MM | MLM | EML | EMM | MSDM | MIM |
| Darnah | Measured and SPs | EMJ | LSRM | EPFM | MMLM | MM | MLM | EMM | EML | MSDM | MIM |
| Espiaa | Measured and SPs | EMJ | EPFM | LSRM | MMLM | MM | EMM | MSDM | MLM | MIM | EML |
| Misratah | Measured | EMJ | EML | EPFM | LSRM | MMLM | MM | MLM | EMM | MSDM | MIM |
| | SPs | EMJ | EPFM | LSRM | MMLM | MM | MLM | EMM | EML | MSDM | MIM |
| Nalut | Measured and SPs | EMJ | EPFM | LSRM | MMLM | MM | MLM | EMM | EML | MSDM | MIM |
| Sabha | Measured and SPs | EMJ | EPFM | LSRM | MMLM | MM | MLM | EML | EMM | MSDM | MIM |
| Tripoli | Measured and SPs | EMJ | EPFM | LSRM | MMLM | MM | EML | EMM | MLM | MSDM | MIM |

## IV. DISCUSSION AND CONCLUSIONS

Understanding the volatile potential of wind energy is vital for advising Libyan policymakers and investors. This understanding helps in the selection of ideal sites and methods to measure wind speed, which influences decision-making in wind energy initiatives. The evaluation of wind speed variation is crucial during the feasibility assessment of wind power systems. The use of satellite data and reanalysis are necessary due to limited in situ measurements. Based on the findings, the annual wind speed at the selected sites is above 2 m/s at an altitude of 10 m, and the average monthly wind speed lies within the range of 2.12-6.13 m/s. Additionally, the mean monthly wind speed data for Benghazi are 6.13 m/s, 4.69 m/s, and 4.60 m/s based on mast measurements, EAR5 and EAR5-Ag, respectively, fort Darnah are 5.75 and 5.15 m/s focusing on MERRA2 and TerraClimate, accordingly, and for Misratah are 4.47 and 4.63 m/s contigent on EAR5-Land and CFSR, correspondingly, which were higher compared to other locations. The results demonstrate that MERRA-2, EAR5-Land, EAR5-Ag, and TerraClimate performed the best, while CFSR and EAR5 were the weakest in terms of average monthly wind speed data. Therefore, it can be concluded that the selection of an SP and reanalysis of the data to evaluate wind energy potential depend on the specific location [12, 22]. In [22], it was displayed that CFSR and ERA5-Land were the most suitable for evaluating wind resources. According to [12], spatial resolution plays a crucial role in both satellite data and reanalysis, significantly influencing the level of detail. Higher-resolution data offer a more comprehensive understanding of Earth's features, capturing subtle variations. Additionally, accuracy can be influenced by processing algorithms, introducing potential inconsistencies in the data.

This study also investigated the wind energy potential in different locations in Libya engaging different data sources and the Weibull distribution function. Ten different numerical methods were utilized to estimate the Weibull distribution parameters. The accuracy of these methods was assessed using different statistical analysis techniques. Subsequently, WPD was calculated based on the estimated parameters, considering the results obtained from these methods. The outcomes showed that the EMJ and the EPFM were the most effective approaches to analyze the mean monthly data series at selected locations. The former aalso exhibited that Benghazi and Darnah had the highest values of WPD. Previous studies support this finding, as in [20], where the maximum annual wind speed was recorded in Benghazi followed by Dernah, in [35] the highest mean wind speeds were obtained in Dernah, Misurata, and Tobruk, and in [36], the highest annual wind speed was recorded in Benghazi followed by Dernah.

This study introduces a wind energy roadmap to attract investors in clean energy for sustainable development in Libya, address energy problems, and meet domestic demands. Wind energy aligns with the goals of sustainable development, reducing emissions. Despite initial costs, benefits include energy security and reduced dependence on fossil fuels, which help sustainable development. Furthermore, this study identified the three most important grid datasets for assessing the country's wind potential, improving the accuracy of the assessments for investors and policymakers.

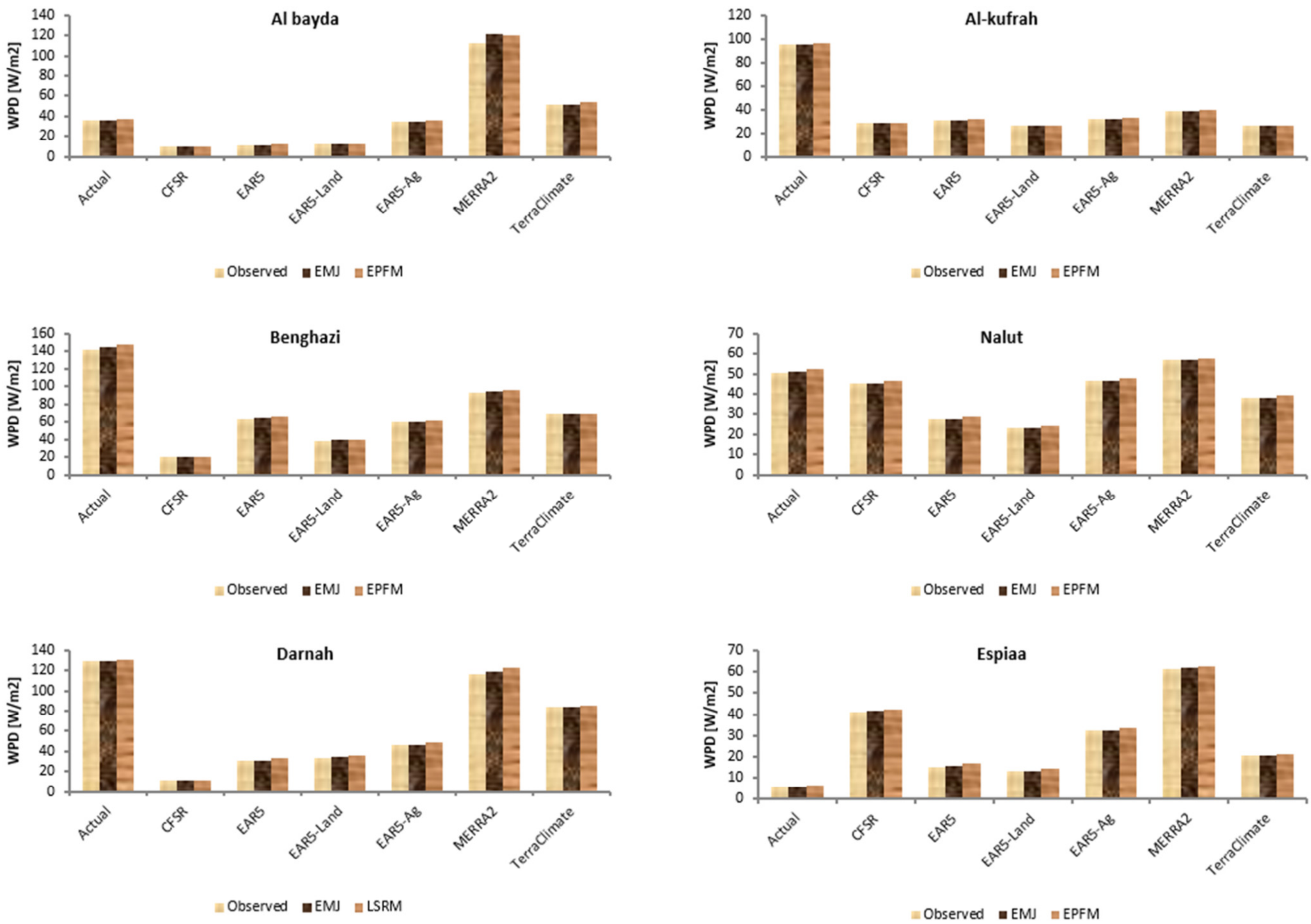


Fig. 4. Annual WPD based on multiple data sources.

## V. FUTURE WORK

Future studies could evaluate the accuracy of satellite data and selected reanalysis by comparing daily or hourly measured data. This comparative analysis can help to gain insight into the limitations and uncertainties associated with the data, leading to a better understanding of their reliability and applicability to assess the wind potential in Libya. This study showed that Benghazi, Darnah, and Misratah are suitable for installing wind farms in the future. Therefore, future studies can perform techno-economic analysis of wind turbines with various specifications using mathematical modeling and/or simulation tools. In addition, future research should focus on examining the economic data on the performance of wind farms in different locations in Libya.

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