Journal of Sustainable Bioenergy Systems, 2026, 16(3), 84-100
https://www.scirp.org/journal/jsbs
ISSN Online: 2165-4018
ISSN Print: 2165-400X

# Comparative Analysis of NASA POWER and ERA5 Reanalysis Data for Assessing Wind Energy Potential in Kassa (Guinea)

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**How to cite this paper:** Camara, M.A., Emmanuel, O., Soumah, S., Barry, K.A., Kourouma, O., Condé, S.F. and Diallo, A.O. (2026) Comparative Analysis of NASA POWER and ERA5 Reanalysis Data for Assessing Wind Energy Potential in Kassa (Guinea). *Journal of Sustainable Bioenergy Systems*, **16**, 84-100.
https://doi.org/10.4236/jsbs.2026.163005

**Received:** July 7, 2026
**Accepted:** August 18, 2026
**Published:** August 21, 2026



## Abstract

This study aims to evaluate the consistency and reliability of mean wind speed data derived from two widely used atmospheric reanalysis datasets, namely NASA POWER (based on MERRA-2) and ERA5, in the context of wind resource assessment. In the absence of in situ measurements, an inter-source comparative approach was adopted to examine the differences and similarities between these two datasets for the Kassa site (Guinea). The methodology is based on the use of three complementary statistical indicators: Mean Bias Error (MBE), Root Mean Square Error (RMSE), and Spearman's rank correlation coefficient ($\rho$), which were used to assess, respectively, the systematic error, the overall deviation, and the monotonic relationship between the two datasets. For each month, these indicators were first calculated from the six annual pairs of wind speed data obtained from the NASA POWER and ERA5 databases over the 2020-2025 period. The values reported in this abstract correspond to the arithmetic means of the twelve monthly statistics, thus providing a synthetic assessment of the agreement between the two datasets. The results indicate an average **Mean Bias Error (MBE) of 0.336 m/s**, reflecting a slight overall overestimation of wind speeds by ERA5 relative to NASA POWER. **The average Root Mean Square Error (RMSE) is 0.783 m/s**, indicating a moderate overall level of discrepancy between the two datasets. **The average Spearman's rank correlation coefficient is $\rho$ = 0.324**, indicating an overall weak positive monotonic relationship between the two datasets. However, the monthly analysis reveals strong seasonal variability, with some periods showing excellent agreement, while others exhibit weak or even negative correlations. Overall, the results demonstrate satisfactory agreement between the two data sources, although noticeable differences remain, mainly due to the specific characteristics of the reanalysis models, particularly in terms of spatial resolution and data assimilation methods. These differences may influence wind resource assessment and should therefore be taken into account in energy-related studies. This study therefore confirms the value of reanalysis datasets as an alternative to direct measurements for the preliminary assessment of wind energy potential in regions with limited observational data, while emphasizing the need for local validation using in situ measurements to improve the accuracy and robustness of the estimates.

## Keywords

Wind Energy Potential, ERA5 Reanalysis, NASA Power, MERRA-2, Wind Speed Assessment, MBE, RMSE, Spearman Correlation ($\rho$)

## 1. Introduction

Wind energy today represents one of the most promising renewable energy technologies for sustainable electricity generation, due to its technological maturity and low environmental impact [1] [2]. In Sub-Saharan Africa, and particularly in Guinea, the development of wind energy potential remains largely underexploited, despite favorable climatic conditions in certain regions [3].

A reliable assessment of wind energy potential primarily depends on the availability and quality of wind speed data. However, in situ measurements are often limited, costly, and spatially constrained, which has led to the widespread use of datasets derived from remote sensing and atmospheric reanalysis models [4]. Among these sources, data provided by the National Aeronautics and Space Administration (NASA) and the ERA5 reanalysis product from the European Centre for Medium-Range Weather Forecasts (ECMWF) are widely used in energy and climatological studies [5] [6].

NASA datasets, particularly those derived from the POWER (Prediction Of Worldwide Energy Resources) project, provide global estimates of meteorological parameters with a resolution suitable for energy-related studies [7]. In contrast, ERA5 data offer a finer spatio-temporal resolution and incorporate advanced numerical models, enabling a more accurate representation of atmospheric processes [6]. Nevertheless, discrepancies may arise between these different sources due to differences in assimilation methods, spatial and temporal resolution, and parameterization schemes, which can affect the estimation of wind energy potential [8].

In this context, several studies have emphasized the importance of comparing and validating these datasets prior to their use in energy applications [9] [10]. Comparative analysis based on statistical indicators such as the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and correlation coefficients constitutes a robust approach for assessing the performance and reliability of the data [11].

Accordingly, the present study aims to compare monthly mean wind speeds derived from NASA and ERA5 datasets over a six-year period (2020-2025), with the objective of evaluating their consistency and suitability for wind energy potential assessment. The study is based on a comprehensive graphical and statistical analysis, highlighting seasonal trends, discrepancies between the two data sources, and the performance of the ERA5 model relative to NASA data.

Recent studies have shown that the reliability of atmospheric reanalysis datasets strongly depends on local climatic, topographic and coastal conditions. Validation studies conducted along the Moroccan coast demonstrated that bias adjustment significantly improves the performance of ERA5 and MERRA-2 wind datasets for wind resource assessment, while investigations in Central Africa confirmed the usefulness of ERA5 for preliminary wind resource assessment but emphasized the need for local validation using in situ observations [12] [13].

The remainder of this paper is structured as follows: Section 2 presents the study area as well as the data sources used, particularly the NASA and ERA5 datasets. Section 3 describes the adopted methodology, with a focus on statistical analysis tools such as the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and the Spearman correlation coefficient ($\rho$). Section 4 is devoted to the presentation and analysis of the obtained results, including monthly and seasonal comparisons of wind speeds from the two datasets. Finally, Section 5 concludes the study by summarizing the main findings and proposing perspectives for improving wind energy potential assessment.

## 2. Materials and Methods

### 2.1. Materials

#### 2.1.1. Description and Geographical Setting of the Study Site (Kassa, Guinea)

Kassa Island is located in Guinea (**Figure 1**), in the Atlantic Ocean, within the Los Islands archipelago, approximately 15 to 20 kilometers southwest of Conakry, the country's capital. It constitutes a special urban municipality under the administrative jurisdiction of the city of Conakry. The geographical coordinates of Kassa are as follows: latitude 9.477˚ North and longitude −13.749˚ West [12].

Due to its proximity to Conakry, the island occupies a strategic geographical position, facilitating both economic exchanges and maritime transportation [12]. The municipality of Kassa has a structured administrative organization composed of two main districts. The Kassa district comprises seven sectors: Kassa 1, Kassa 2, Kassa 3, Koromandja, Mangué, Soro, and Room. The second district, Fotoba, is subdivided into three sectors: Fotoba Centre, Rogbanet, and Boom.

Climatically, Kassa Island is characterized by a humid tropical climate marked by the alternation of two distinct seasons. The rainy season generally extends from May to November, while the dry season covers the period from December to April

[13] [14]. Average annual temperatures range between 24˚C and 32˚C, reflecting a relative thermal stability typical of tropical coastal regions [13]. Precipitation is abundant, with a peak observed in July, during which the relative humidity may exceed 90% [14].

From a demographic perspective, the island's population is estimated at approximately 9257 inhabitants. This population is relatively evenly distributed between males (50.7%) and females (49.3%), reflecting a stable demographic structure [15]. This configuration, combined with its proximity to the capital Conakry, gives the municipality of Kassa a strategic role both in socio-economic terms and in the dynamics of mobility and maritime exchanges.

Thus, the administrative, climatic, and demographic characteristics of Kassa make it a relevant study area for analyzing the interactions between insular environments, human dynamics, and economic activities.

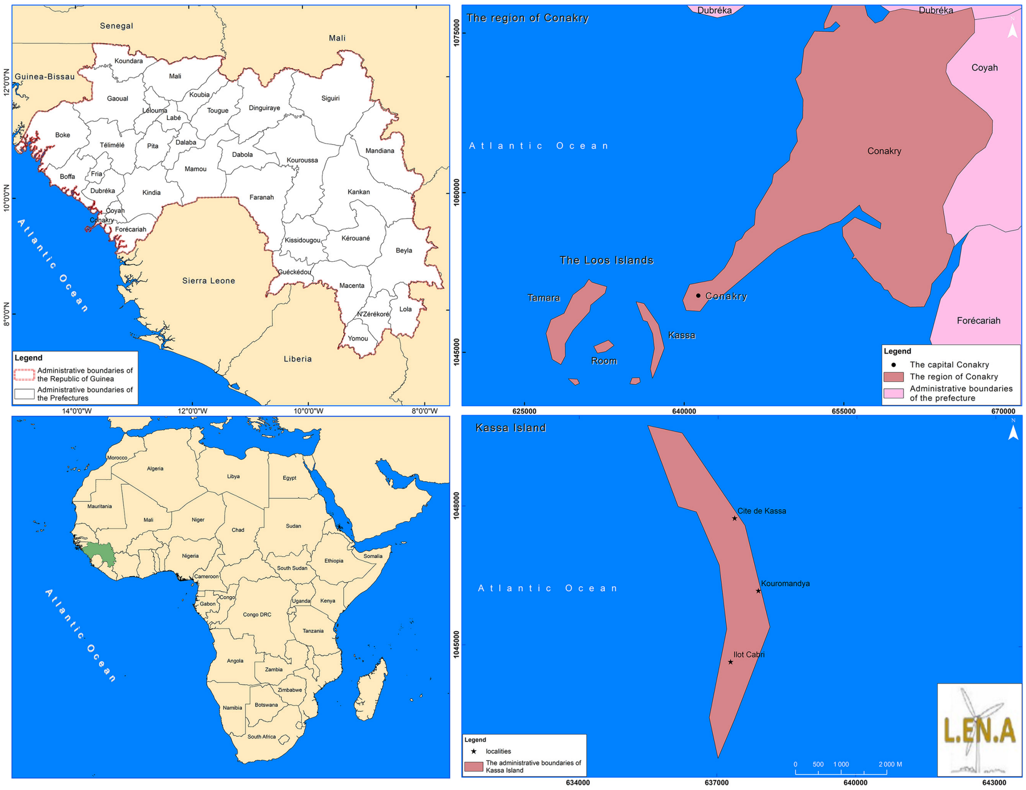



**Figure 1.** Location of Kassa Island within the Loos Islands archipelago (Conakry).

### 2.1.2. Sources of Wind Speed Data from ERA5 and NASA

In the context of the present study, wind speed data were extracted from two reference sources, both providing measurements at a standard height of 10 m above the ground surface. These include, on the one hand, the ERA5 reanalysis dataset produced by the Copernicus Climate Change Service (C3S), and, on the other hand, the NASA POWER (Prediction of Worldwide Energy Resources) database [6] [16].

These two datasets provide reliable time series that are widely used in climatological and energy-related studies [6] [8] [16]. The wind speeds derived from these sources cover a six (6)-year period, spanning from 2020 to 2025. This analysis period allows for the characterization of interannual variations in wind regimes and ensures a robust comparative basis between the different data sources [8] [17].

Thus, the combined use of ERA5 and NASA POWER data enhances the quality of the analysis by confronting two independent datasets, thereby contributing to a better assessment of uncertainties and enabling an inter-source comparison of the obtained results [16] [17].

**1) ERA5 dataset**

The ERA5 dataset, provided by the Copernicus Climate Change Service (C3S), enables the acquisition of wind data in the form of two orthogonal vector components: the zonal component ($u$), oriented along the East-West axis, and the meridional component ($v$), oriented along the North-South axis [6] [8].

In the context of this study, data corresponding to the Kassa site were extracted based on the geographical coordinates defined in Section 2.1.1. The data used correspond to an atmospheric pressure level close to the surface, approximately 1000 hPa, which is representative of near-sea-level conditions [6] [18].

From the $u$ and $v$ components, wind speed was determined at each time step using the following vector relationship:

$$V = \sqrt{u^2 + v^2} \tag{1}$$

where:

- $V$: denotes the wind speed (in m/s);
- $u$: represents the zonal component of the wind velocity;
- $v$: represents the meridional component of the wind velocity.

This relationship allows the resultant wind speed to be derived from its orthogonal components at each observation time step [8] [17]. The computed values were subsequently aggregated to determine monthly mean wind speeds, which were used for the assessment of the site's wind energy potential [17] [18].

The use of this approach ensures methodological consistency with international standards in wind data analysis and enables the comparability of results with those derived from other datasets, particularly the NASA POWER database [6] [17].

**2) NASA POWER dataset**

In the context of this study, the variable considered is the monthly mean wind speed at 10 m above ground level, denoted WS10M and expressed in m/s. These data are derived from the MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications, Version 2) atmospheric reanalysis model, as provided through the NASA POWER platform [7] [19].

The MERRA-2 model integrates a wide range of satellite observations and assimilated meteorological data, enabling the generation of consistent and spatially homogeneous time series of atmospheric parameters [18] [19]. The data were extracted for the Kassa site (Guinea), using the same geographical coordinates as those defined in Section 2.1.1. Unlike ERA5 data, where wind speed is derived from its vector components, WS10M data are directly provided as scalar wind speed values [7], They are therefore immediately usable for wind regime analysis without requiring prior processing.

This feature facilitates their use in comparative analyses and wind energy potential assessment, while ensuring consistency with data derived from other reanalysis sources [17] [18].

## 3. Methodology for Data Comparison

The main objective of this study is to compare the mean wind speeds derived from the NASA POWER and ERA5 datasets in order to assess their consistency and analyze potential discrepancies between these two reanalysis sources. In the absence of reference data from in situ measurements, this approach relies on an inter-source comparative analysis, enabling the evaluation of the relative agreement between datasets, a method commonly used in validation studies of climatic and energy datasets [6] [8].

To this end, three complementary statistical indicators were employed: the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and the Spearman correlation coefficient ($\rho$). These indicators are widely used in the evaluation of atmospheric model performance and reanalysis datasets, as they respectively characterize systematic error, overall error, and the statistical relationship between data series [17] [18].

### 3.1. Mean Bias Error (MBE)

The Mean Bias Error (MBE) is a statistical measure used to assess the systematic deviation between two data series. It corresponds to the average of the differences between observed values and estimated values, and constitutes a key indicator for detecting tendencies of overestimation or underestimation in climatic data [18].

In this study, NASA-derived data are considered as reference values, while ERA5 data are treated as predicted values, in accordance with methodologies commonly adopted in comparative studies of atmospheric reanalysis datasets [6] [17].

The expression of the Mean Bias Error is given by:

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}\left(X_i^{era5} - X_i^{nasa}\right) \quad (2)$$

where:

- MBE : Mean Bias Error (in m/s);
- $X_i^{nasa}$ : mean wind speed derived from NASA data (in m/s);
- $X_i^{era5}$ : mean wind speed derived from ERA5 data (in m/s);
- $n$ : number of observations.

The MBE is frequently used in wind energy potential assessment studies to identify systematic biases in models [8]. The quality of the Mean Bias Error (MBE), along with its interpretation according to the different value ranges, is presented in **Table 1**.

Table 1. Interpretation of MBE (adapted from [17] [18]).

| No. | MBE (m/s) | Interpretation | Quality |
|---|---|---|---|
| 1 | MBE ≈ 0 | No bias | Excellent |
| 2 | 0 < MBE < 0.5 | Slight overestimation | Very good |
| 3 | 0.5 ≤ MBE < 1 | Moderate overestimation | Acceptable |
| 4 | MBE ≥ 1 | Significant overestimation | Requires correction |
| 5 | −1 < MBE ≤−0.5 | Moderate underestimation | Acceptable |
| 6 | −0.5 < MBE < 0 | Slight underestimation | Very good |
| 7 | MBE ≤−1 | Significant underestimation | Requires correction |

## 3.2. Root Mean Square Error (RMSE)

The RMSE (Root Mean Square Error) is a statistical measure widely used to assess the overall accuracy between two data series. Unlike the MBE, it does not provide information on the direction of the error, but rather on its magnitude, making it a robust indicator of the dispersion of deviations [18].

It is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i^{era5} - X_i^{nasa}\right)^2} \tag{3}$$

where:

- RMSE : Root Mean Square Error (in m/s);
- $X_i^{nasa}$ : mean wind speed derived from NASA data (in m/s);
- $X_i^{era5}$ : mean wind speed derived from ERA5 data (in m/s);
- $n$ : number of observations.

The RMSE is a standard indicator in validation studies of wind data derived from ERA5 and MERRA-2 reanalyses, particularly in the field of wind energy [8] [17]. The lower the RMSE value, the closer the two data series are, indicating better agreement.

The quality of the Root Mean Square Error (RMSE), along with its interpretation according to the different value ranges, is presented in Table 2.

Table 2. Interpretation of RMSE (adapted from [18]).

| No. | RMSE | Interpretation | Quality |
|---|---|---|---|
| 1 | RMSE ≈ 0 | Near-perfect agreement | Excellent |
| 2 | RMSE < 0.30 | Very low error | Very good |
| 3 | 0.30 ≤ RMSE < 0.50 | Low error | Good |
| 4 | 0.50 ≤ RMSE < 0.80 | Moderate error | Average |
| 5 | 0.80 ≤ RMSE < 1.20 | High error | Poor |
| 6 | 1.20 ≤ RMSE < 1.50 | Very high error | Very poor |
| 7 | RMSE ≥ 1.50 | Extremely high error | Very poor |

### 3.3. Spearman Correlation Coefficient ($\rho$)

The Spearman correlation coefficient ($\rho$) is a non-parametric measure used to assess the strength and direction of a monotonic relationship between two variables, without assuming a linear relationship or a normal distribution of the data. This method is particularly suitable for environmental data, which are often non-Gaussian and affected by extreme values [20]. Unlike the Pearson coefficient, Spearman's correlation is based on the ranks of the observations, making it more robust to outliers [20].

It is given by:

$$\rho = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{4}$$

where:

- $d_i$ : difference between rank ( $X_i^{era5}$ ) and rank ( $X_i^{nasa}$ );
- $X_i^{nasa}$ : mean wind speed derived from NASA data (in m/s);
- $X_i^{era5}$ : mean wind speed derived from ERA5 data (in m/s);
- $n$ : number of observations.

This coefficient is widely used in comparative studies of climate datasets to assess their temporal consistency [8]. The quality of the Spearman correlation coefficient ($\rho$), along with its interpretation according to the different value ranges, is presented in **Table 3**.

**Table 3.** Interpretation of Spearman ($\rho$) (adapted from [20]).

| No. | $\rho$ value | Interpretation | Quality |
|---|---|---|---|
| 1 | $\rho \approx +1$ | Strong positive correlation | Excellent |
| 2 | $+0.5 \le \rho < +1$ | Significant correlation | Very good |
| 3 | $0 < \rho < +0.5$ | Weak correlation | Low |
| 4 | $\rho \approx 0$ | No relationship | Very low |
| 5 | $-0.5 < \rho < 0$ | Weak negative correlation | Very low |
| 6 | $-1 < \rho \le -0.5$ | Significant negative correlation | Average |
| 7 | $\rho \approx -1$ | Strong negative correlation | Poor |

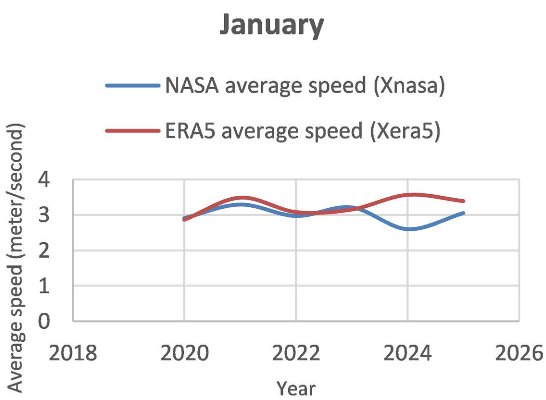
The combined use of these three indicators provides a comprehensive assessment of the agreement between ERA5 and NASA POWER data, taking into account biases, overall deviations, and statistical relationships, as recommended in recent studies on the evaluation of reanalysis data for wind energy applications [6] [8] [17] [18].

## 4. Results and Discussion

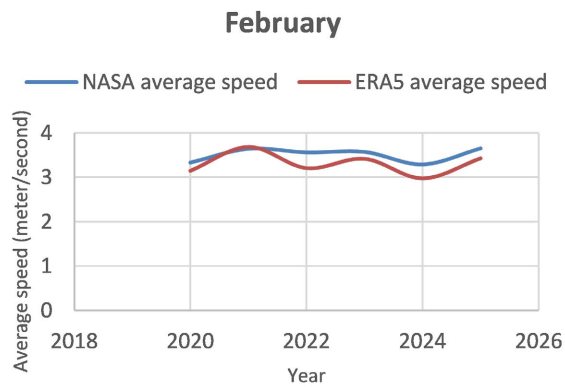
### 4.1. Comparative Analysis of Monthly Mean Wind Speeds (NASA vs ERA5) over the Period 2020-2025

The graphs presented in **Figure 2** illustrate the comparison of monthly mean wind speeds derived from the NASA and ERA5 datasets for each of the twelve months of the year, from January to December, over a six-year observation period (2020-2025). Each graph corresponds to a specific month and presents the mean values observed over the six years, allowing a direct comparison between the data provided by the two sources.

This representation enables the analysis of potential discrepancies between the two datasets, the identification of seasonal variations, and the evaluation of the consistency and reliability of wind speed estimates, with a view to assessing the wind energy potential of the study site.




(a)

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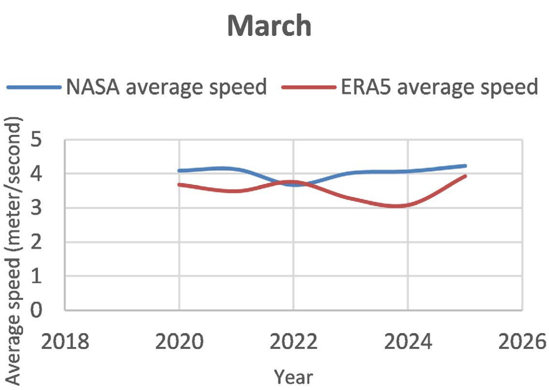


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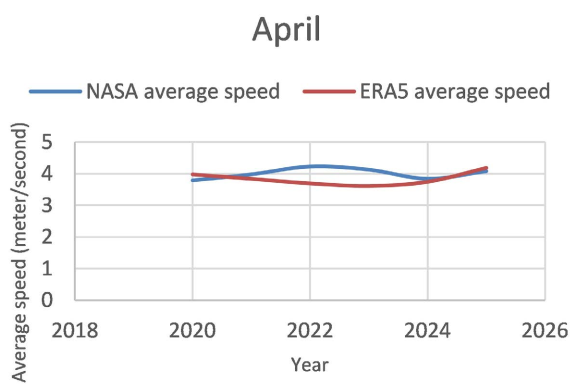


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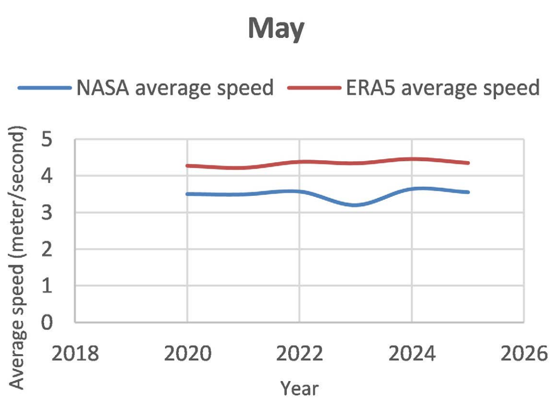


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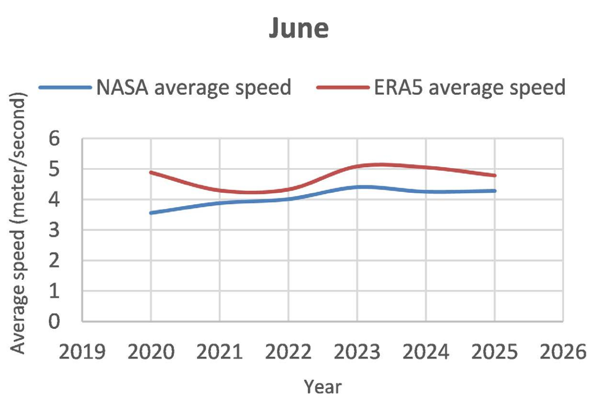


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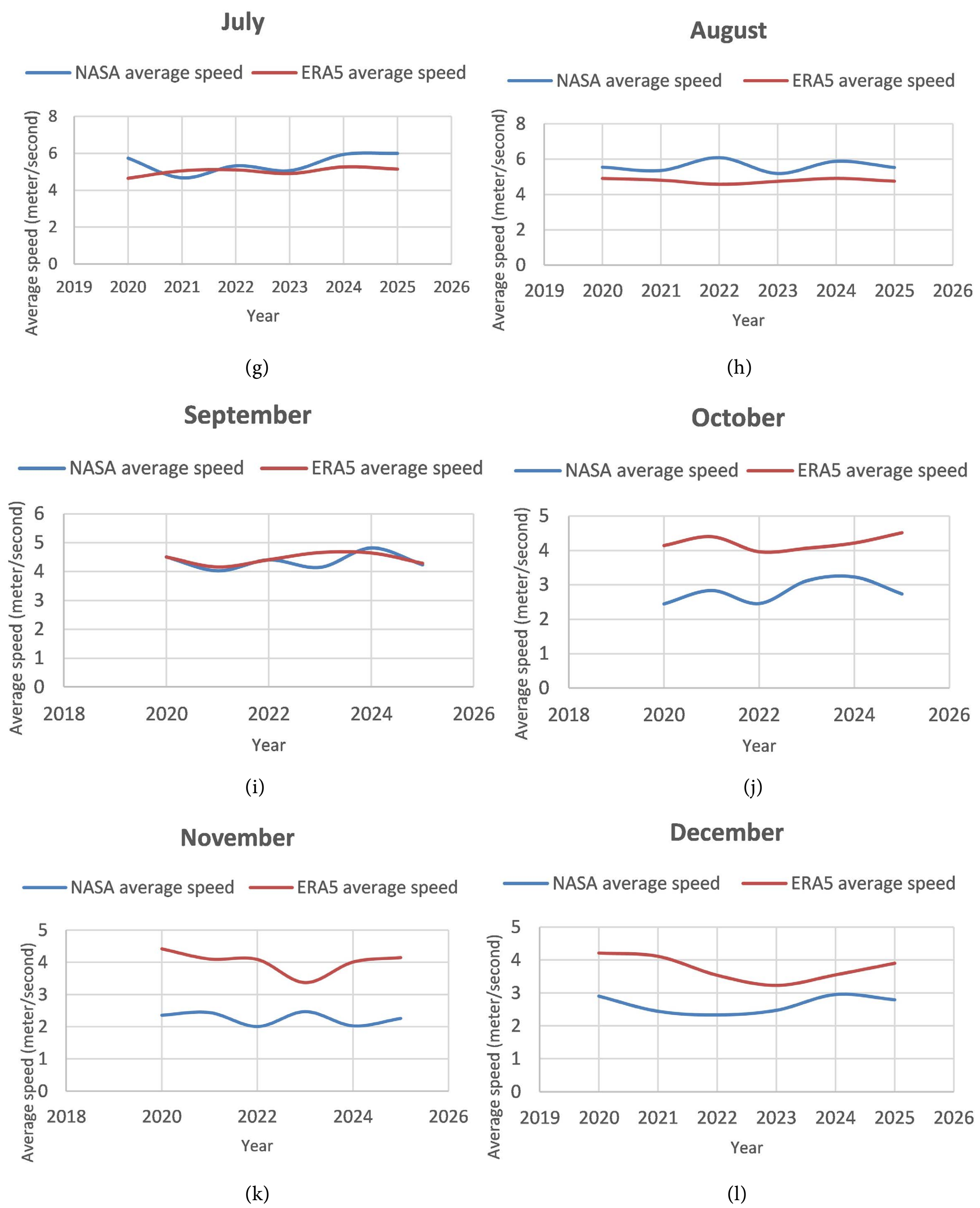


**Figure 2.** Comparative analysis of monthly mean wind speeds between NASA and ERA5 datasets over the period 2020-2025.

Figure 2 presents a comparative analysis of monthly mean wind speeds derived from the NASA and ERA5 datasets for each of the twelve months of the year over the period 2020-2025.

Overall, graphs (a-i) show a general agreement between the two datasets, reflecting a good reproduction of the seasonal trends in the wind regime. For most months, the profiles of mean wind speeds from both datasets evolve in a similar manner, with consistent interannual variations, indicating a certain reliability of ERA5 data relative to NASA data.

However, occasional discrepancies are observed depending on the month, manifested as periods of slight overestimation or underestimation. These differences are more pronounced during specific periods, suggesting the influence of seasonal meteorological conditions as well as the inherent characteristics of the modeling approaches and the spatial and temporal resolutions of each dataset.

Furthermore, the interannual analysis highlights a moderate variability in wind speeds, indicating a relatively stable wind regime over the study period, although some fluctuations can be observed for specific months. This overall consistency between the two data sources reinforces their relevance for wind energy potential assessment, while emphasizing the need for local validation to identify the dataset that best represents the actual conditions of the study site.

## 4.2. Analysis of Statistical Performance Indicators

### 4.2.1. Analysis of Mean Bias Error (MBE)

The monthly Mean Bias Error (MBE) values reveal a marked seasonal variability in the bias between the ERA5 and NASA POWER datasets. During **January, May, June, and September**, positive MBE values indicate that ERA5 generally **overestimates** wind speeds relative to NASA POWER, although this overestimation remains slight to moderate during most of these months. Conversely, **February, March, April, July, and August** exhibit negative MBE values, indicating a slight to moderate **underestimation** by ERA5. The largest positive biases occur during **October, November, and December**, with November reaching the maximum value (1.76 m/s), highlighting a substantial overestimation during the late part of the year. Overall, the results indicate a clear seasonal variation in the magnitude and direction of the bias rather than a predominance of either underestimation or overestimation throughout the study period.

The monthly Mean Bias Error (MBE) values, their interpretation, and the corresponding quality levels over the 2020-2025 study period are presented in Table 4.

Table 4. Monthly MBE values over the six-year study period (2020-2025).

| No. | Month | MBE (m/s) | Interpretation | Quality |
|---|---|---|---|---|
| 1 | January | 0.25 | Slight overestimation | Very good |
| 2 | February | −0.20 | Slight underestimation | Very good |
| 3 | March | −0.50 | Slight underestimation | Very good |
| 4 | April | −0.16 | Slight underestimation | Very good |
| 5 | May | 0.85 | Moderate overestimation | Acceptable |
| 6 | June | 0.68 | Moderate overestimation | Acceptable |
| 7 | July | −0.44 | Slight underestimation | Very good |

**Continued**

| | | | | |
|---|---|---|---|---|
| 8 | August | −0.81 | Moderate underestimation | Acceptable |
| 9 | September | 0.08 | Negligible bias | Excellent |
| 10 | October | 1.41 | Significant overestimation | Requires correction |
| 11 | November | 1.76 | Significant overestimation | Requires correction |
| 12 | December | 1.11 | Significant overestimation | Requires correction |

#### 4.2.2. Analysis of the Root Mean Square Error (RMSE)

The RMSE values corroborate the trend observed with the MBE, highlighting a clear seasonal variation in model accuracy. Errors remain low to very low at the beginning of the year, particularly in February and September, indicating excellent model performance during these periods. However, a gradual increase in errors is observed from May onward, with elevated levels in August and especially toward the end of the year.

The months of October (1.452) and November (1.807) exhibit very high to extremely high error values, reflecting a substantial degradation in model performance. This pattern suggests that the ERA5 model performs less effectively under specific atmospheric conditions, likely associated with pronounced seasonal transitions.

The monthly Root Mean Square Error (RMSE) values, together with their interpretation and the associated quality levels for each of the twelve months of the study period (2020-2025), are presented in Table 5.

Table 5. Monthly RMSE values over the six-year study period (2020-2025).

| No. | Month | RMSE (m/s) | Interpretation | Quality |
|---|---|---|---|---|
| 1 | January | 0.431 | Low error | Good |
| 2 | February | 0.237 | Very low error | Very good |
| 3 | March | 0.609 | Moderate error | Average |
| 4 | April | 0.322 | Low error | Good |
| 5 | May | 0.856 | High error | Poor |
| 6 | June | 0.753 | Moderate error | Average |
| 7 | July | 0.654 | Moderate error | Average |
| 8 | August | 0.888 | High error | Poor |
| 9 | September | 0.228 | Very low error | Very good |
| 10 | October | 1.452 | Very high error | Very poor |
| 11 | November | 1.807 | Extremely high error | Very poor |
| 12 | December | 1.163 | High error | Poor |

#### 4.2.3. Analysis of Spearman's Rank Correlation Coefficient ($\rho$)

The analysis of the monthly Spearman correlation coefficients reveals substantial variability in the relationship between the NASA POWER and ERA5 datasets across the different months.

However, since each coefficient was calculated from only six pairs of annual observations, these results should be interpreted with caution. They primarily provide an exploratory indication of the interannual consistency between the two data sources.

Accordingly, the relatively high coefficients observed in February, May, and June suggest good agreement in the ranking of the years for these months, whereas the low or negative coefficients obtained for other months (April and November) indicate more limited interannual consistency.

The monthly values of the Spearman correlation coefficient ($\rho$), together with their interpretation and the associated quality levels for each of the twelve months of the study period (2020-2025), are presented in **Table 6**.

**Table 6.** Monthly Spearman correlation coefficient ($\rho$) over the six-year study period (2020-2025).

| No. | Month | Spearman's ($\rho$) | Interpretation | Quality |
|---|---|---|---|---|
| 1 | January | 0.086 | Weak relationship | Low |
| 2 | February | 0.943 | Strong positive agreement (variables move together) | Excellent |
| 3 | March | 0.314 | Weak relationship | Low |
| 4 | April | −0.543 | Significant inverse relationship | Moderate |
| 5 | May | 0.829 | Strong monotonic relationship | Very good |
| 6 | June | 0.771 | Strong monotonic relationship | Very good |
| 7 | July | 0.543 | Moderate monotonic relationship | Good |
| 8 | August | 0.086 | Weak relationship | Low |
| 9 | September | 0.429 | Weak relationship | Low |
| 10 | October | 0.200 | Weak relationship | Low |
| 11 | November | −0.086 | Weak inverse relationship | Very low |
| 12 | December | 0.314 | Weak relationship | Low |

#### 4.2.4. Comparative Analysis and Interpretation of Statistical Indicators (NASA vs ERA5)

The graphs presented in **Figure 3** and **Figure 4**, respectively showing a grouped bar chart with error bars and a line plot of the monthly evolution of the indicators, highlight an overall agreement between wind speed values derived from the NASA and ERA5 datasets, although occasional discrepancies are observed depending on the periods considered.

Overall, both datasets reproduce similar trends, reflecting consistency in the temporal and seasonal variability of wind speeds. However, certain divergences, manifested as periods of overestimation or underestimation, may be attributed to differences in spatial and temporal resolution, parameterization schemes, and data assimilation approaches inherent to each product.

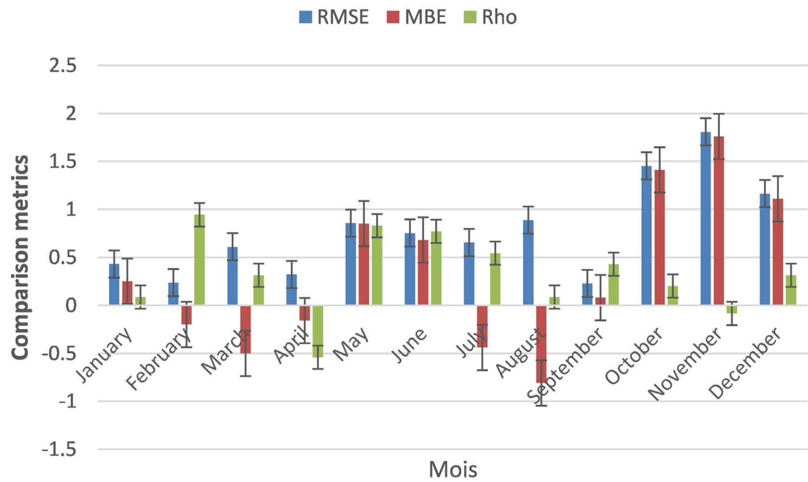


**Figure 3.** Grouped bar chart with error bars.

This graph illustrates the monthly distribution of the statistical indicators (RMSE, MBE, and Spearman's correlation coefficient $\rho$), as well as their variability through error bars. It shows that RMSE values are relatively low at the beginning of the year, indicating good accuracy, and then gradually increase to reach high levels in October and November, reflecting a deterioration in model performance.

The MBE reveals a variable bias depending on the month, characterized by a dominant underestimation from February to September, with a minimum in August, and overestimation toward the end of the year. The error bars also highlight greater dispersion during certain periods, confirming the influence of seasonal conditions on model stability.

Finally, the correlation coefficient $\rho$ shows generally satisfactory agreement, although notable decreases are observed in April and November.

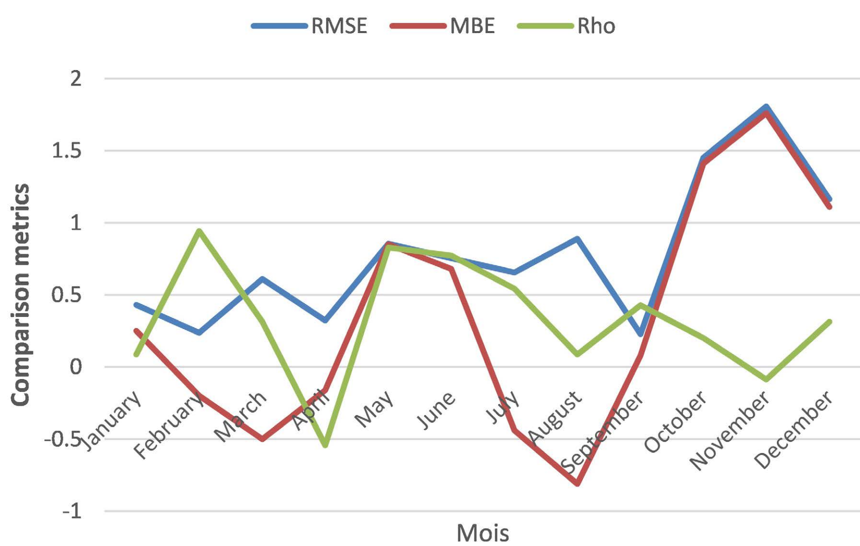


**Figure 4.** Line graph of the monthly evolution of the indicators.

This graph allows the temporal dynamics of the statistical indicators to be visualized and their fluctuations throughout the year to be better understood. The RMSE curves confirm good model accuracy at the beginning of the year, followed by a progressive deterioration that peaks in October and November. The evolution of the MBE highlights a clear alternation between underestimation (from February to September) and overestimation at the end of the year, reflecting a pronounced seasonal bias. In addition, the Spearman correlation coefficient ($\rho$) curve reveals generally moderate to strong agreement, with peaks in February and May, and significant decreases in April and November, indicating periods of model instability.

Overall, the combined analysis of these two figures confirms that the ERA5-based model performs reasonably well compared to NASA data, but is strongly influenced by seasonal variability. This dependence highlights the need for appropriate calibration and parameter adjustment in order to improve model accuracy, robustness, and stability across all studied periods, with a view to reliable wind energy potential assessment for the considered site.

**General summary of the section**

The overall analyses indicate a generally acceptable performance of the ERA5 model compared to NASA data, with good accuracy at the beginning of the year and a gradual deterioration toward the end of the year. The results confirm a strong influence of seasonal variability on the statistical indicators (MBE, RMSE, and $\rho$), emphasizing the need for seasonal model calibration to improve its reliability and robustness for wind energy potential assessment.

It should be emphasized that this study is based on wind speed data measured or estimated at the standard height of **10 m above ground level**, as provided by the NASA POWER and ERA5 datasets. Although these data are widely used for climatological studies and comparative analyses, they do not directly represent the wind conditions at the hub heights of modern wind turbines, which are typically between **80 and 120 m**. Therefore, the present results should be regarded as a **preliminary assessment** of the wind resource and as a **site-screening tool** rather than a definitive evaluation of the exploitable wind energy potential. A comprehensive assessment for wind farm development would require vertical extrapolation of wind speeds to hub height using appropriate atmospheric boundary-layer models, together with validation based on in situ measurements.

## 5. Conclusions

The main objective of this study was to compare wind speed data derived from the NASA POWER (MERRA-2) and ERA5 reanalysis datasets in order to assess their consistency and reliability in the context of wind energy potential analysis in the absence of in situ measurements.

The results obtained through the combined use of well-established statistical indicators, namely the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and Spearman's correlation coefficient ($\rho$), highlighted the degree of agreement between these two data sources. Overall, the inter-source comparative analysis showed satisfactory consistency between the two datasets, although discrepancies remain, reflecting differences in reanalysis models, data assimilation schemes, and spatial and temporal resolutions.

These findings confirm that atmospheric reanalysis data constitute a relevant alternative for preliminary wind resource assessment in areas lacking measurement stations, as demonstrated in several recent studies. However, the observed discrepancies highlight the need for caution in their use, particularly for applications requiring high accuracy, such as wind farm design and sizing.

Furthermore, the methodological approach adopted in this study, based on rigorous statistical analysis, proves effective for characterizing the relative performance of climate datasets. It could be extended to other regions or meteorological parameters to improve the understanding of uncertainties associated with reanalysis data.

In future work, it would be relevant to integrate in situ measurements to provide absolute validation of these datasets. Moreover, the use of additional indicators and advanced analytical methods would help refine the assessment and strengthen the robustness of the conclusions. Finally, higher temporal resolution analyses (daily or hourly) could provide a better understanding of wind variability and its impact on energy production.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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