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ASSESSING CLIMATE CHANGE IMPACTS ON WIND POWER POTENTIAL AND ELECTRICITY GENERATION IN NORTH AFRICA

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***ABSTRACT*:**

Reliable long-term planning of wind energy systems requires evaluating the effects of climate change on wind resources, especially in areas with substantial wind potential like North Africa.

This study employs high-resolution regional climate models from the CORDEX framework combined with a multi-model ensemble (MME) approach to evaluate projected changes in wind speed and wind power density (WPD) under the RCP 4.5 scenario for the period 2021–2050.

When model outputs are compared to ERA reanalysis data, a constant positive bias in simulated wind speeds is found, necessitating the use of bias correction methods. Model results indicate better agreement with observed conditions after rectification. According to the results, there won't be any notable long-term trends in the wind resources across North Africa. Nonetheless, there is evident seasonal variation, with fall displaying more fluctuation and summer displaying the maximum wind potential. Projected wind energy potential is more confident and less unpredictable according to the MME technique.

***Keywords**: Wind energy; Wind power density (WPD); Climate change; CORDEX; Multi-model ensemble (MME); Bias correction; North Africa; Seasonal variability*

INTRODUCTION

Climate change is increasingly recognized as a major driver of changes in atmospheric dynamics and energy systems worldwide. The increase in greenhouse gases has resulted in global warming, which has been associated with variations in large-scale circulation patterns, wind speed in the near surface layer, and extreme events [1], [2]. These phenomena are of significant importance in the context of RE systems, particularly wind energy systems, as energy production is highly dependent on wind patterns and atmospheric conditions. Wind energy has emerged as a major component of global energy transition strategies in recent years due to its maturity level, cost competitiveness, and availability in energy transition strategies worldwide [3]. However, wind energy production is highly dependent on climatic patterns; wind power density is proportional to the cube of wind speed. Thus, there is a possibility of large fluctuations in wind patterns and energy production, which raises concerns regarding wind energy production in future climate patterns.

North Africa is one of the best regions in the world in terms of wind energy production due to strong wind patterns in the region, particularly along the Atlantic Ocean and Red Sea regions [4], [5]. At the same time, the region is classified as a climate change hotspot, where projected warming and associated changes in pressure systems may influence regional wind patterns through modifications in atmospheric circulation [1], [6]. The projected changes, therefore, result in a certain level of uncertainty with regard to wind availability and its temporal characteristics, especially in relation to seasonal changes.

Even though a significant number of studies have already focused on the relationship between climate change and wind energy, certain limitations are still evident in these studies. Firstly, most studies are based on global climate models, which are not sufficient in determining wind energy potential at a regional level. Moreover, most studies

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are based on wind speed, while its relationship with energy-based parameters, such as wind power density [7], [8], is not taken into consideration. In addition, the effect of systematic model bias is not taken into consideration, which is a significant factor in determining wind energy potential.

Considering these limitations, this study aims to provide a high-resolution, region-specific assessment of wind energy potential in North Africa, taking into consideration climate change projections and energy-based parameters, while considering uncertainties associated with climate models. The analysis is based on regional climate model outputs combined within a multi-model ensemble framework, with particular emphasis on the application of bias correction techniques and the assessment of seasonal variability. The purpose of this research is to create a more consistent and realistic representation of future wind behavior, considering both wind speed and wind power density, to improve planning and decision-making in wind energy development under varying climate conditions.

STUDY AREA AND CLIMATE DATA SOURCES

2.1 Study Area

This study covers North Africa in the range of **20°W to 50°E** longitude and **10°N to 37°N** latitude as shown in Figure 1 above. The region is characterized by arid and semi-arid climates; hence, there is a significant difference in temperature due to land/sea interactions and strong pressure systems that influence wind patterns. As a result, North Africa is a highly suitable region for wind energy production. Moreover, there is a significant impact of large-scale atmospheric circulation and stable coastal winds in the region; thus, wind energy projects can be used to analyze the effects of climate variability on wind energy production.

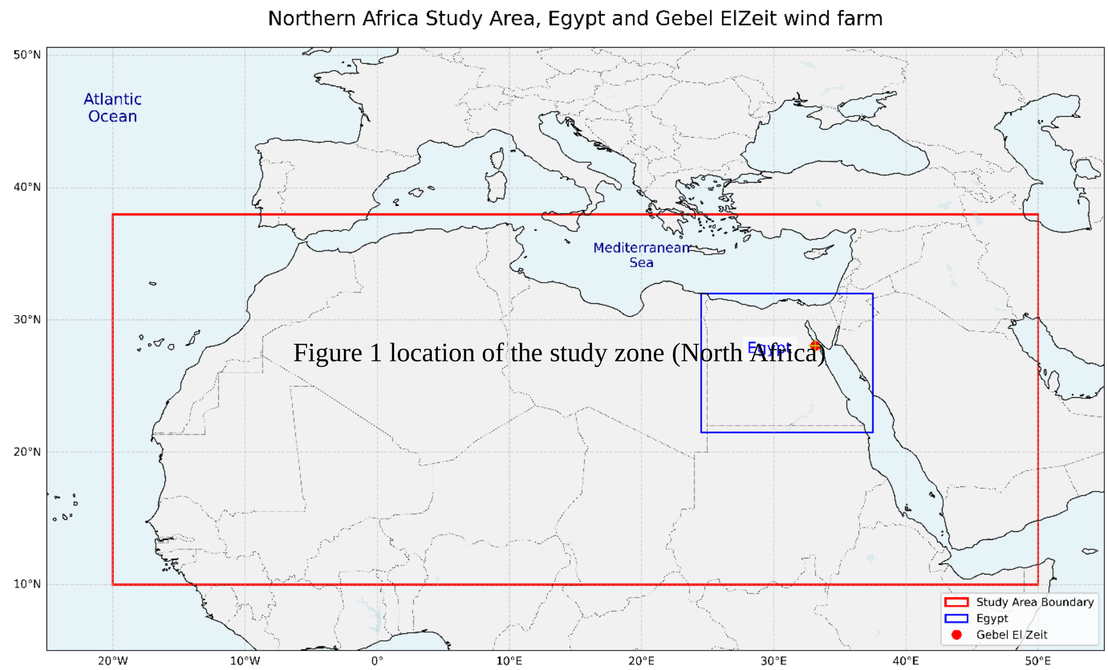

Figure 1 location of the study zone (North Africa)

2.2 Observational and Reanalysis Data

For characterizing the historical climate conditions and validating the performance of the climate models, the present study uses a combination of global reanalysis data and in-situ observational measurements. For historical near-surface wind speed, air temperature, and surface pressure data, this study relies on the ERA5 global reanalysis data product. ERA5 data is provided by the Copernicus Climate Change Service (C3S) and is accessible through the Earth System Grid Federation (ESGF), which is operated by the Deutsches Klimarechenzentrum (DKRZ) [9]. The ERA5 data has a resolution of 31 km in the horizontal direction and reaches up to 100 m above ground level. This will provide better reliability in the use of reanalysis data for representing historical wind characteristics, making it appropriate for validating regional climate model simulations and subsequent wind energy assessments over North Africa. [10]. The CORDEX framework's high-resolution regional climate models were used to analyze future wind conditions in North Africa. Because the regional climate models are dynamically downscaled from a

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set of different global climate models (GCMs), they provide an improved and more realistic reproduction of the regional processes that influence the wind energy resource.

To assess the future wind resource, a multi-model ensemble (MME) of five regional models (RACMO22E, RCA4, and REMO), using GCM forcing from the HadGEM2-ES, ICHEC-EC-EARTH, and MPI-ESM-LR models, was used in this analysis. The GCMs used to drive the regional models were utilized more than once, creating several different configurations of the regional models and expanding the extent of representation of uncertainty related to both the structure of the regional model, as well as the GCM large-scale circulation that forces the regional model. In order to characterize the variability among the models, an ensemble or MME approach was used. Through the ensemble method of combining different regional models available for predicting wind speeds and densities with regards to the uncertainties shown to be inherent in each individual model, an unbiased estimate of both the wind speed and wind power density is attainable. From the results shown; the differences in the wind speed and density predictions from the individual models provided by the different regional models can be attributed to differences in how the different models perform in simulating and predicting boundary layer processes, surface roughness, and large-scale atmospheric circulation patterns. By using various combinations of RCM-GCM models to create a multi-model ensemble analysis, we are able to generate a more complete estimate of the uncertainty associated with the future wind conditions predicted by the multi-model ensemble analysis and improve the overall robustness of the analysis.

2.3 Regional Climate Model Data

To acquire future climate projections, high-resolution regional climate model (RCM) outputs were utilized, which were developed as part of the Coordinated Regional Climate Downscaling Experiment (CORDEX) suite of dynamically downscaled climate projections from global climate models (GCMs). This helps to better capture regional-scale atmospheric processes that are significant for wind energy assessment. In this study, a multi-model approach was adopted, consisting of a set of prominent CORDEX RCMs that were selected on the basis of data availability, performance, and previous usage in numerous climate as well as wind energy impact studies. A list of regional climate models, their respective institutions, GCMs, and references are given in Table 1.

Table 1 Summary of CORDEX Regional Climate Models Used in This Study

No.	Model Name	RCM	Driving GCM	Institution	References
1	Model A	RACMO22E	HadGEM2-ES	KNMI	[11]
2	Model B	RCA4	ICHEC-EC-EARTH	SMHI	[12]
3	Model C	RACMO22E	ICHEC-EC-EARTH	KNMI	[13]
4	Model D	REMO	ICHEC-EC-EARTH	GERICS/MPI	[14]
5	Model E	REMO	MPI-ESM-LR	GERICS/MPI	**[15]**

2.4 Wind Energy–Relevant Variables

The data collections were subject to treatment to derive wind characteristics relevant to wind power production. The wind velocities were interpolated to a standard height range of wind turbines from 80 to 100 m using conventional boundary layer relationships. In addition, density variations were considered using temperature and pressure information, which have a direct impact on wind energy production. The results can be used as an initial basis for further wind resource assessment, Weibull distribution analysis, and wind power prediction. Simultaneously using the monitoring records, re-analysis data, and regional climate model predictions offers a robust approach for the assessment of the current and future changes in wind power production and electric power production in North Africa.

2.5 Data Processing and Model Evaluation

To produce trustworthy final results, we processed climate information by integrating high-resolution projections of the regional climate with reference observational data. In order to obtain climate projections, Regional Climate Models (RCMs) were used under the CORDEX framework. RCMs generate simulations at a finer scale (approximately 10–50 km) than the Global Climate Models (GCMs) (typically between 100–300 km), which leads to a more accurate representation of the climate of the region than GCMs. The data analyses were done both by year, for the entire data set, and seasonally (December, January, February, March, April, May, June, July, August, September, October, November) to reflect the variability in wind and potential for energy over time. To correct

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the systematic biases in climate models, a mean bias correction (MBC) (or delta change) approach has been employed in correcting the climate model outputs. The MBC is a method in which a long-term mean of the climate model outputs is compared to a long-term mean of ERA Interim data and then corrected accordingly by subtracting the bias from the climate model outputs. As a result, the corrected climate model outputs are more representative of the observed climate mean and thus more physically correct and suitable for impact assessment purposes.

The quality of bias correction was validated using standard performance measures, such as MB and RMSE. This is evident from the results, which show a considerable reduction in the value of RMSE and the elimination of almost all the systematic bias with the correction applied, thereby validating the robustness of the method. In order to further improve the robustness of wind speed and wind power density projections, a multi-model ensemble (MME) approach was used. The MME combined simulations from multiple RCMs that are driven by several GCMs using the CORDEX framework. The MME equals the average of each model's simulation and is a common modelling method used to mitigate the errors of each simulation and produce a more accurate projection of the future climate. Additionally, using the MME provides a more complete assessment of uncertainty in the wind speed and wind power density projections. High-resolution regional modelling combined with an ensemble average and bias correction produces a reliable methodology to assess the potential for wind energy production under present and future climate conditions.

METHODOLOGY

The general framework for the methodology used in the study includes the assessment of the data for climate information, wind resource assessment, prediction of wind energy production, with the main purpose of determining the impact of climate change on the potential for wind power production in North Africa. The overall process steps of the approach of this study can be divided into three main steps: climate data review, wind resource assessment, and wind energy production assessment.

3.1 Climate Data Analysis

Data on previous as well as predicted climate conditions were initially considered to identify long-term trends as well as changes in key conditions of the atmosphere, which are significant for wind power. The evaluation of the climate conditions mainly included wind velocity, near-ground heat, as well as atmospheric force. To test the efficiency of the local climate model, the simulated climate conditions were compared to the documented and re-analyzed climate conditions for the historical period of record (1960-1990).

The efficiency of the model was determined through the application of statistical parameters such as the Mean Bias Error (MBE), the Root Mean Square Error (RMSE), and correlation coefficients.

These parameters allow an impartial evaluation of systemic skew, total divergence, as well as timing correlation of simulated as well as documented wind conditions. Consequently, the collective method was adopted to mitigate the associated uncertainties of climate model reproductions.

3.2 Wind Resource Assessment

Wind potential assessment was conducted through statistical models of wind velocity spreads. The Weibull distribution was used to illustrate the frequency spread of wind velocity at every investigation point, as it is widely recognized for its effectiveness in wind power undertakings. The form and scale coefficients were determined for both past and coming time frames to measure the potential changes in wind patterns in the context of environmental changes.

Since wind generators depend on the availability of wind at rotor heights, the near-ground wind speeds were extrapolated to 80 to 100 m heights using boundary layer power law correlations. In addition, the seasonal and yearly variations of the wind characteristics were analyzed to assess the possibility of variations in the availability of the wind.

3.3 Wind Energy Estimation

The power output of wind energy was estimated by correlating wind speed distribution patterns with specific power curves of large wind farms, which are characteristic of the region. The wind power formula was used to

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determine the energy generated by the wind energy, taking into consideration the density changes in the air resulting from the temperature and pressure changes.

Wind Speed Extrapolation to Hub Height

The wind speed data available at a reference height was extrapolated up to the turbine hub height using a logarithmic wind profile, which is widely used in wind energy analysis under neutral stability conditions. The wind speed profile in the vertical direction is represented by the equation:

$$V(z) = V(z_{ref}) \times [\ \ln(z / z0) / \ln(z_{ref} / z0)\ ]$$

where

$V(z)$ is the wind speed at height z (m/s),

$V(z_{ref})$ is the wind speed at the reference height z_{ref} (m/s),

z is the target height (m),

z0 is the surface roughness length (m). [15]

Air Density Calculation

The changes in air density were specifically considered due to their direct impact on wind power estimation. Air density has been ascertained under the ideal gas law, thus:

$$\rho = p / (R \times T)$$

where

ρ is air density (kg/m³),

p is atmospheric pressure (Pa),

T is air temperature (K),

R is the specific gas constant for dry air (287 J/kg·K). [16]

Wind Power Density

Wind power density (WPD), which indicates the available kinetic energy of the wind, was determined by applying the following equation:

$$WPD = 0.5 \times \rho \times V^3$$

where

ρ is air density (kg/m³),

V is wind speed at hub height (m/s). [17]

Wind Power Output

Theoretical wind power available to the wind turbine was determined by applying the following equation:

$$P = 0.5 \times \rho \times A \times V^3$$

where

P is wind power (W),

ρ is air density (kg/m³),

A is the rotor swept area (m²),

V is wind speed at hub height (m/s). [18]

The detailed steps of the above algorithm are indicated in Figure 2.

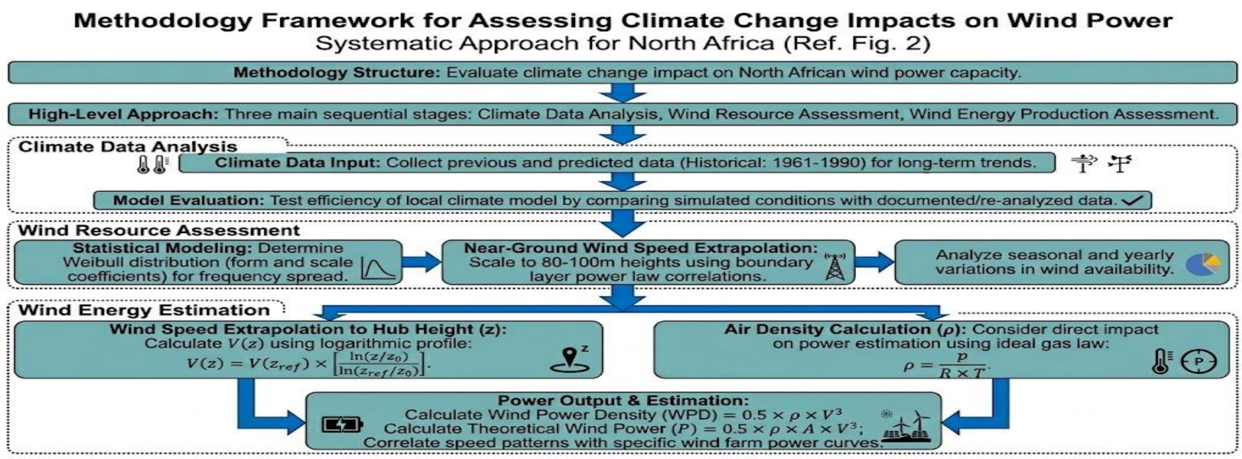

Figure 2. flow diagram of the systematic approach adopted in assessing the impacts of climatic changes on wind energy potential and output in North Africa.

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RESULTS AND DISCUSSION

4.1 Evaluation of Climate Model Performance (Historical Period)

This section evaluates the performance of regional climate models in reproducing historical wind speed conditions over North Africa during the reference period (1960–1990), as illustrated in **Figure 3**.

The ERA reanalysis dataset indicates relatively stable wind conditions, characterized by low interannual variability and the absence of any clear long-term trend. This confirms that the historical wind regime over North Africa is generally steady and does not exhibit significant temporal fluctuations.

In contrast, all regional climate models consistently overestimate wind speed compared to the ERA reference data. This overestimation is evident across the entire period and reflects a systematic positive bias inherent in the model outputs. Although the multi-model ensemble (MME) reduces inter-model variability and smooths fluctuations, it still produces higher wind speed values than the reference dataset, indicating that the bias persists even after ensemble averaging. This The discrepancy may be explained by the difficulty of representing important physical processes such as the boundary layer, surface roughness, and regional atmospheric circulation patterns. Therefore, direct application of raw outputs from these models may cause considerable overestimation of wind energy potential. More information is also provided by Figure 4, which illustrates the pattern of wind power density (WPD) for different models. The MME indicates a stable median value ranging from 170 to 175 W/m². In contrast, individual models show noticeable dispersion and inconsistencies, reflecting model-specific uncertainties. Overall, these results emphasize the need to apply bias correction techniques prior to the use of climate model results in wind energy assessment. Although the MME method improves consistency and decreases uncertainty, it does not remove systematic bias completely.

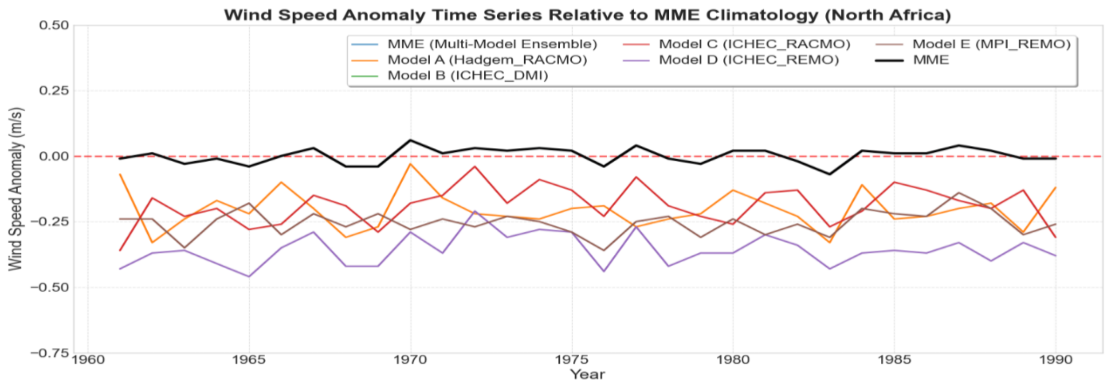

Figure 3. The temporal variation of wind speed on an annual basis at 100 meters above ground level in North Africa during the years of reference (1960-1990). The figure displays ERA data against the output from each regional climate model used for this study, in addition to the output from the MMEs.

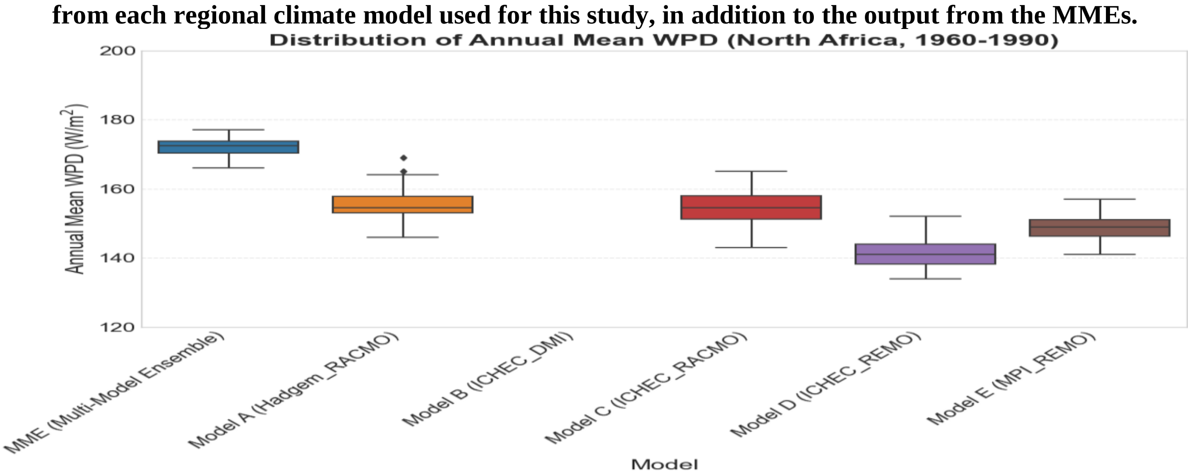

Figure 4 Distribution of Annual variation of multi-model mean wind speed (or wind power density) over North Africa.

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4.2 Changes in Wind Speed under Climate Change

Projected changes in wind speed under the RCP 4.5 scenario for the period 2021–2050 are presented in Figures 5–8, which illustrate seasonal variations based on raw and bias-corrected model outputs.

Across all seasons, raw multi-model ensemble (MME) results consistently overestimate wind speed, with values exceeding corrected estimates by approximately 1.5–2.2 m/s, corresponding to a relative overestimation of about 25–35%. This again validates the existence of systematic bias as seen in the historical analysis.

After applying bias correction, wind speed values are significantly reduced and fall within a more realistic range, with improved agreement among individual models. The corrected outputs exhibit relatively narrow variability bands, indicating enhanced consistency and reduced uncertainty across the ensemble.

In spite of these corrections, no statistically significant long-term increasing or decreasing trend is seen over the entire period (2021–2050). This suggests that wind conditions across North Africa remain largely stable under moderate climate change forcing.

However, seasonal variation is clearly seen. As depicted in Figure 7, the summer season (JJA) is the one where the maximum wind speeds are recorded, ranging between 5.6 and 5.8 m/s, making it the best time for wind power generation. In contrast, winter (DJF), illustrated in Figure 5, exhibits lower wind speeds, generally between 4.3 and 4.6 m/s, but maintains relatively stable conditions.

Spring (MAM), shown in Figure 6, represents an intermediate regime with wind speeds around 4.9–5.1 m/s and relatively low variability. Autumn (SON), presented in Figure 8, displays comparatively higher interannual variability, with wind speeds fluctuating between approximately 4.6 and 5.3 m/s, indicating greater sensitivity to atmospheric changes.

Overall, the results indicate that while wind speed magnitude varies seasonally, the long-term wind resource remains stable under the RCP 4.5 scenario.

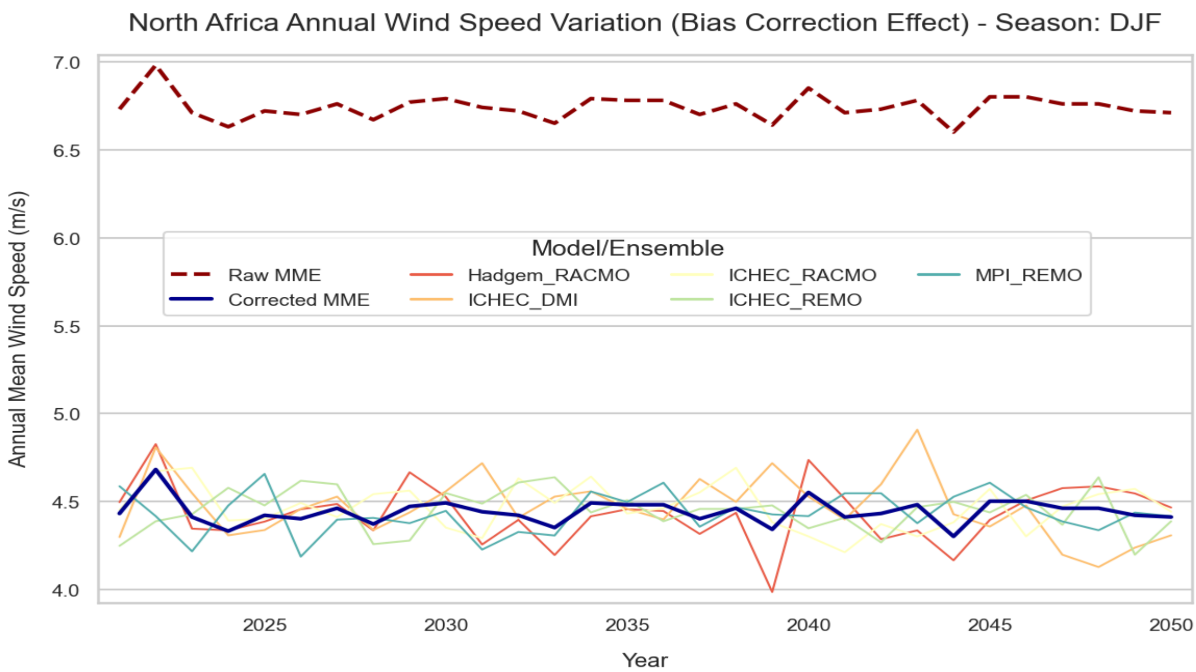

Figure 5. Annual variation of mean wind speed at 100 m over North Africa during the future period under the RCP 4.5 scenario (DJF season), showing raw multi-model ensemble (MME), bias-corrected MME, and individual regional climate model outputs.

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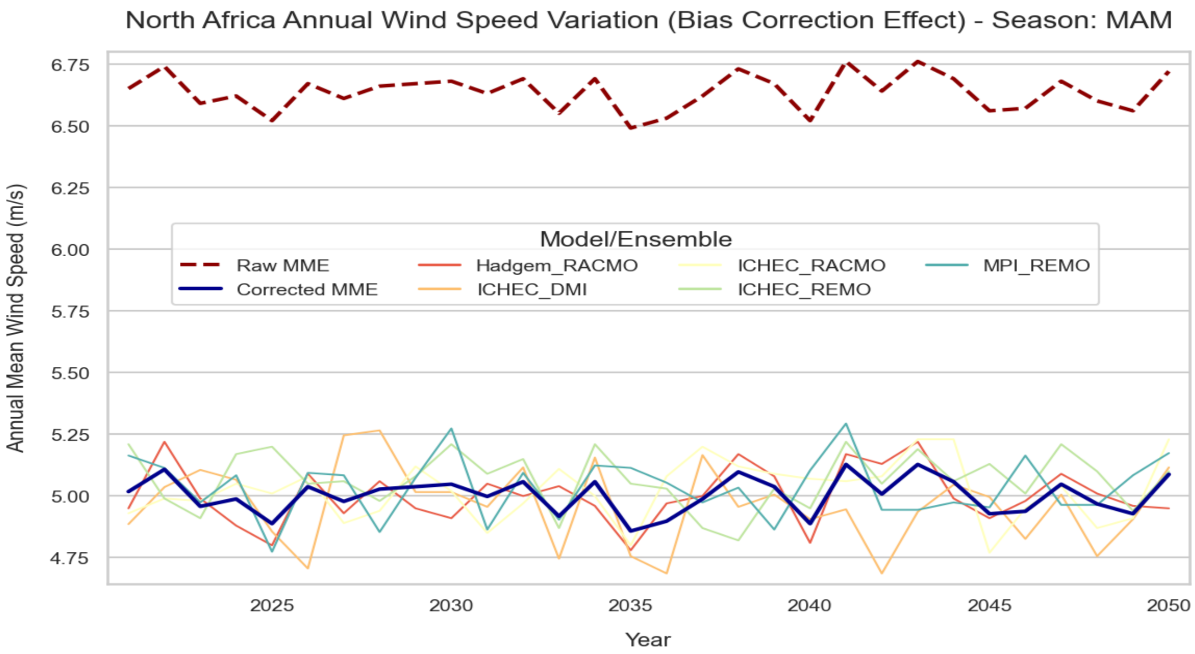

Figure 6. Annual variation of mean wind speed at 100 m over North Africa during the spring season (MAM) under the RCP 4.5 scenario, showing raw multi-model ensemble (MME), bias-corrected MME, and individual regional climate model outputs.

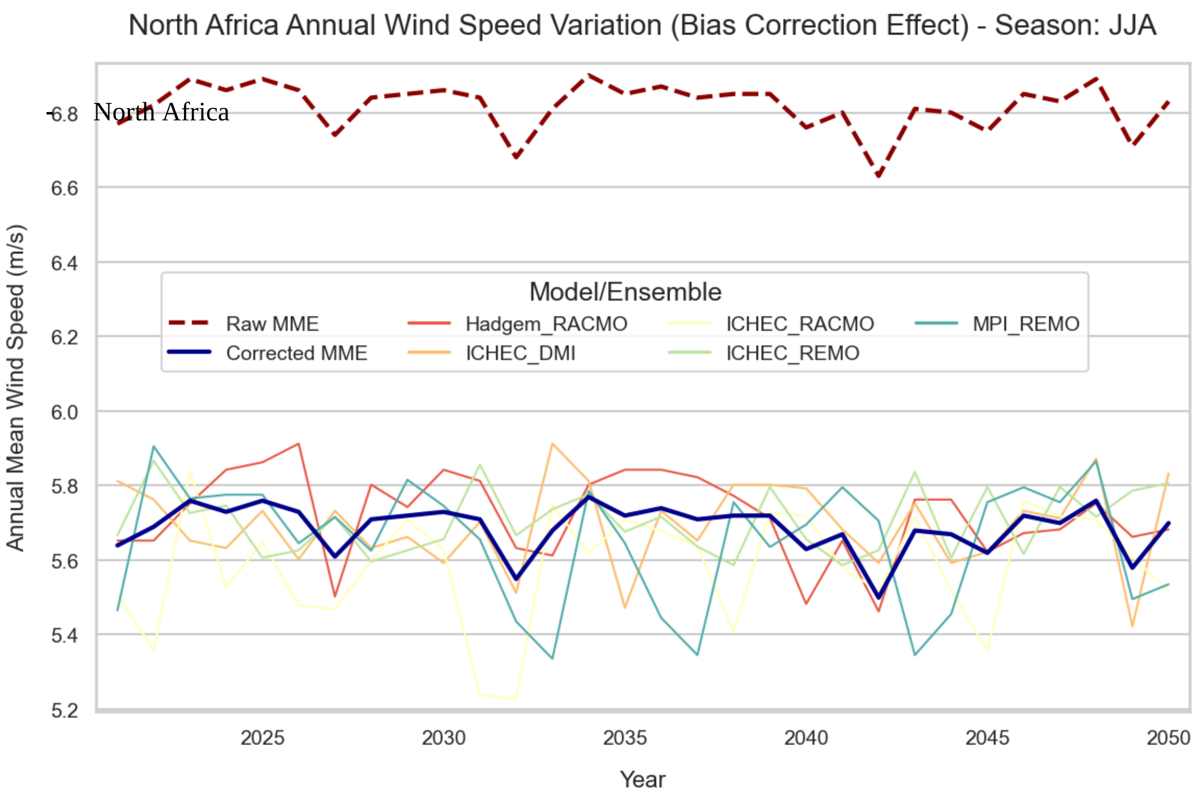

Figure 7. Annual variation of mean wind speed at 100 m over North Africa during the summer season (JJA) under the RCP 4.5 scenario, showing raw multi-model ensemble (MME), bias-corrected MME, and individual regional climate model outputs.

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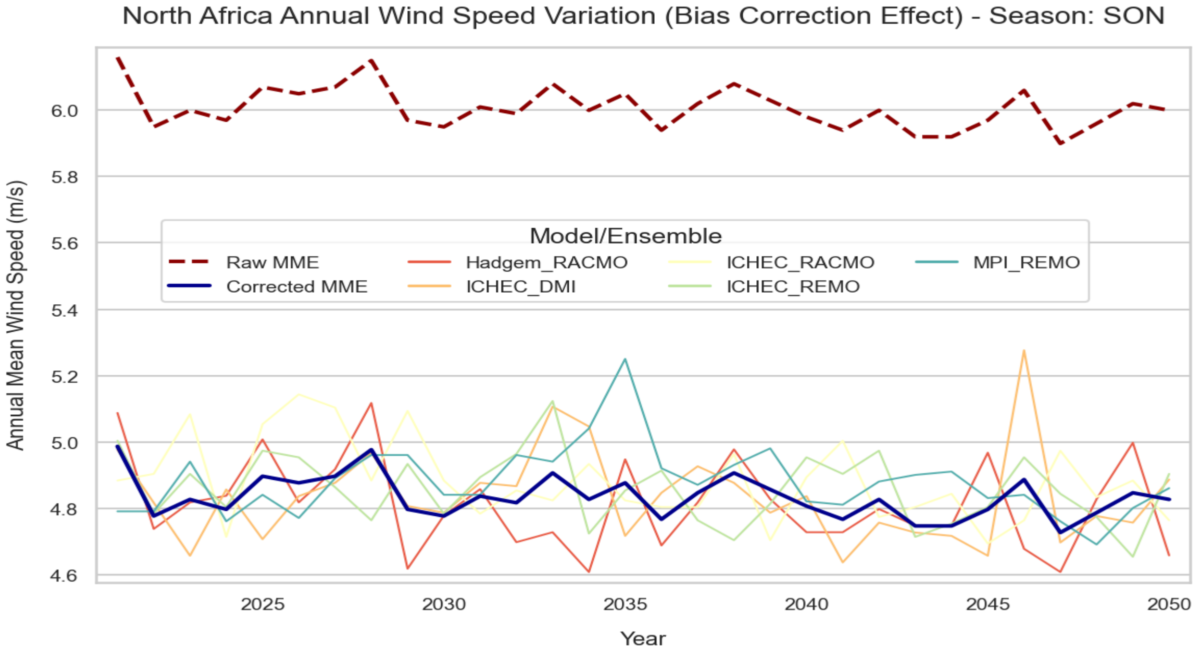

Figure 8. Annual variation of mean wind speed at 100 m over North Africa during the autumn season (SON) under the RCP 4.5 scenario, showing raw multi-model ensemble (MME), bias-corrected MME, and individual regional climate model outputs.

4.3 Seasonal Variability and Anomaly Analysis

The seasonal behavior of wind speed and wind power density is further examined through anomaly analysis, as presented in **Figure 9**.

From the results, it is evident that the seasonal variation in wind speeds remains centered around the historical baseline, with the majority of the anomaly values being concentrated around zero. This shows that future wind conditions do not differ significantly from the historical conditions.

However, the results show variation in the level of variability during different seasons. Summer (JJA) and autumn (SON) exhibit a wider spread of anomalies, indicating increased variability and sensitivity to atmospheric fluctuations during these periods. On the other hand, winter (DJF) and spring (MAM) show a more constrained distribution, indicating a more stable and predictable wind pattern.

The wind power density follows a similar pattern, but with increased variability due to its cubic relationship with wind speed. Thus, any small changes in wind speed are found to induce significant changes in WPD, showing a higher dispersion in anomaly distribution.

This indicates that seasonal variability is indeed the dominant mode of change, as opposed to long-term trends. While wind energy potential remains generally stable across North Africa, the increased variability observed in certain seasons—particularly JJA and SON—may influence short-term energy production and should be considered in energy planning strategies.

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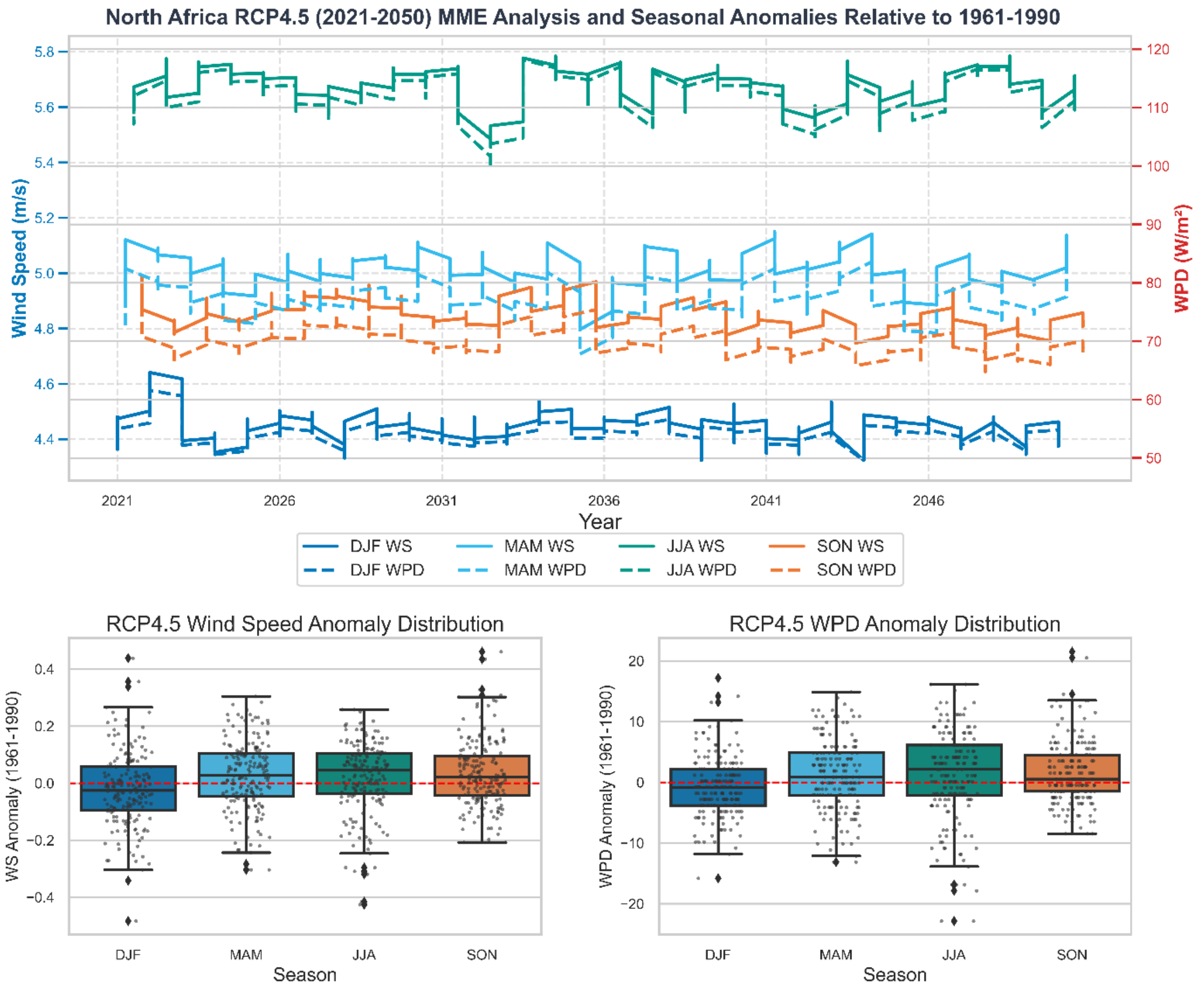

Figure 9. Multi-model ensemble (MME) projections of seasonal wind speed (WS) and wind power density (WPD) over North Africa under the RCP 4.5 scenario for the period 2021–2050, along with the distribution of seasonal anomalies relative to the historical baseline (1961–1990).

4.4 Wind Power Density (WPD) Analysis

Wind power density (WPD), as a key indicator of available wind energy, is analyzed in relation to the projected wind speed patterns under the RCP 4.5 scenario, as illustrated in Figure 9.

The results show that the WPD varies seasonally, as with the wind speed, with clear differentiation between seasons. The maximum WPD is found during the summer season (JJA), as with the wind speed during this season. The minimum WPD is found during the winter season (DJF), as with the wind speed during this season. The WPD during the spring season (MAM) and autumn season (SON) is moderate, with the autumn season having greater variability compared to the rest of the seasons. Despite the overall stability in wind speed trends, WPD exhibits noticeably higher variability. This phenomenon is largely accounted for by the cubic relationship existing between wind speed and wind power density. As a result, even minor variations in wind speed lead to disproportionately large changes in WPD. This amplification phenomenon is clearly evident in the increased spread of WPD anomalies in relation to wind speed. The anomaly analysis further confirms this pattern. Although wind speed anomalies still retain their concentration around the baseline, wind power density anomalies have higher values of dispersion, especially during summer (JJA) and autumn (SON).

Furthermore, the application of multi-model ensemble (MME) increases the reliability of wind power density projections. This is because, by averaging different regional climate models, the multi-model ensemble eliminates the uncertainty of individual models and offers a more consistent projection of wind energy potential in the future.

Compared to individual models, which have highly variable values of wind power density, the multi-model ensemble offers a more stable and robust projection of wind energy availability.

The results suggest that wind energy potential in North African countries remains relatively stable under the RCP 4.5 scenario. However, the results also suggest that the increasing variability in wind power density, especially during specific seasons, must be taken into consideration. The nonlinear response of wind power density to wind speed variations underlines the need to accurately project wind speed to ensure reliable estimation of wind energy availability.

DISCUSSION

It is found that regional climate models systematically overestimate the wind speed, even with the implementation of multi-model ensemble techniques, which highlights the necessity for bias correction to obtain accurate wind energy estimates [7], [8]. Despite the overestimation, the wind speed projected with the RCP 4.5 scenario does not show any statistically significant long-term trend, indicating that the wind energy potential over North Africa is expected to remain unchanged in the future, as found in the previous studies [9].

In contrast, the seasonal effects are found to be the major factor influencing the wind energy potential. The wind speed is found to be higher during the summer season, while the increased variability during the autumn season is due to the sensitivity of the wind regimes to the atmospheric circulation dynamics and the climatic conditions [6]. In addition, the wind power density is found to be more variable due to the cubic dependence on the wind speed, indicating that the wind energy potential is significantly sensitive to the wind speed [11]. Moreover, the implementation of the multi-model ensemble techniques is found to be effective in reducing the uncertainty associated with the climate models, ensuring the accuracy and reliability of the wind energy potential estimates [12].

CONCLUSION

This study examines the effects of climate change on wind energy potential in North Africa based on different climate models and multi-model ensemble (MME) of regional climate models (RCMs) under the RCP 4.5 scenario. Due to the tendency for climate models to often over predict the amount of wind for a reference dataset prior to bias correction being applied when using model output to assess wind energy availability, there is a definite demand for the application of bias correction methods prior to using the model output for wind energy assessments by agencies. The results from the historical study period indicate that patterns of wind speed in North Africa are highly likely to remain mostly unchanged through the forecast period of 2021-2050 without exhibiting any significant long-term increasing nor decreasing trend; however they do exhibit considerable seasonal variations. Highest wind speeds and highest amount of energy produced from the wind occur consistently during the summer (JJA) season, however, there are large variations and therefore a high sensitivity to the effects of climate change that sometimes have occurred during the autumn (SON) season. The winter (DJF) and spring (MAM) seasons have moderate to low levels of variability but they typically show relatively stable and predictable wind conditions. The wind power density behaviour is influenced by wind speed, but the variability is pronounced because of the nonlinear relationship to wind speed. Using an ensemble of models reduces disagreements among the individual models and gives greater consistency in representing the wind resource projections. Overall, the results indicate that the potential for wind energy development in North Africa is expected to withstand moderate climate changes, with the long-term trends having less effect than the effects of the seasons.

Implications for Future Work

These results offer several opportunities for wind energy developments. First, the consistent overestimate of wind potential based on raw output from climate models emphasises the need to incorporate bias corrections into the wind resource assessment as a standard step. If bias corrections are not made, wind energy potential could be overestimated significantly. Second, the clear seasonality of the wind energy resource suggests that a seasonal approach should be applied to wind energy planning based on the relatively strong and predictable summer winds. Given the greater uncertainty of the autumn winds, the impact of this uncertainty should be factored into the design of systems and operational planning. Thirdly, the results prove the importance of using multi-model ensemble techniques since more reliable results can be obtained compared to individual climate models. This is especially important in regions where model uncertainty remains a key challenge.

Fourthly, based on the high sensitivity of energy density from wind power to fluctuations in wind speeds, slight variations in weather patterns can significantly influence the quantity of energy harnessed from wind power systems. As a result, it is important to use high-resolution models to develop and interpret projected future wind data.

In future analyses extending beyond RCP 4.5, there should be an emphasis on using even finer resolution models to better characterise local wind patterns and integrating climate projections into techno-economic assessments of long-term wind energy system viability and sustainability throughout the area.

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