Impacts of Climate Change on Wind Generation Potential in Rio Grande do Norte and Ceará

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Abstract

Wind energy has emerged as one of the main sustainable alternatives for electricity generation in Brazil. Among the states with the greatest potential, Rio Grande do Norte and Ceará stand out due to their favorable climatic and geographic conditions, which ensure strong and consistent wind regimes. However, the availability of this resource is highly dependent on climatic variability, making it essential that long-term energy planning incorporates reliable projections of future wind behavior. This study analyzed climate scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) and their potential impacts on the wind energy sector, using outputs from Global Climate Models (GCMs) regionalized through the Eta model (BESM, CanESM2, HadGEM2-ES, and MIROC5), refined through machine learning techniques. Historical observational series were integrated into these projections, resulting in a hybrid modeling framework capable of providing high-accuracy forecasts for the next three decades. The results indicate a general trend of slight decreases in mean wind speeds, ranging from 2% to 7% by the mid-21st century. Ceará shows a more stable and homogeneous pattern, with modest reductions and low spatial variability, while Rio Grande do Norte exhibits more heterogeneous declines, particularly in inland areas. Despite these projected reductions, both states remain highly favorable for wind power expansion and for strengthening the green hydrogen production chain, consolidating the Northeast region as a strategic axis in Brazil’s energy transition.

Keywords: Wind Energy; Energy Planning; Climate Change; Global Climate Models.

1. Introduction

Climate change is an important topic in high-level decision-making worldwide, highlighting the need to reliably predict its consequences for key economic sectors and social well-being. Energy production has become a central issue in these discussions because clean energy generation depends fundamentally on natural resources that are intrinsically linked to any climatic changes (Cruz et al., 2024; Kara, 2023). Greater diversification of the energy matrix increases the sector’s resilience to climate change; consequently, wind energy emerges as a viable alternative to strengthen national and international energy systems, gaining considerable attention and investment over the last decade (Cruz et al., 2024). Brazil holds substantial untapped wind-power potential due to the abundance and quality of the resource across different parts of its territory, a result of its geographic extent and favorable climatological characteristics. Understanding the future availability of wind resources is crucial for planning investments, expanding generation capacity, and developing new technologies for the sector (Cruz et al., 2024; Kara, 2023).

Understanding the future climate is fundamental for the development of Brazil’s energy sector and for the country’s consolidation as a key player in the global energy transition, since climate change will directly influence energy production at the global scale (Cruz et al., 2024; Kara, 2023). In this context, not only wind power but most forms of power generation in Brazil are affected; in recent years renewable sources have supplied the majority of the country’s electricity. According to the National Energy Balance 2024 (base year 2023), electricity from hydro sources accounted for approximately 58.9% of Brazilian production, followed by wind and solar generation with 13.2% and 7%, respectively (EPE, 2024).

The uncertain climatic future has received growing emphasis in academia, and its behaviour is increasingly

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studied through a suite of models that project different scenarios describing climate change and its patterns via Global Climate Models (GCMs). These models rely on the analysis of diverse climatological variables affected by climate change; such studies are widely disseminated across countries and institutions and follow the guidance of the Intergovernmental Panel on Climate Change (IPCC, 2013; 2021), which serves as the global reference in this research field. From the IPCC's work, scenarios are derived that seek to represent different possible futures, ranging from less critical to extreme climatic conditions.

Global climate models are complex computational tools that divide the planet into a three-dimensional grid and compute essential climate variables—such as temperature, humidity, and circulation patterns—using physical equations that describe natural processes like heat transfer and fluid dynamics. They are commonly used to project future climates based on parameters outlined by the IPCC. Model reliability can be assessed by their ability to reproduce historical climate patterns, which enhances their robustness (IPCC, 2021).

To increase spatial detail and improve projection accuracy for more specific situations, global models are often regionalized into smaller domains (downscaling). The models regionalized for Brazil include BESM, CanESM2, HadGEM2-ES, and MIROC5, which are part of the Eta products developed for South America. This technique aims to reduce geographic scale and thereby increase model precision. The National Institute for Space Research (INPE) is responsible for regionalizing these data for Brazil, with recent works highlighting methodological updates and validation improvements (Almagro et al., 2020).

Because broad-scale projections inherently face accuracy issues, bias correction and adjustment techniques based on the region's climatological history are used to improve forecast precision (Costoya et al., 2020; Tiwari et al., 2022). Currently, the use of artificial intelligence models is widespread for time series adjustments and for producing accurate projections through learning processes; although relatively recent, this approach has increasingly demonstrated higher accuracy indices compared with other methods (Coburn, 2022; Campos, 2022).

This work investigates the impact of climate change on wind resource availability in northeastern Brazil, focusing on 12 studied stations. The central problem is the uncertainty regarding the evolution of mean wind speeds at local and decadal scales, which undermines investment planning and energy security. The objective is to quantify and interpret the projected changes for the decades from 2013 to 2054, seeking to calibrate and validate statistical models with observational series, compare regressor responses to the outputs of climate models, estimate percentage variations per decade, and evaluate the implications for generation and energy planning. The study is justified by the strategic relevance of wind energy to the electrical matrix.

2. **Methodology**

Data from four wind complexes, encompassing a total of 30 wind measurement stations distributed across the states of Rio Grande do Norte and Ceará, were used in this study. To ensure that the subsequent data analysis yielded coherent and reliable results consistent with the proposed objectives, only stations with measurement records starting in 2016 or earlier were selected. The datasets contain hourly wind speed measurements taken at heights ranging from 80 to 123 meters.

In addition to the historical time series, climate projections from the regional models EtaBESM, EtaCanESM2, EtaHadGEM2-ES, and EtaMiroc5 were used. These projections were obtained from the *Projeta* system developed by CPTEC/INPE. The projections were generated in 20×20 km grid cells and spatially adjusted to match the geographical coordinates of the wind stations under study, based on greenhouse gas concentration scenarios RCP4.5 and RCP8.5. The selected climatic variable was wind speed at 100 meters above ground level (W100), with daily frequency. The projection periods began between 2011 and 2016, depending on data availability for each station (Almagro et al., 2020).

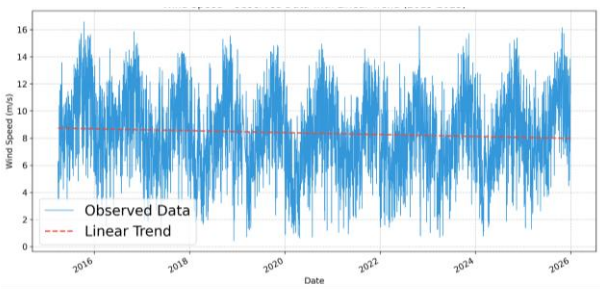
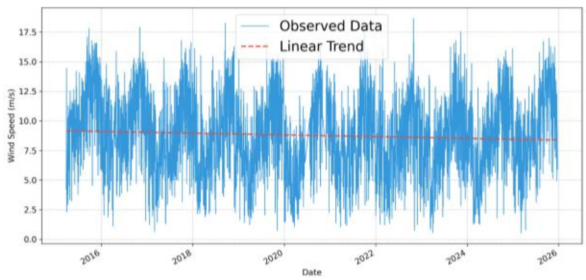
The observed datasets, originally recorded at hourly intervals, were aggregated into quarterly and annual values for comparison with the climate projections. Similarly, the climate projections, initially available at daily frequency, were transformed into quarterly and annual data, ensuring temporal consistency between datasets. Both observed and projected data were used for model training and testing, enabling a detailed analysis of potential future wind speed trends in the studied regions (Ruffato-Ferreira et al., 2017; Bishop & Christopher, 2006).

Feature engineering and the creation of lagged series included a time lag of up to 182 days to capture seasonal and long-term wind speed patterns. The dataset was divided into training and testing subsets, with data up to 2020 used for training and data from 2021 to 2024 reserved for model validation. Regression algorithms such as Linear Regression, Decision Tree, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Support Vector Regression (SVR) were applied to generate forecasts. The evaluation metrics used to assess predictive performance were the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) (Mitchell, 1997; Goodfellow, 2014).

For performance assessment, the MAE and MAPE of the machine learning models were compared to the projections provided by *Projeta*, specifically the EtaHadGEM2-ES model, which served as a benchmark to evaluate the accuracy and improvement achieved through the developed predictive model.

3. Results and Discussions

Table 1: Observed data from selected stations in Ceará

<table>
<tr><td>SR1
</td><td>SR2
</td></tr>
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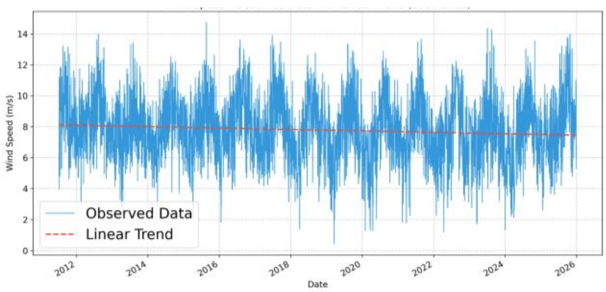
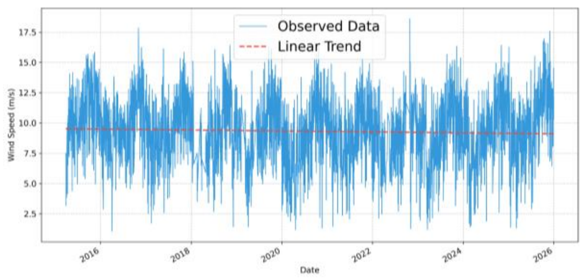
</td><td>SR4
</td></tr>
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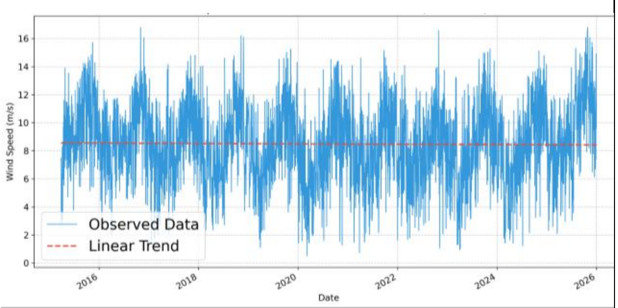</td><td></td></tr>
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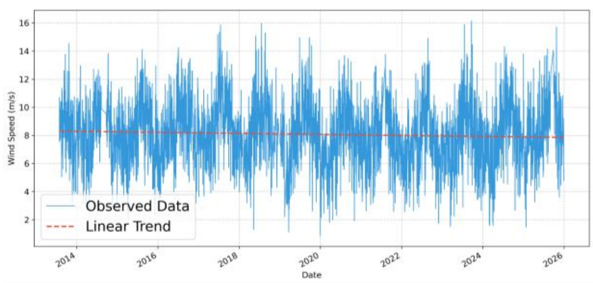
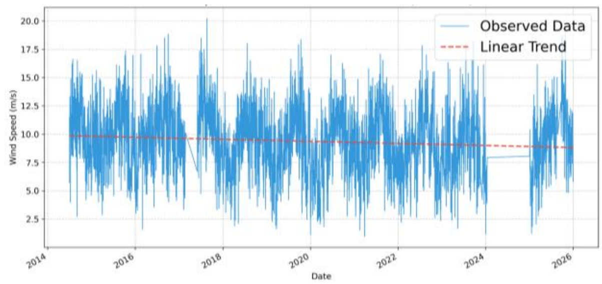
Table 2: Observed data from selected stations in Rio Grande do Norte

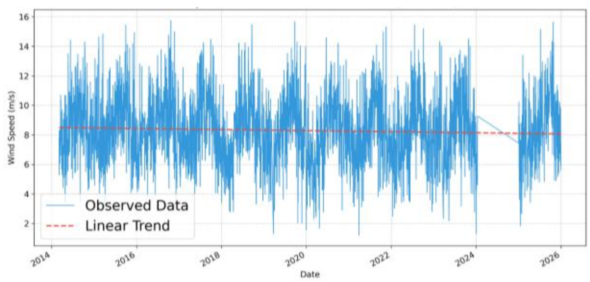
LN1



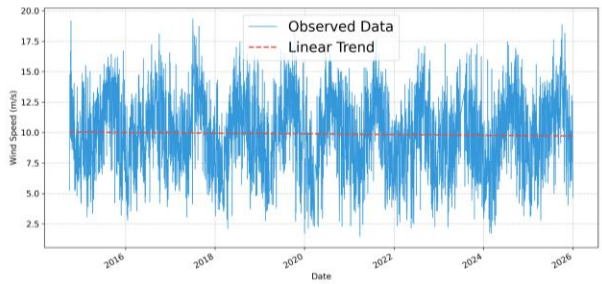
LN2



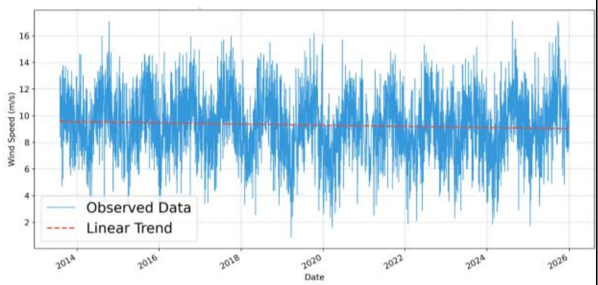
LN3



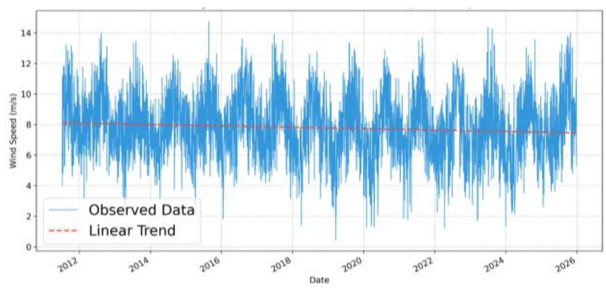
LN4



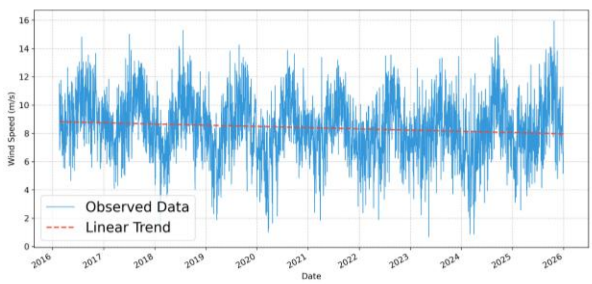
LN5



JC1



JC2



When analyzing the observed data, it becomes evident that the wind measurement stations in the states of Ceará and Rio Grande do Norte have shown a consistent decrease in mean wind speed over the past decade. Observational analyses focused on Brazil confirm the presence of mixed regional signals and identify areas of the Northeast exhibiting a weakening trend in specific periods and seasons, which supports the local detection presented here (Lima, 2024; Moura et al., 2021). Despite this decline, there has been a steady increase in wind energy production throughout the last decade, as analyzed by Andrade, Melo, Lucena, and Abrahão (2021). This growth is more closely related to technological advancements in equipment—particularly the introduction of more efficient and productive modern wind turbines. It is noteworthy that this apparent contradiction reinforces the importance of understanding future wind speed trends over the coming decades. The standard rotor height has increased from approximately 90 meters to 150 meters in the past decade.

Table 2 presents the validation metrics of the artificial intelligence regression models used to project wind speed trends. In this case, it is possible to observe the different models and the accuracy achieved by each, depending on their predictive approach and suitability for the study in question (Goodfellow, 2014).

Table 3: Validation of the Random Forest model at stations in the state of Rio Grande do Norte

State	Station	Metrics	Decision Tree	Linear Regressor	KNN	Random Forest
Ceará	SR1	MAE	1,31	1,73	0,76	0,54
		MAPE	20,40%	26,00%	11,00%	8,70%
	SR2	MAE	0,48	2,04	0,6	0,31
		MAPE	6,60%	29,50%	7,90%	4,00%
	SR3	MAE	0,43	1,68	0,36	0,27
		MAPE	6,40%	25,20%	4,90%	3,80%
	SR4	MAE	0,85	1,93	0,83	0,46
		MAPE	12,20%	25,10%	11,50%	7,30%
	SR5	MAE	0,57	1,61	0,44	0,31
		MAPE	8,10%	22,40%	6,00%	4,10%
Rio Grande do Norte	JC1	MAE	0,45	0,8	0,42	0,47
		MAPE	6,00%	10,80%	5,70%	6,30%
	JC2	MAE	0,74	0,7	0,71	0,53
		MAPE	9,20%	8,50%	8,00%	6,70%
	LN1	MAE	0,73	0,63	0,48	0,48
		MAPE	9,10%	10,00%	6,50%	6,70%
	LN2	MAE	0,59	1,52	0,67	0,65
		MAPE	7,60%	19,10%	8,20%	8,10%
	LN3	MAE	0,78	0,7	0,36	0,35
		MAPE	9,80%	9,10%	7,60%	4,50%
	LN4	MAE	1,08	0,8	0,68	0,58
		MAPE	15,00%	9,60%	8,00%	6,90%
	LN5	MAE	1,06	1,87	0,54	0,4
		MAPE	13,80%	22,20%	7,30%	5,60%

The performance analysis of the regression models — Decision Tree, Linear Regression, KNN, and Random Forest — for wind speed forecasting in both states revealed substantial variation across models and stations (Maulud & Abdulazeez, 2020). In the Ceará region, Random Forest achieved the best overall performance at every station, producing the lowest MAE and MAPE values across SR1–SR5. Notably, Random Forest obtained a MAE of 0.54 and a MAPE of 8.70% at SR1, 0.31 and 4.00% at SR2, 0.27 and 3.80% at SR3, 0.46 and 7.30% at SR4, and 0.31 and 4.10% at SR5. The Decision Tree model showed reasonable performance as well, for example at SR5 (MAE 0.57, MAPE 8.10%), but it was generally outperformed by the ensemble approach. Linear Regression performed weakest in this region, with particularly high percentage errors (e.g., MAPE 29.50% at SR2, 25.10% at SR4 and 22.40% at SR5), indicating its limited capacity to represent the nonlinear variability of wind speeds. KNN produced intermediate results (for instance, SR1 MAPE 11.00%

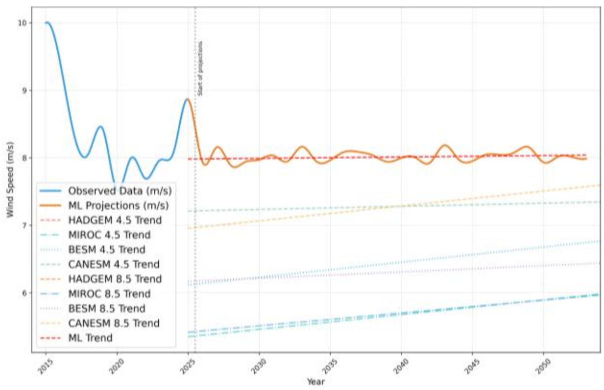
and SR5 MAPE 6.00%), performing better than Linear Regression in some cases but not matching the consistency of tree-based methods (Grömping, 2009).

In the Rio Grande do Norte stations Random Forest again proved strong overall but with a few important exceptions. At JC1 the Decision Tree very slightly outperformed Random Forest (Decision Tree MAE 0.45, MAPE 6.00% versus Random Forest MAE 0.47, MAPE 6.30%), while at JC2 Random Forest delivered the lowest errors (MAE 0.53, MAPE 6.70%). In the LN cluster performance varied by site: LN1 showed a tie in MAE between Random Forest and KNN (both MAE 0.48) with KNN marginally better by MAPE (KNN MAPE 6.50% vs Random Forest 6.70%), whereas LN2 proved more challenging for all algorithms — Decision Tree produced the lowest MAPE there (MAE 0.59, MAPE 7.60%) while Random Forest recorded MAE 0.65 and MAPE 8.10%. For LN3, LN4 and LN5 Random Forest was again the most robust choice (LN3 RF MAE 0.35, MAPE 4.50%; LN4 RF MAE 0.58, MAPE 6.90%; LN5 RF MAE 0.40, MAPE 5.60%). Linear Regression and KNN were occasionally competitive (for example, KNN at LN1), but they generally exhibited higher percentage errors and less consistency than tree-based models (Segal, 2004).

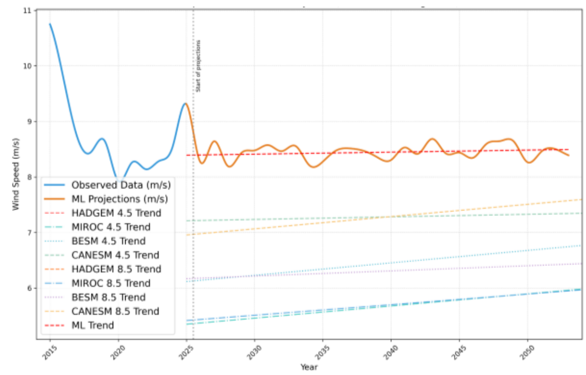
Overall, Random Forest is the best-performing model across the majority of stations in SR, JC and LN, showing the lowest absolute and percentage errors in most cases, although Decision Tree or KNN outperform it at a few specific sites (notably JC1 and LN1, respectively) and LN2 remains a station where modeling is comparatively difficult. These results underscore the superiority of tree-based ensemble methods for wind speed forecasting in this dataset, while also highlighting that no single algorithm is uniformly optimal at every measurement site; local station characteristics can favor alternative approaches. The relative underperformance of Linear Regression reflects its limited ability to capture the nonlinear and complex dynamics present in wind regimes (Coburn, 2022; Campos, 2022).

Table 4. Random Forest projection for stations in the state of Ceará from 2024 to 2055

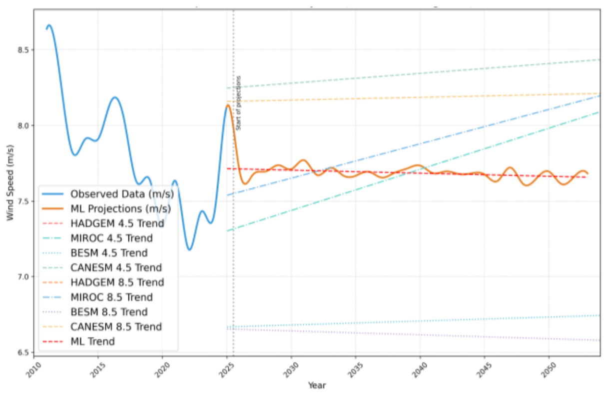
SR1



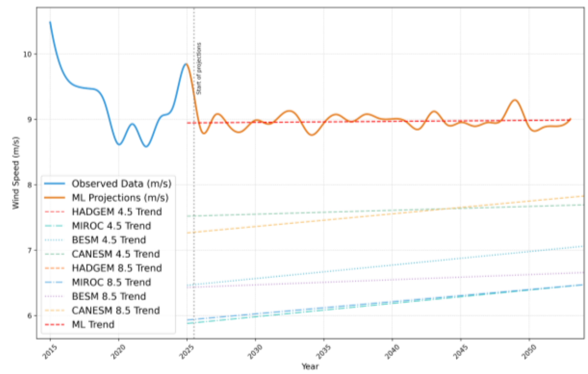
SR2



SR3



SR4



SR5

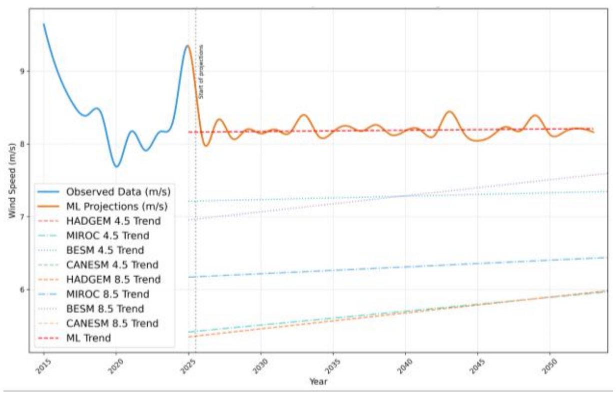
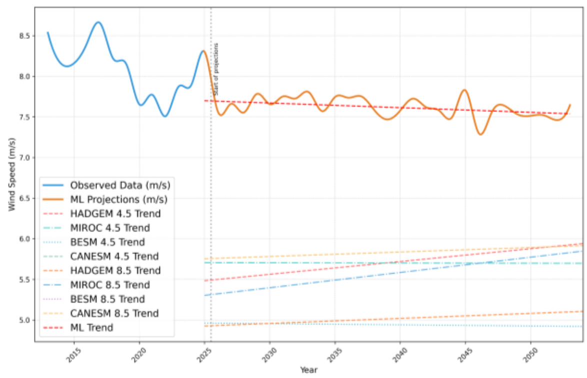
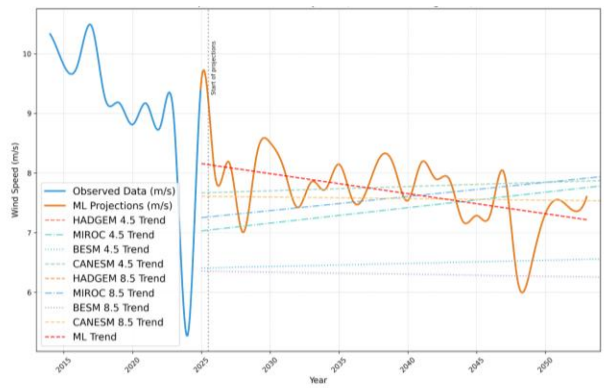


Table 5. Random Forest projection for stations in the state of Rio Grande do Norte from 2025 to 2054

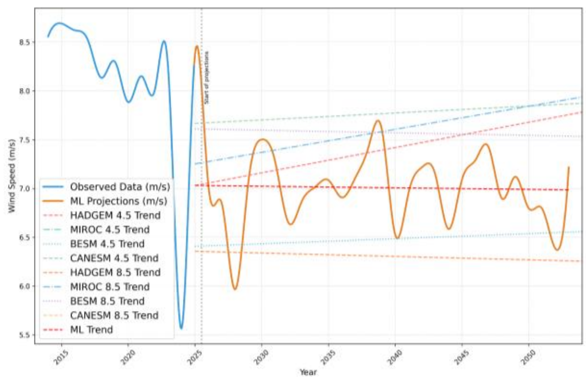
LN1



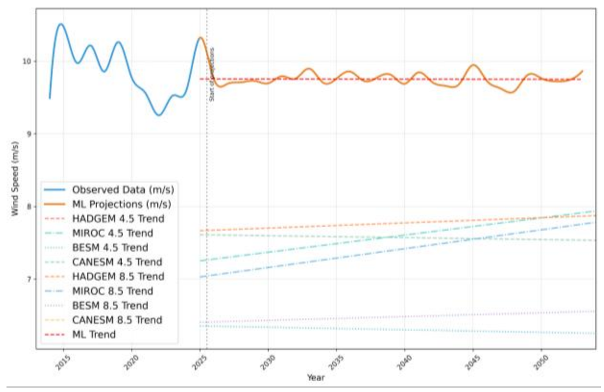
LN2

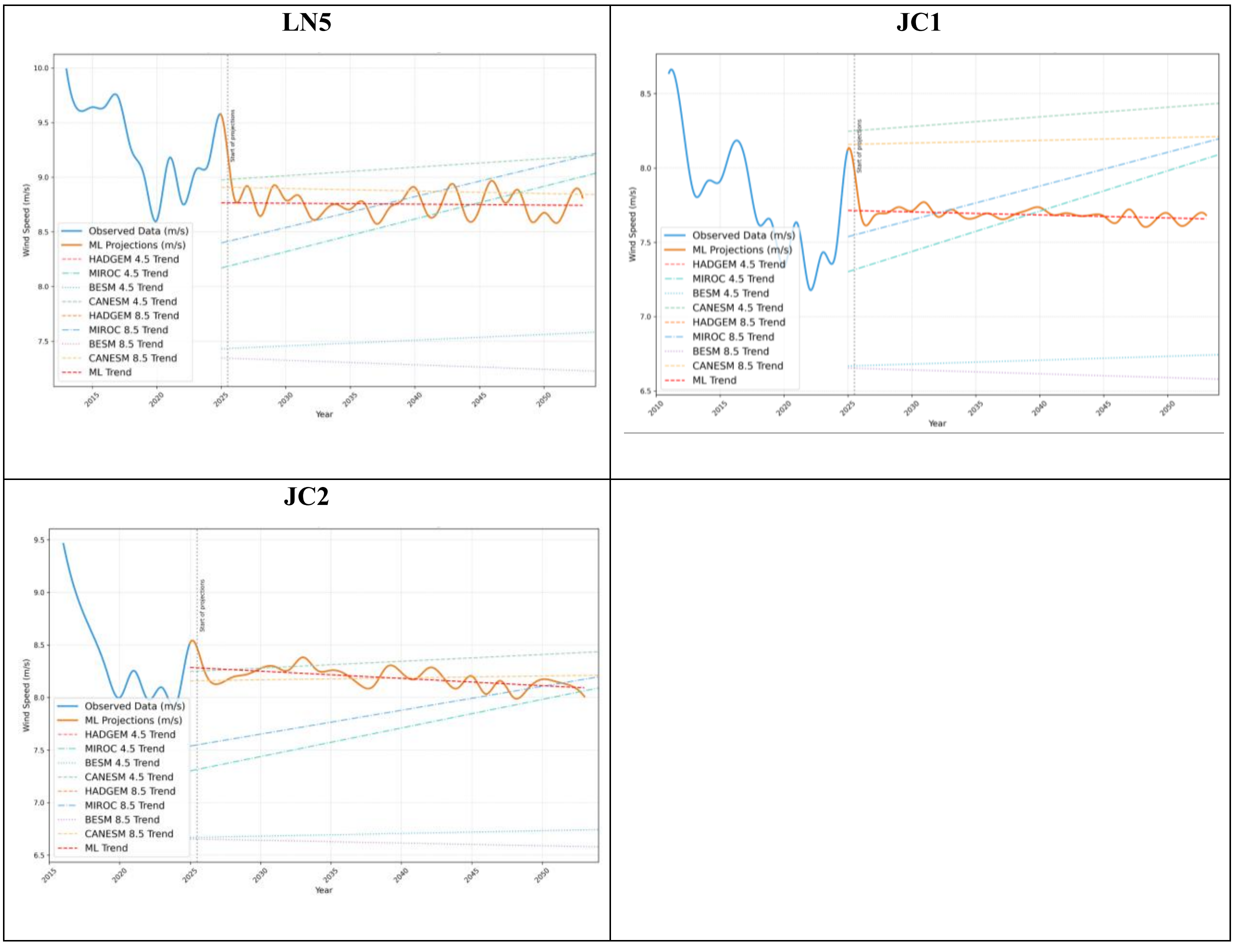


LN3



LN4





The projections obtained from the Random Forest and Decision Tree models, calibrated with observational data and fed by outputs from the Eta–GCMs (BESM, CanESM2, HadGEM2-ES, and MIROC5), indicate a general trend of slight decreases in mean wind speeds over the coming decades in both Ceará and Rio Grande do Norte. On average, the projected reductions range between 2% and 7% by the 2045–2054 decade, with small variations among models and locations. This trend aligns with patterns observed in historical series, which also show a slight weakening of winds over the historical period, particularly in inland areas of both states.

Analyzing the decade-to-decade variation reveals a gradual intensification of the reduction trend over the projection horizon. During the first period (2013–2025), wind speeds remain close to reference values, showing stability and good reproducibility of the calibrated models. From 2026–2034, a slight reduction begins, still within the natural variability range. This weakening becomes more noticeable between 2035–2044, when several measurement points, especially in Rio Grande do Norte, present average declines exceeding 4%. Finally, in the 2045–2054 decade, the most pronounced reductions consolidate, with averages between 5% and 7% at several stations, characterizing a continuous and gradual downward trend in wind speed.

This progressive behavior suggests that the effects of climate change on the wind regime tend to manifest cumulatively and slowly, consistent with previous studies indicating gradual alterations in surface wind circulation throughout the 21st century (Lima, 2024; Moura et al., 2021). Moreover, the maintenance of a stable and monotonic trend, without abrupt reversals, reinforces the internal consistency of the projections, indicating no signs of abrupt forced variability or statistical discontinuity during the analyzed period.

Analysis of the Eta–GCM coupled climate models reveals relevant differences in the magnitude and direction of projections, although the average behavior remains coherent among them. The HadGEM2-ES (Eta–HadGEM) and CanESM2 (Eta–CanESM) models tend to project slight increases or stabilization of mean wind speeds, particularly in the first decades, reflecting higher sensitivity to ocean warming patterns and intensification of thermal gradients. In contrast, BESM (Eta–BESM) and MIROC5 (Eta–MIROC) show more consistent reductions, aligning better with empirically observed behaviors at the stations. This heterogeneity among regional climate models is widely reported in the literature and is attributed to differences in turbulence parameterizations and the representation of large-scale circulation controlling trade winds over northeastern Brazil (Gomes et al., 2019; de Jong et al., 2019).

The ensemble mean of the Eta–GCMs suggests a slight increase or stabilization of wind speed until mid-century; however, the reductions predicted by the Random Forest and Decision Tree models, adjusted with observational data, indicate that the local signal tends toward weakening, particularly in continental areas. This difference between regional ensemble and statistical models underscores the importance of downscaling and local calibration, as Eta–GCMs—even with enhanced resolution—still smooth out topographic features and coastal effects essential for local wind dynamics (Silva, Lima & Martins, 2023).

In Ceará, the wind regime remains relatively stable across all time windows, with mild and evenly distributed reductions among stations. Stations SR2 and SR4, located in higher-relief areas with stronger orographic influence, show minor reductions, indicating greater resilience of the wind regime in these areas. Station SR5, closer to the coast, exhibits more pronounced seasonal oscillations, although without a significant negative trend. Overall, Ceará's stations display structural stability in wind patterns, consistent with the dominant trade winds and lower interannual variability in the state.

In contrast, Rio Grande do Norte presents more pronounced and spatially heterogeneous variations, with some stations showing sharper declines, especially in inland areas. Stations LN1 and JC1, located on plateaus and farther from the coast, show the strongest reductions, exceeding 6% in long-term projections for both Random Forest and Decision Tree models. Station LN2, closer to the coast, exhibits a less pronounced trend and higher interdecadal variability, likely influenced by interactions between sea breeze systems and regional circulation. This pattern aligns with studies indicating higher climate sensitivity for inland areas of Rio Grande do Norte, due to their distance from the ocean and lower thermal replenishment capacity of the boundary layer (Moura et al., 2021; Lima, Martins & Silva, 2022).

The integrated analysis indicates that northeastern Brazil, despite slight reductions in mean wind speeds, maintains favorable conditions for long-term wind energy generation. Signs of weakening are gradual and spatially concentrated in continental areas, while coastal zones preserve greater stability. The behavior of both Eta–GCMs and statistical models suggests that the reduction trend is neither homogeneous nor strictly monotonic but depends on the analysis scale and model considered. This heterogeneity is typical of regions strongly influenced by local processes and reinforces the importance of using multiple projection sources, combining dynamic simulations and machine learning statistical approaches to ensure robust analyses.

From an energy perspective, although the projected reductions are small, they require attention in policy formulation and planning strategies. Given the cubic relationship between wind speed and power, even modest variations can have amplified effects on production. Thus, policies encouraging high-efficiency turbines for moderate winds, wind-solar integration, and adaptive planning based on uncertainty ranges are recommended. These measures help mitigate potential impacts of wind reductions and ensure continuity in renewable energy expansion.

Finally, the slight decrease identified in this study does not compromise the strategic role of the Northeast in the global energy transition. On the contrary, by integrating the established wind matrix with growing solar potential, the region strengthens its position as a central hub for green hydrogen production, consolidating Brazil as a key player in the low-carbon economy. The results presented provide valuable insights for regional energy planning, supporting the development of resilient long-term strategies in the face of future climate uncertainties.

4. **Conclusions**

The integrated analysis of observed data, statistical models, and outputs from the regional Eta–GCM climate models indicates that the wind regime in northeastern Brazil is likely to experience a slight weakening over the coming decades, with spatial and temporal variations differing between Ceará and Rio Grande do Norte. This trend, identified both in historical series and in projections obtained from the Random Forest and Decision

Tree models, aligns with recent literature reporting terrestrial stilling in various regions of Brazil and worldwide (Lima, 2024; Moura et al., 2021; Zeng et al., 2019).

Overall, the projected mean reductions range between 2% and 7% by 2050, following a gradual decade-by-decade decline. Between 2013 and 2025, wind speeds remain stable without significant changes, while from 2026 to 2034 a moderate downward trend begins, consolidating during the 2035–2044 and 2045–2054 decades. This temporal trajectory suggests that climate change effects on wind in the Northeast are slow and cumulative, without abrupt breaks, reflecting gradual adjustments in atmospheric circulation and boundary layer stability.

Ceará exhibits the most stable behavior among the analyzed states. Projections indicate subtle reductions of around 2% to 3%, with low spatial dispersion and high temporal coherence. This stability is associated with the strong influence of trade winds and the constancy of oceanic and thermodynamic conditions controlling the coastal wind regime. In contrast, Rio Grande do Norte shows more pronounced and heterogeneous reductions, particularly in inland areas such as LN and JC, where declines exceed 6% in the final period. Coastal stations, such as Serra do Mel, display higher interdecadal variability and smaller reduction amplitudes, suggesting that local factors, including maritime influence, mitigate the effects of global warming on wind speeds.

Significant differences were also observed among the Eta-coupled climate models. Eta–HadGEM2-ES and Eta–CanESM2 projected slight increases or stabilization of mean wind speeds, whereas Eta–BESM and Eta–MIROC5 indicated more consistent reductions, approaching the projections obtained by the statistical models. This divergence within the ensemble highlights the importance of inter-model uncertainties and emphasizes that locally calibrated statistical approaches, such as those applied in this study, are essential for capturing the specific characteristics of the northeastern wind regime. Consequently, the results demonstrate that hybrid modeling—combining GCMs, Eta–GCMs, and machine learning methods—represents the most robust approach to assessing the climatic impact on wind resources.

From an energy perspective, the projected slight weakening does not compromise the region's wind potential but underscores the need for adaptive energy planning that incorporates safety margins and technology strategies focused on efficiency. Since wind power scales with the cube of wind speed, even modest average reductions can result in disproportionately larger production losses. In this context, the adoption of turbines designed for efficient operation under moderate wind conditions and the strengthening of wind-solar integration—whose seasonal complementarities in the Northeast are well recognized—are recommended (Souza et al., 2023).

Beyond direct implications for electricity generation, these results reinforce the strategic importance of the northeastern wind regime for the development of the green hydrogen sector. Even with slight reductions in mean wind speeds, regional climatic conditions remain highly favorable for renewable electricity production for water electrolysis. Ceará, with its stable wind regime and consolidated port infrastructure, emerges as an export hub, while Rio Grande do Norte, with its extensive installed base and interior expansion potential, plays a strategic role in diversifying and supplying the domestic market. Thus, future scenarios indicate that northeastern Brazil will continue to be a global epicenter of renewable generation and sustainable hydrogen production, integrating climate mitigation policies with industrial development.

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