

The wind resource of Northeast Brazil as a climate variable: decadal variability, regional model bias and projected change at turbine hub height

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Abstract

Wind is a climate variable on which the electricity supply of Northeast Brazil depends, yet regional climate projections had never been confronted with measurements at turbine hub height. We analyze 1.16 million hourly records from 12 meteorological masts (78 to 95 m) of three wind complexes in Rio Grande do Norte and Ceará (2011/2015 to 2025) and 20-km Eta regional simulations nested in four global models under RCP4.5 and RCP8.5. All stations show a decline of 5 to 12% per decade, significant at seven, but its structure is a level shift rather than a trend, with windy years (2015 to 2017) and calm years (2018 to 2024) in phase with El Niño–Southern Oscillation on the Ceará highlands and with the tropical Atlantic at the Rio Grande do Norte sites, and recovery in 2025. The Eta reproduces the seasonal phase ($r = 0.79$ to 0.97) but underestimates hub-height speed by up to 36%, mainly in the rainy season, and its interannual anomalies are uncorrelated with observations, as expected from free-running simulations. Machine-learning regressors fed by Eta output therefore cannot outperform climatology and transmit only 17 to 36% of the projected change signal, a caution for hybrid downscaling anywhere. After quantile delta mapping, the ensemble projects changes of +3 to +5% through 2054 on the highlands and near zero elsewhere, smaller than the decadal variability already observed, with inter-model spread exceeding the scenario difference. Over project lifetimes, adapting energy-yield estimation to ocean-driven decadal variability matters more than the mean climate-change signal.

1 Introduction

Wind is a climate variable, and where a power system depends on it the decadal variability and long-term change of the wind climate become questions of adaptation. Northeast Brazil is a clear case. Wind power is the second-largest source of electricity in Brazil, with 116.5 TWh generated in 2025 (14.9% of the domestic supply), 93% of it in the Northeast (ABEEólica 2026a; EPE 2026), and it accounted for 92% of the electricity generated in the state of Rio Grande do Norte (RN) and 70% in Ceará (CE) (Galiza et al. 2026). The sensitivity of the Brazilian hydrothermal system to the hydrological cycle has long been documented (de Queiroz et al. 2016; Lucena et al. 2009; Tiezzi et al. 2019), and diversification through wind and solar power came to be treated as an adaptation strategy (Lucena et al. 2010), which makes the climate sensitivity of the wind resource itself a question of the same order. The regional regime is governed by the trade winds, modulated by the South Atlantic Subtropical High and by the seasonal migration of the Intertropical Convergence Zone (ITCZ), with a maximum between August and November and a minimum in the rainy season (Barreto et al. 2025; Hastenrath 2012); on the interannual scale, El Niño tends to strengthen and La Niña to weaken the trades (Barreto et al. 2025; Duque-Gardeazabal et al. 2026), and the interannual variability of wind power density in the region is high compared with other major producing regions (Pryor et al. 2020). Curtailment of generation due to grid constraints, about 20% of the available wind and solar energy in 2025 (ABEEólica 2026a; ONS 2025), adds a second dimension to expansion planning.

The two sides of the observational and modeling literature do not yet meet. On the observational side, 10-m records indicate negative trends at coastal stations of the Northeast (Lima et al. 2024; Santos and Silva 2013) within a global picture of terrestrial stilling between the 1980s and the 2000s (McVicar et al. 2012; Vautard et al. 2010) followed by a reversal after 2010 driven by decadal ocean–atmosphere oscillations (Deng et al. 2021; Zeng et al. 2019), but anemometers at 10 m are subject to roughness and urbanization effects and lie far below the rotor of a modern turbine. On the modeling side, the consensus points to an increase of the resource under warming, from about +10% in speed to +25 to +50% in power density (Barreto et al. 2025; de Jong et al. 2019; Ferreira et al. 2024; Lucena et al. 2010; Pereira et al. 2013; Poyer et al. 2026; Reboita et al. 2018), with Brazil as one of the few global “hot spots” of resource increase, in contrast with the decline projected for the Northern Hemisphere mid-latitudes (Karnauskas et al. 2018; Martinez and Iglesias 2024a, b), medium confidence assigned by the IPCC to stronger mean winds over much of South America (Ranasinghe et al. 2021), and a median of +11.5% in projected Northeast wind generation across the recent literature (Cruz et al. 2025). Yet almost all projections rely on 10-m winds or coarse grids, the lack of in situ

measurements at about 100 m against which to verify the models has been identified as a central limitation of the field (Pryor et al. 2020), the wind fields of the Eta regionalizations used in Brazil had never been evaluated against observations at any height, and the changes projected for mid-century are comparable in magnitude to the interannual and decadal variability of the resource itself (Carvalho et al. 2017; Pryor and Barthelmie 2010; Pryor et al. 2020), so that transfer techniques, from quantile-based bias correction (Cannon et al. 2015; Costoya et al. 2020; Maraun 2016) to statistical and machine-learning mappings (Goutham et al. 2021; Moradian et al. 2024; Sailor et al. 2008), are rarely tested explicitly with free-running climate scenarios and hub-height data.

This work confronts, at the same sites, hourly series not previously analyzed, measured at 78 to 95 m on 12 masts of three operating wind complexes (2011/2015 to 2025), with the 20-km Eta simulations nested in four global models under RCP4.5 and RCP8.5. We characterize the observed regime, its trends and its relation to ENSO and the tropical Atlantic, evaluate for the first time the Eta 100-m wind against hub-height measurements, test whether machine-learning regressors can transfer the projection signal to the stations in comparison with quantile-based correction, and quantify the projected changes per decade for 2025 to 2054, with their inter-member spread and their implications for power density and planning. Although the sites lie in one region, three of the results reach beyond it. The hub-height record shows that decadal variability in a trade-wind regime, in phase with ocean modes, can exceed the change projected for mid-century, a condition likely shared by other tropical wind provinces; the controlled comparison of transfer methods shows that regressors trained on free-running simulations attenuate the change signal, which bears on hybrid downscaling wherever it is applied to scenarios; and the seasonal structure of the regional-model bias at turbine height documents a limitation of resource maps derived from uncalibrated dynamical downscaling. The central methodological message is that the confrontation between projections and stations must be made on the scale of the distribution rather than the chronology of the simulations.

2 Data and methods

2.1 Anemometric data

The study area comprises three wind complexes in commercial operation in northern Northeast Brazil, one on the Ibiapaba Plateau in northwestern CE (670 to 790 m of elevation, about 80 km from the coast), one on the Serra de Santana in interior RN (660 to 720 m, about 100 km), and one on the low coastal plateau of northern RN (230 to 260 m, less than 40 km). Under the confidentiality agreement with the data owner, farms and company are not identified, stations are designated by codes, and locations are given through elevation and coast-distance classes and the 20-km model cell of each mast (Table 1). The data are cup-anemometer series from meteorological masts with three measurement levels, including two redundant anemometers at the top, exported from Windographer with invalid records flagged by the operator following practices compatible with IEC 61400-50-1 (IEC 2022). Among the 30 masts available, the 12 whose records begin in 2016 or earlier were selected, guaranteeing at least ten years of observation before the projection horizon; the highest level of each mast (78 to 95 m) corresponds to the hub heights of the turbines installed in the region up to the 2010s (Cacciuttolo et al. 2025). Altogether the stations provide 1,160,708 valid hourly records and 48,180 valid days (Table 1). Records were aggregated into daily, monthly, and annual means with completeness thresholds that avoid the seasonal bias of incomplete years (Text S1). The annual ratio between the redundant top anemometers remained within 0.98 to 1.01 at all stations and years, ruling out sensor degradation as the cause of the observed trends; full quality-control, harmonization, and shear-extrapolation details are given in Supplementary Text S1.

Table 1

Characteristics of the anemometric stations (anonymized codes) and of the measurement level used. Complex A is the Ibiapaba Plateau (CE), complex B the Serra de Santana (RN), and complex C the northern coast of RN. Period and completeness refer to months with at least 20 valid days; α is the mean power-law exponent between the lower and upper levels of the mast; U100 eq. is the mean speed equivalent to 100 m (Text S1). The last column gives the 20-km Eta cell that contains the mast.

Station	Complex	State	Elevation (m)	Height (m)	Period	Valid days (%)	Mean ($\text{m}\cdot\text{s}^{-1}$)	α	U100 eq. ($\text{m}\cdot\text{s}^{-1}$)	Eta cell
SR1	A	CE	670	80	04/2015–12/2025	98	7.61	0.22	7.99	A
SR2	A	CE	670	80	04/2015–11/2025	98	7.73	0.18	8.05	A
SR3	A	CE	690	80	04/2015–12/2025	99	7.48	0.23	7.88	A
SR4	A	CE	790	80	04/2015–12/2025	94	8.37	0.18	8.71	B
SR5	A	CE	720	80	04/2015–12/2025	97	7.70	0.28	8.18	A
LN1	B	RN	710	90	08/2013–12/2025	95	7.80	0.15	7.92	C
LN2	B	RN	690	78	07/2014–12/2025	88	8.93	0.18	9.35	D
LN3	B	RN	720	90	03/2014–12/2025	86	8.15	0.19	8.31	D
LN4	B	RN	660	78	10/2014–12/2025	97	9.41	0.21	9.90	D
LN5	B	RN	710	80	08/2013–12/2025	98	8.98	0.19	9.37	E
JC1	C	RN	230	80	07/2011–12/2025	98	7.96	0.38	8.66	F
JC2	C	RN	260	95	03/2016–11/2025	99	8.56	0.27	8.68	F

Centers of the Eta cells (latitude/longitude): A, -3.825/-41.225; B, -3.825/-41.075; C, -6.075/-36.725; D, -6.075/-36.575; E, -6.075/-36.425; F, -5.475/-35.975.

2.2 Downscaled climate projections

Projections were obtained from the PROJETA platform of CPTEC/INPE (Hölbig et al. 2018), which provides the Eta regional model (Mesinger et al. 2012) run at 20-km resolution over South America, nested in four global climate models (GCMs), namely BESM (Nobre et al. 2013), CanESM2 (Arora et al. 2011), HadGEM2-ES (Collins et al. 2011), and MIROC5 (Watanabe et al. 2010), for the historical period 1961–2005 and the RCP4.5 and RCP8.5 scenarios from 2006 to 2099 (Chou et al. 2014a, b); published evaluations of these runs cover temperature and precipitation only (Almagro et al. 2020; Chou et al. 2014b). The daily wind speed at 100 m (W100) was extracted for the six 20-km cells that contain the masts (Table 1) for the four members and two scenarios and aggregated like the observations. Because the scenario runs start in 2006, the overlap with the observations corresponds to free-running simulations whose daily and interannual sequences are not synchronized with the real chronology; only the climatology and the long-term change

are comparable, a property verified empirically in Sect. 3.2. The RCP scenarios of CMIP5 have been succeeded by the SSPs of CMIP6 (Eyring et al. 2016; O'Neill et al. 2016), but no Eta regionalization of CMIP6 models was available by the completion of this work (Cruz et al. 2025), and RCP4.5 and RCP8.5 are close in radiative forcing to SSP2-4.5 and SSP5-8.5.

2.3 Statistical analysis

Monotonic trends of the deseasonalized monthly series were assessed with the Mann–Kendall test under the Hamed–Rao autocorrelation correction (Hamed and Rao 1998), with magnitudes from the Sen slope (Sen 1968), and level shifts with the Pettitt test (Pettitt 1979) on the annual means. The relation to ENSO was measured through Pearson correlations between monthly percentage anomalies and the Oceanic Niño Index (ONI, version 6) (NOAA CPC 2026a) on monthly, quarterly, and annual scales, and with the tropical North and South Atlantic indices (TNA and TSA) (Enfield et al. 1999; NOAA PSL 2026) in simple and partial form (controlling for the ONI). The raw Eta series were evaluated against the observations through the mean bias, the RMSE of monthly means, the correlation and amplitude ratio of the seasonal cycle, the correlation and standard-deviation ratio of deseasonalized anomalies, the overlap of daily-speed distributions (Perkins skill score, PSS) (Perkins et al. 2007), and the ratio of cube means; definitions are given in Supplementary Text S1.

2.4 Transfer of the projections and energy metrics

Two transfer routes were confronted. In the first, machine-learning regressors (linear regression, K-nearest neighbors, Random Forest, and Gradient Boosting) were fitted to map the monthly Eta W100, with lags of one to three months and harmonic calendar terms, onto the observed speed, under leave-one-year-out cross-validation, and compared with the monthly climatology of the training period, with the monthly observation/model ratio correction, and with an autoregressive reference fed by the observations themselves; each fitted regressor was then applied to the future Eta series to measure the fraction of the raw change signal it transmits. Details are given in Text S1. In the second route, adopted for the projections, the daily series of each member were corrected by month-wise multiplicative quantile delta mapping (QDM) (Cannon et al. 2015; Costoya et al. 2020), which preserves the relative change of each quantile, and the change factor (delta) method (Maraun 2016) was computed in parallel; the model reference period is 2006–2024 and the future windows are 2025–2034, 2035–2044, 2045–2054, and 2070–2099. For each station, scenario, and window we report the mean and range across members, adopt agreement of at least three of four members as the robustness criterion, and test the significance of each member's future-minus-reference difference with the Mann–Whitney test at 5% (Carvalho et al. 2017). Power density was computed from the means of cubes of the daily corrected series, which captures changes in the shape of the distribution; for small changes $\Delta P/P \approx 3 \cdot \Delta U/U$ (Pryor and Barthelmie 2010). A generative AI assistant supported the writing and review of the analysis code and the translation and revision of the text, under the direction of the authors, who reviewed the content and take full responsibility for it.

3 Results

3.1 Observed wind regime, recent trends, and oceanic modulators

Figure 1 presents the monthly and annual series observed at the 12 stations, and Table 2 summarizes the statistics and trend tests. The regime is typical of trade winds, with mean speeds of 7.5 to $9.4 \text{ m}\cdot\text{s}^{-1}$, a marked seasonal cycle peaking in October in CE and August to September in RN, minima in the rainy season, and a seasonal amplitude (2.6 to $3.8 \text{ m}\cdot\text{s}^{-1}$) larger than the interannual variability, whose coefficient of variation of the annual means is 3.2 to 8.8% (Table 2), consistent with the regional climatology (Barreto et al. 2025; Gurgel et al. 2024; Hastenrath 2012). The temporal structure is dominated by a step (Figs. 1 and 2), with strongly positive anomalies in 2015 to 2017 ($+9$ to $+20\%$ in CE from April to December 2015), negative anomalies from 2018 onward with minima in 2020 and 2022, and

recovery in 2025 (+ 3 to + 4.5% in CE); the Pettitt test places the most likely change point between 2017/2018 and 2019/2020 at all stations, significantly at LN1 and JC1 (Table 2). The Sen slope of the deseasonalized monthly series ranges from - 5.0 to -12.3% per decade, significant under Mann–Kendall with autocorrelation correction at the seven RN stations ($p \leq 0.002$) and not significant at the five CE stations ($p = 0.16$ to 0.25), whose series are shorter and more variable.

Table 2

Statistics of the observed annual series (period mean, coefficient of variation of the annual means, years of minimum and maximum, and change point from the Pettitt test, * $p < 0.05$) and trend tests (Sen slope and Mann–Kendall test with the Hamed–Rao correction, MK-HR, for the deseasonalized monthly series; p of the Mann–Kendall test on the annual means).

Station	Mean ($\text{m}\cdot\text{s}^{-1}$)	Annual CV (%)	Annual min. (year)	Annual max. (year)	Change point (Pettitt)	Sen slope ($\text{m}\cdot\text{s}^{-1}$ decade ⁻¹)	Sen slope (%) decade ⁻¹)	Z (MK- HR)	p (MK- HR)	p (annual MK)
SR1	7.61	8.8	6.83 (2020)	9.12 (2015)	2019/2020	-0.94	-12.3	-1.37	0.170	0.161
SR2	7.73	7.0	7.06 (2020)	8.85 (2015)	2017/2018	-0.75	-9.7	-1.42	0.157	0.350
SR3	7.48	6.4	6.88 (2020)	8.50 (2015)	2017/2018	-0.61	-8.1	-1.14	0.254	0.276
SR4	8.37	4.6	7.76 (2020)	9.09 (2015)	2017/2018	-0.48	-5.7	-1.35	0.177	0.276
SR5	7.70	4.9	7.18 (2020)	8.46 (2015)	2017/2018	-0.48	-6.2	-1.23	0.219	0.213
LN1	7.80	3.5	7.38 (2022)	8.24 (2017)	2019/2020*	-0.51	-6.5	-4.12	< 0.001	0.024
LN2	8.93	4.7	8.31 (2022)	9.49 (2017)	2018/2019	-0.84	-9.4	-3.87	< 0.001	0.074
LN3	8.15	3.2	7.66 (2020)	8.51 (2017)	2017/2018	-0.41	-5.0	-3.12	0.002	0.161
LN4	9.41	3.5	8.81 (2022)	9.85 (2015)	2019/2020	-0.66	-7.0	-3.29	0.001	0.029
LN5	8.98	3.4	8.47 (2020)	9.40 (2015)	2018/2019	-0.51	-5.7	-4.53	< 0.001	0.115
JC1	7.96	4.5	7.43 (2022)	8.61 (2012)	2017/2018*	-0.61	-7.7	-4.19	< 0.001	0.004
JC2	8.56	4.8	8.13 (2022)	9.34 (2016)	2018/2019	-1.05	-12.2	-3.99	< 0.001	0.032

The chronology of the step coincides with the sequence of ENSO phases (Fig. 2), namely the very strong El Niño of 2015–2016, the triple La Niña of 2020–2023, and the El Niño of 2023–2024. In CE, monthly speed anomalies correlate positively with the ONI at all stations ($r = 0.24$ to 0.44 depending on the scale; $p \leq 0.009$), in the physically expected direction of stronger winds during El Niño, although ENSO explains only 10 to 20% of the monthly variance; in RN the correlation is null or slightly negative along the coast (Table S1). The picture reverses when the reference is the tropical Atlantic (Table S2). The monthly anomalies correlate *negatively* with the TSA index across the whole set, and most

strongly precisely where the ENSO signal is absent, with $r = -0.45$ for the RN mean ($p < 0.001$) against -0.29 for the CE mean. On the annual scale the two indices take turns exactly where the other fails. The ONI is significant only at the CE stations ($r = 0.63$ to 0.68 ; Table S1), whereas the TSA reaches -0.76 ($p = 0.002$) for the RN mean and at JC1, and the partial correlation controlling for the ONI (-0.45 in RN) indicates a signal independent of ENSO. The TNA – TSA gradient is weak because the TNA covaries with the TSA over the period; the relevant signal is the warming of the tropical Atlantic as a whole, whose 2019–2024 warm phase coincides with the calm years of the masts. Two complementary modulators therefore emerge, the CE step in phase with ENSO and the RN step in phase with the tropical Atlantic (Sect. 4.1). This pattern converges with the 10-m observational analyses for the region (Lima et al. 2024; Santos and Silva 2013), but here the signal appears at hub height, at rural elevated sites free from roughness and urbanization effects, and with the structure of a level shift rather than a gradual decline. Despite the decline, wind generation in the two states grew continuously over the same period, from 7.6 to 30.7 TWh in RN and 4.5 to 6.7 TWh in CE between 2015 and 2025 (ABEEólica 2026a; Galiza et al. 2026), through capacity expansion and turbine evolution (Cacciuttolo et al. 2025) rather than resource improvement.

3.2 Representation of the 100-m wind by the Eta-GCMs

The comparison between observations and raw Eta-GCM series (Table 3 and Fig. 3, with station-level detail in Table S3 and Fig. S1) reveals a systematic negative bias that is nevertheless very uneven across members and sites, from -6 to -11% in the best case (Eta-CanESM2 on the Ibiapaba Plateau) to -25 to -36% in the worst (all members at LN1), with the northern coast nearly unbiased in two members; averaged over members, the bias ranges from -4% (JC1) to -31% (LN1), and the difference between the two scenarios of the same member in the historical period shows that part of the “bias” of an 11 to 15 year sample is sampling itself. The seasonal cycle is reproduced in phase by all members ($r = 0.79$ to 0.97 between monthly climatologies) but with amplitude exaggerated by a factor of 1.2 to 2.2 (Fig. 3), and the exaggeration concentrates in the rainy season, when the models collapse the highland winds; the mean bias is therefore essentially a rainy-season bias (details by complex and member in Text S2). The overlap between modeled and observed daily-speed distributions is 0.67 to 0.78 per member (PSS; Table 3; Fig. S1), and the ratio of cube means is 0.58 to 0.85, so the raw power density of the models is 15 to 42% below the observed one.

Table 3

Evaluation metrics per member, averaged over the available stations and scenarios, comprising the relative bias, the RMSE of the monthly means, the correlation between the monthly climatologies, the ratio between the seasonal amplitudes (model/observation), the correlation between the deseasonalized monthly anomalies [minimum; maximum across stations and scenarios], the ratio between the standard deviations of those anomalies, the overlap of the daily distributions (PSS), and the ratio between the means of the cubes of the daily speed.

Member	Stations	Mean bias (%)	Monthly RMSE ($\text{m}\cdot\text{s}^{-1}$)	r seasonal cycle	Seasonal amplitude ratio	r monthly anomalies [min; max]	σ ratio, anomalies	Daily PSS	U^3 ratio
Eta-BESM	12	-21.2	2.31	0.92	1.83	0.12 [0.03; 0.22]	1.02	0.67	0.62
Eta-CanESM2	12	-8.4	1.50	0.92	1.43	0.08 [-0.04; 0.17]	1.01	0.78	0.85
Eta-HadGEM2-ES	12	-22.4	2.28	0.93	1.56	0.07 [-0.08; 0.25]	1.20	0.68	0.58
Eta-MIROC5	12	-17.0	2.08	0.88	1.62	-0.01 [-0.15; 0.17]	1.23	0.71	0.71

Two results in Table 3 are decisive for the choice of transfer method. First, the correlation between deseasonalized monthly anomalies of models and observations is null (-0.01 to 0.12 per member), confirming that the free-running simulations do not reproduce the chronology of windy and calm years, something no climate scenario can do by construction. Second, the magnitude of interannual variability is well represented, with model-to-observed standard-deviation ratios of 1.0 to 1.2 and comparable coefficients of variation of annual means. In other words, the models get right how much the wind varies, but not when. Consistently, the raw annual Eta-GCM trends over the observed period bear no relation to the observed ones, and the Eta-HadGEM2-ES under RCP8.5 even simulates, through internal variability, a decline larger than observed in the CE cells, illustrating the amplitude of decadal fluctuations possible in the region.

3.3 Machine-learning regressors as transfer functions

Table 4 summarizes the leave-one-year-out performance of the regressors fed by the Eta W100, averaged over stations, members, and scenarios. No regressor outperforms the monthly climatology of the training period (MAE of 0.57 to 0.63 $\text{m}\cdot\text{s}^{-1}$ against 0.56 $\text{m}\cdot\text{s}^{-1}$), the monthly-ratio correction is much worse (0.99 $\text{m}\cdot\text{s}^{-1}$), and the correlation between predicted and observed deseasonalized anomalies is null or negative (-0.14 to -0.25) for all regressors, showing that the interannual information of the Eta only adds noise while the apparently good total correlation ($r = 0.78$ to 0.82) stems from the seasonal cycle alone. The autoregressive reference fed by the observations themselves reaches an MAE of 0.50 $\text{m}\cdot\text{s}^{-1}$, but its one-step-ahead skill fades within months and is inapplicable to projections. The decisive result is in the last row. Applied to the future Eta series, the regressors transmit only 17% (linear regression) to 35–36% (tree-based methods) of the change signal of the models, gravitating around the training climatology; this explains why “hybrid” projections trained on the calm 2020–2024 years appeared to project a decline, and it is why the projections below rely on change factors and QDM.

Table 4

Performance of the regressors and of the references under leave-one-year-out cross-validation (monthly scale; average over 12 stations $\times$ 4 members $\times$ 2 scenarios, 96 combinations). Predictors are the Eta W100 in the current month and the three previous months plus harmonic calendar terms; for the “obs. lags” models, the observed speed at months $t-1$ and $t-12$ plus the calendar terms. The last row gives the fraction of the 2006–2024 $\rightarrow$ 2045–2054/2070–2099 change signal of the Eta-GCMs transmitted by each regressor (slope of the regression between the change projected by the regressor and the change of the raw model series, 192 combinations).

Model	MAE ($\text{m}\cdot\text{s}^{-1}$)	RMSE ($\text{m}\cdot\text{s}^{-1}$)	MAPE (%)	r	r of anomalies
Climatology (training)	0.56	0.71	7.2	0.83	–
Monthly ratio Eta/obs	0.99	1.30	12.9	0.58	0.00
Linear regression (Eta)	0.57	0.73	7.4	0.82	-0.25
KNN (Eta)	0.62	0.78	8.0	0.79	-0.15
Random Forest (Eta)	0.60	0.77	7.8	0.80	-0.18
Gradient Boosting (Eta)	0.63	0.80	8.1	0.78	-0.14
Linear regression (obs. lags)	0.50	0.63	6.4	0.86	0.13
Random Forest (obs. lags)	0.56	0.71	7.1	0.82	0.03
Fraction of change signal transmitted	Linear regression: 0.17	Random Forest: 0.35	Gradient Boosting: 0.36		

3.4 Projections for 2025–2054

Figure 4 shows, for each station, the QDM-corrected annual series of the members (ensemble mean and range, as 10-year running means) with the observed annual means; Fig. 5a, b summarizes the decadal changes and Fig. 5c, d the spread across members, while Tables S4 to S6 give the values. Change-factor and QDM results are nearly identical for the mean (median difference of 0.3 percentage point), so QDM values are reported. On the Ibiapaba Plateau, the ensemble projects a slight decline in 2025–2034 (down to -3.0% under RCP8.5), null changes in 2035–2044, and increases of + 3.1 to + 4.7% in 2045–2054 with three of four members positive, but the spread across members is much larger than the mean signal, with individual values from - 1.4% to + 9.7%, and only the Eta-CanESM2 under RCP8.5 differs significantly from its own reference period. At the RN sites the picture is stability, with slight declines in 2025–2034 (-1 to -3%), null changes thereafter through 2054, and decline at the end of the century under RCP8.5, of -0.8 to -2.7% on the northern coast and - 5.1 to -5.7% on the Serra de Santana, with all four members negative; no change through 2054 is significant. The difference between scenarios is small through 2054 and separates only at the end of the century, when the Eta-CanESM2 under RCP8.5 projects increases of 25 to 33% in CE and the ensemble + 7 to + 12%, whereas in RN all members project decline (Table S6). Member-by-member details are given in Text S3.

3.5 Implications for power density

Through the cubic relation, the speed changes amplify by a factor close to 3 in power density, meaning increases of + 9.6 to + 14.0% on the Ibiapaba Plateau in 2045–2054, null changes on the northern coast, and - 2.3 to + 0.4% on the Serra de Santana (Table S5). The changes obtained directly from cube means are slightly larger than the $3 \cdot \Delta U/U$ approximation because the members that project an increase of the mean also widen the upper tail of the distribution. For scale, the total uncertainty across members and scenarios for 2045–2054 is comparable to the difference between a windy and a calm observed year (Fig. 2) and smaller than the 20 to 40% capacity-factor gain of replacing 2 MW, 80 to 90 m turbines by 4 to 6 MW, 120 m machines (Cacciuttolo et al. 2025).

4 Discussion

4.1 The observed decline is a step of variability, not a forced signal

The central observational result is that hub-height wind speed declined at all 12 stations over the last decade, significantly at the seven RN stations, with the structure of a level shift rather than a gradual decrease. Three elements support the reading of internal variability. The first is the chronology, since the observed period opens with the very strong El Niño of 2015–2016, crosses the triple La Niña of 2020–2023, and ends with recovery under neutral conditions in 2025, with CE anomalies tracking the ONI in the physically expected direction, as during El Niño the ITCZ remains displaced northward and the trades strengthen over the Northeast (Barreto et al. 2025; Hastenrath 2012). The second is the absence of an instrumental cause, given that the redundant top anemometers agree within 1 to 2% in all years and the decline is simultaneous at masts 80 to 200 km apart. The third is the behavior of the models themselves, since the Eta-HadGEM2-ES simulates, through internal variability alone, a decline larger than observed in the CE cells over the same years (Sect. 3.2), showing that decadal fluctuations of this magnitude belong to the natural variability of the trade-wind regime, in line with the dominance of internal oscillations over radiative forcing in surface-wind decadal variability (Zeng et al. 2019) and with the warning that short windows absorb that variability as if it were a climate-change signal (Pryor et al. 2020).

The novel element is the role of the tropical Atlantic. The negative covariation between wind and the TSA index, with an annual r of -0.76 in RN that is independent of the ONI in partial correlation (Table S2), shows that the 2019–2024 warm phase of the tropical Atlantic accompanied the calm years exactly where ENSO does not explain the step, so the two states respond to complementary modulators, ENSO on the Ibiapaba Plateau and the tropical Atlantic at the RN sites, consistent with the known response of the ITCZ and the trades to both drivers (Duque-Gardeazabal et al. 2026;

Hastenrath 2012). The causal direction is not unique, because weakened trades also warm the sea surface through wind–evaporation–SST coupling (Hastenrath 2012), and the negative trends found in coastal 10-m series (Lima et al. 2024; Santos and Silva 2013) may likewise contain decadal components, which reinforces the need for longer records. A conceptual caveat completes the reading. Attributing the step to ENSO-phase variability does not exclude a second-order anthropogenic influence, because the statistics of ENSO itself may be changing under warming; projections indicate more frequent extreme El Niño and La Niña events (Cai et al. 2014, 2015; Coquereau et al. 2025), although the IPCC AR6 found no consensus on a systematic change of ENSO temperature-variability amplitude (Cai et al. 2021; Lee et al. 2021), and natural multidecadal modulation still precludes formal attribution. If the projected intensification is confirmed, shifts like that of 2017–2020 will tend to become more frequent or wider, which reinforces rather than weakens the recommendation to incorporate decadal variability into yield estimates. The practical implication is twofold. Decadal variability is real and economically relevant, since between 2015 and 2020 the CE stations registered a 15 to 25% difference in annual mean speed, equivalent through the cubic relation to 39 to 58% in power density, a swing of the same order as the 20 to 30% difference in wind production between opposite phases of the North Atlantic Oscillation in Europe (Ravestein et al. 2018). Conversely, extrapolating a 10 to 14 year trend to coming decades, implicit in any linear fit or regressor trained on that window, is not defensible, as the apparent decline summarizes the step between phases, already reversing in 2025, and regressors trained on it merely perpetuate the climatology of the calm years (Sect. 3.3).

4.2 Eta biases at hub height and the transfer of the scenario signal

The first evaluation of the Eta W100 against hub-height measurements in Brazil reveals negative biases of up to 36%, concentrated in the rainy season and strongly dependent on the boundary global model. The seasonal pattern, with reasonable agreement between August and November and collapse between February and May, suggests that the 20-km cell represents the intense dry-season trades governed by large-scale circulation but not the orographic acceleration and boundary-layer mechanisms that sustain 6 to $7 \text{ m}\cdot\text{s}^{-1}$ on the highlands when the synoptic flow weakens; the step-mountain topography and physical schemes of the Eta (Chou et al. 2014a; Mesinger et al. 2012), the interpolation to 100 m, and the boundary conditions are candidate explanations whose investigation requires numerical experiments. The biases are of the same order as those reported for CORDEX regional models on the RN and CE coast (Gurgel et al. 2024), and the large inter-member differences indicate that much of the bias is inherited from the global models, consistent with the underestimation of South American winds by CMIP models (Shen et al. 2022). Two conclusions follow. First, power densities computed from raw regional-model fields underestimate the resource of the Northeast highlands by 15 to 42% on average, recommending caution with potential maps derived from uncalibrated models (de Jong et al. 2019; Lucena et al. 2010). Second, any correction must be seasonally resolved, since a single annual factor would overcorrect the dry season and undercorrect the rainy one; the month-wise QDM meets this requirement and transfers the projected change without transferring the bias (Cannon et al. 2015; Costoya et al. 2020), while the equivalence between QDM and delta results shows that for the mean the simple correction suffices, the QDM becoming necessary for cubic quantities and percentiles.

The machine-learning test completes this picture and reaches beyond this study. Mappings from model output to stations produce sizable gains in weather forecasting (Goutham et al. 2021), where model and observation share the same chronology and the regressor corrects synchronous errors, but in climate scenarios the chronology is independent, so the only transferable content is the seasonal cycle, which climatology already provides, while the interannual information of the model enters as noise. Worse, tree-based methods do not extrapolate beyond the training range and linear regression assigns the predictor a small coefficient, so the change signal is attenuated to 17 to 36% of its value and the projection gravitates around the training climatology, appearing to “project” a decline whenever the window ends in calm years. This mechanism should be considered when reading studies that apply regressors trained on historical periods to scenario output (Moradian et al. 2024; Sailor et al. 2008); unless synchrony is

guaranteed by reanalysis forcing or the regressor is fed distributional statistics only, the transfer should be made by distributional methods (Maraun 2016).

4.3 Inter-member divergence and the hierarchy of uncertainties

The corrected projections indicate small changes through 2054, of + 3 to + 5% in CE and near zero at the RN sites, with scenario differences below 1 percentage point through 2044, and the spread across members (-1.4 to + 9.7% in CE in 2045–2054) as the main source of uncertainty, ahead of the emission scenario, as is typical of mid-century wind projections (Carvalho et al. 2017; Pryor and Barthelmie 2010; Pryor et al. 2020). The Eta-CanESM2 consistently projects the largest increases and the Eta-MIROC5 the smallest (Fig. 5c, d), reflecting the climate sensitivity and circulation trends of the driving global models; because all members share the same regional model, the structural uncertainty of the Eta itself is not sampled. The ensemble signal in CE is compatible in sign and order of magnitude with the literature consensus for the Northeast (Barreto et al. 2025; de Jong et al. 2019; Ferreira et al. 2024), but the RN sites behave differently, with stability through 2054 and decline at the end of the century under RCP8.5 in all members, and the member that projects the largest CE increase projects the largest Serra de Santana decline. This spatial heterogeneity within the Northeast, systematic across members, is a new result. It suggests that the projected strengthening of the trades (Karnauskas et al. 2018) does not distribute uniformly between the Ibiapaba Plateau, exposed to the northeast trades, and the RN sites under southeast trades; a northward displacement of the belt of intense winds, compatible with the projected ITCZ migration and the expansion of the South Atlantic Subtropical High (Reboita et al. 2019), would explain the pattern, but its verification requires the circulation fields. From the standpoint of detectability, with annual coefficients of variation of 3 to 9% in the observations and 3 to 12% in the models, the standard error of a 10-year mean is 1 to 4%, of the same order as the projected changes; differences from the reference only become significant for the Eta-CanESM2 under RCP8.5 in CE in 2045–2054 and for most members under RCP8.5 in 2070–2099. The climate-change signal in the region's wind will therefore not be statistically distinguishable from natural variability before the second half of the century.

4.4 Limitations

Six limitations should be made explicit. First, the observed period (10 to 14 years) is short against the 20 to 30 year windows recommended to separate decadal variability from trend (Pryor et al. 2020; Santos et al. 2015), and the observational results should be read as decadal variability documented at hub height, not as a signal attributable to warming. Second, the CMIP5/RCP scenarios have been succeeded by CMIP6/SSPs, but the Eta-CMIP5 runs remain the only multi-GCM 20-km dynamical projections for the region, and available CMIP6 studies do not differ in sign for CE (Barreto et al. 2025; Ferreira et al. 2024). Third, the 12 masts fall within six Eta cells, so the set is at bottom a sample of six grid points. Fourth, the QDM and delta methods assume a stationary model-to-observation relation and that the cell-scale change applies to the site, an assumption weakest in the rainy season. Fifth, the comparison used measurements at 78 to 95 m against the model W100, with power-law extrapolation only as a complementary analysis accounting for 2 to 9%. Sixth, the power-density conversion used daily means and ignored direction, air density, power curves, wake losses, and curtailment.

4.5 Implications for planning and for green hydrogen

The results suggest that the wind resource of RN and CE is not threatened to a degree that would compromise the planned expansion, since the roughly 50 GW of national wind capacity projected for 2035 (MME/EPE 2026) rests on an uncertainty about the mean resource level, from - 1 to + 10% in CE and about $\pm 3\%$ at the RN sites over three decades, that is small compared with the decadal variability already observed and with the technological gain of turbines. Three recommendations follow. Energy-yield estimates (P50/P90) should incorporate climate uncertainty ranges and, above all, the documented decadal variability, as certification campaigns of 2 to 3 years can fall entirely within a windy or calm phase and bias long-term estimates by $\pm 10\%$, a practice already adopted in European wind-farm studies (Solaun and

Cerdá 2020) and one that the recent national study on climate-change impacts in generation planning begins to institutionalize in Brazil (EPE 2025b). Highland sites, where the resource is most sensitive, favor turbines of moderate wind class with larger rotors, mitigating the cubic sensitivity of production. And the expansion should preserve the seasonal complementarity between Northeast winds, solar generation, and streamflow (de Jong et al. 2019), bearing in mind that solving curtailment is, in the short term, a more severe constraint than any projected change in the resource (ONS 2025). For the green hydrogen hubs planned at the port of Pecém in CE and in RN, whose competitiveness rests on cheap and abundant wind electricity (hydrogen at 2 to 4 US\$/kg with hybrid wind and solar supply; Feitosa and Costa 2025), the results are favorable across the projected range; a $\pm 5\%$ change in mean speed alters the levelized cost of wind electricity by about $\pm 15\%$, which does not change the competitive position of the region but reinforces the advantage of hybrid wind–solar supply for electrolysis, whose complementarity also attenuates the interannual variability of the wind.

5 Conclusions

This study confronted, at 12 stations of three wind complexes in RN and CE, hub-height wind observations (78 to 95 m; 2011/2015 to 2025) with Eta projections nested in four global models under RCP4.5 and RCP8.5, assessing explicitly how the projected signal should be transferred to the stations.

The observations (Fig. 1; Table 2) show the essential picture. All stations were windier until 2017 and calmer from 2018 to 2024, with recovery in 2025; the drop is equivalent to 5 to 12% per decade and significant at the seven RN stations. Its shape is that of a step synchronized with the very strong El Niño and the triple La Niña (Fig. 2), the redundant anemometers rule out an instrumental cause, and the 2025 recovery confirms its oscillatory character. This is decadal variability in phase with the oceanic modulators, ENSO in CE and the tropical Atlantic in RN (Table S2), not a gradual forced signal, without excluding that the statistics of ENSO itself may be modulated by warming. The cost of the oscillation is large, as the mean speed in CE varied 15 to 25% between the windiest and calmest year, 39 to 58% in power density, more than any change projected through 2054.

In the model evaluation (Fig. 3; Table 3), the Eta tracks the phase of the seasonal cycle but underestimates the mean speed by up to 36%, with the error concentrated in the rainy season, and its interannual anomalies are uncorrelated with the observed ones, as expected from free-running simulations. Without a common calendar, machine-learning regressors fed by the Eta cannot beat a simple climatology and transmit only 17 to 36% of the change signal (Table 4), a negative result that explains apparently declining “hybrid” projections and recommends distributional methods (change factors and QDM) for transferring scenarios to stations.

The corrected projections are condensed in Fig. 5. Through 2054 no projected change leaves the range of a few percent, with a slight gain on the Ibiapaba Plateau (+ 3 to + 5% in 2045–2054, + 10 to + 14% in power density) and stability at the RN sites, and only at the end of the century, under RCP8.5, does the map split, with CE gaining wind and RN losing it in all members. The spread across global models is larger than the mean signal and much larger than the scenario difference, and the projected signal is smaller than the sampling error of a decadal mean. Anywhere within this range the two states remain among the world’s regions of highest wind resource, provided that the decadal variability, larger than the climate signal over project horizons, enters energy-yield estimates (P50/P90) and that curtailment and transmission constraints are resolved. Future work should extend the observed series to the 120-m masts installed from 2019 onward, incorporate CMIP6 regionalizations when available, investigate the origin of the Eta rainy-season bias, stratify the observed variability by ENSO and tropical Atlantic phase, and convert resource changes into generation and revenue using power curves and operational data.

Declarations

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Ethics approval and consent to participate

Not applicable. The study involves no human participants, human data, or animals.

Consent for publication

Not applicable.

Conflicts of interest (competing interests)

The authors have no relevant financial or non-financial interests to disclose. The anemometric data were provided by the operator of the wind complexes under a confidentiality agreement; the provider had no role in the study design, in the analysis or interpretation of the data, in the writing of the manuscript, or in the decision to submit it for publication.

Author contributions

Rafael de Oliveira Tiezzi: conceptualization, data curation, methodology, funding acquisition, investigation, project administration, resources, supervision, writing of the original draft, review and editing. Guilherme Alcantara Barbosa Cunto: conceptualization, data curation, formal analysis, investigation, software, visualization, writing of the original draft. Vinícius Rainer Boniolo: data curation, review and editing. Iuri Emmanuel de Paula Ferreira: methodology (statistics), formal analysis, validation, review and editing. Danilo Roberto Pereira: methodology (machine learning), software, validation, review and editing. All authors read and approved the final manuscript.

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Availability of data and materials

The anemometric series are the property of a private company of the wind sector and were provided to UFSCar under a confidentiality agreement that prohibits the release of the raw data and the identification of the sites; the observational data are presented exclusively in the aggregated form of the figures and tables of the article. The Eta-GCM projections are public and can be obtained from the PROJETA platform (<https://projeta.cptec.inpe.br>), the ONI v6 index from the NOAA Climate Prediction Center, and the TNA and TSA indices from the NOAA Physical Sciences Laboratory. The processing, evaluation, bias-correction, and figure-generation codes (Python 3; pandas, SciPy, scikit-learn, pymannkendall), together with the daily Eta W100 series for the six cells used and the ONI, TNA, and TSA indices, are available at https://github.com/rafaeltiezzi/hubheight-climate-wind-ne-brazil-Tiezzi_Cunto and archived at <https://doi.org/10.5281/zenodo.22649295>.

Use of generative AI

During the preparation of this work the authors used a generative AI assistant (Claude, Anthropic) to support the writing and review of the processing and statistical-analysis code, the generation of figures through reproducible routines, the literature search, and the translation and revision of the text, under the direction of the authors, who reviewed and edited the content and take full responsibility for the publication.

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Figures

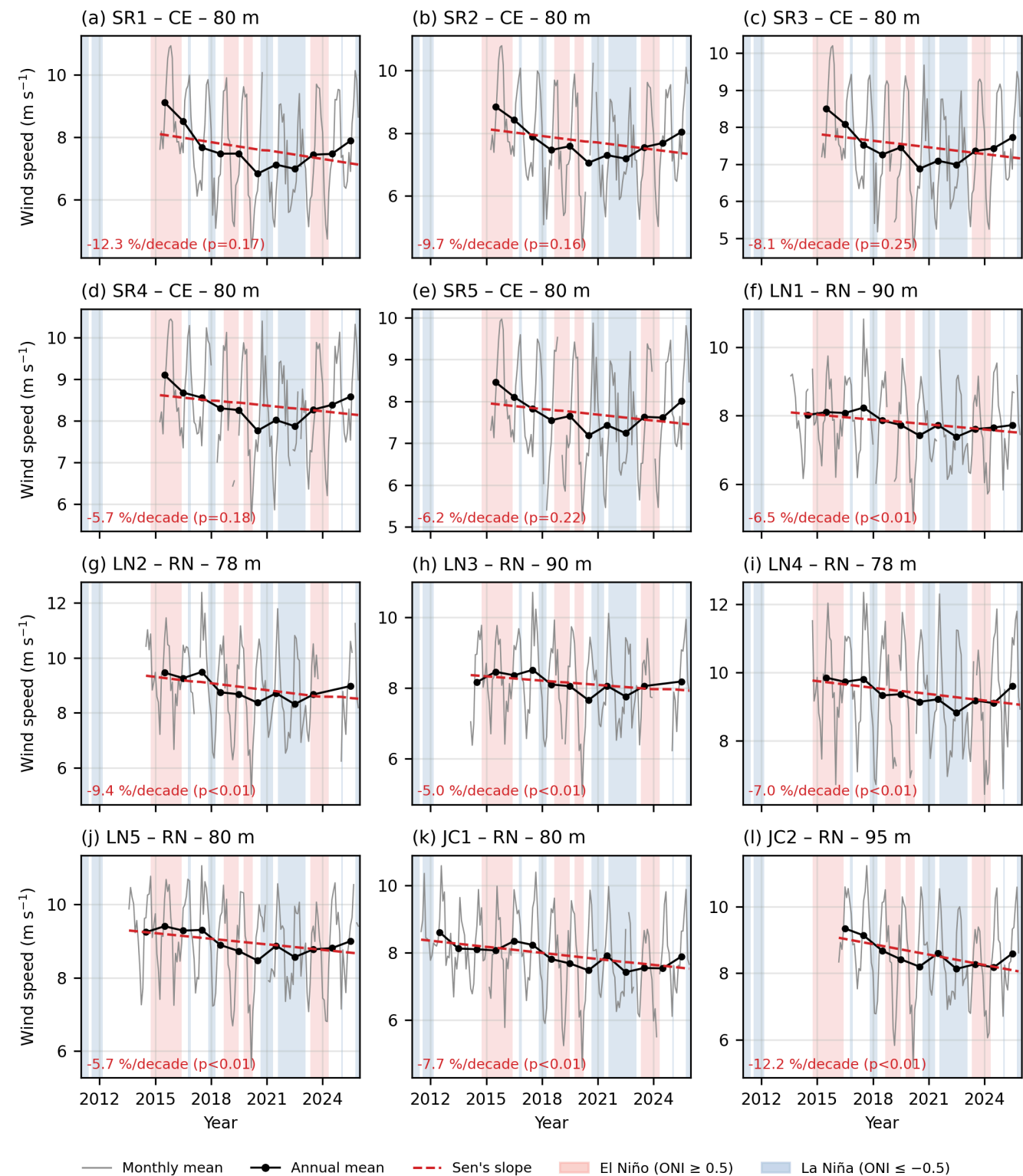


Figure 1

Monthly (gray) and annual (black dots) series of the wind speed observed at the upper level of each mast, with the Sen slope of the deseasonalized monthly series (dashed line; value in % per decade and p of the Mann–Kendall test with the Hamed–Rao correction) and the ENSO phases according to the ONI (red bands, El Niño, $\text{ONI} \geq 0.5\text{ }^{\circ}\text{C}$; blue bands, La Niña, $\text{ONI} \leq -0.5\text{ }^{\circ}\text{C}$). (a)–(e) CE; (f)–(l) RN.

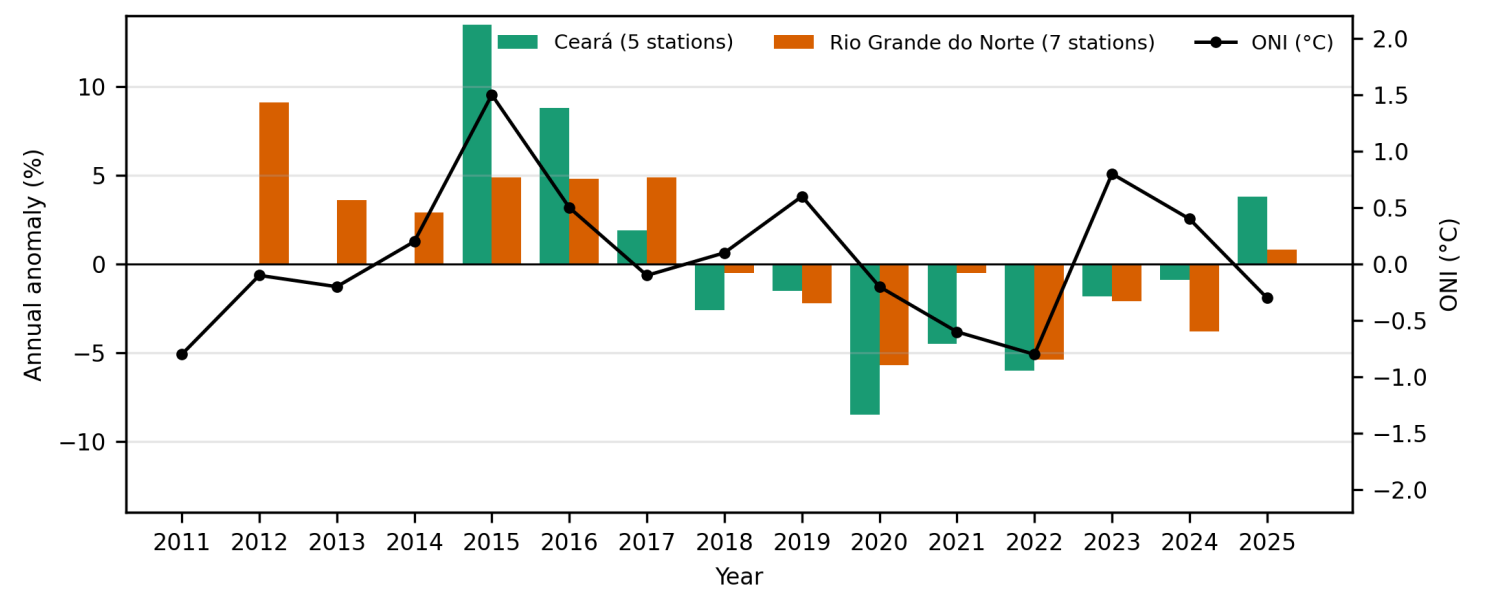


Figure 2

Annual anomalies of wind speed (% of the climatology of each station), averaged over the CE and RN stations, and annual mean of the ONI. The number of stations with data varies in the early years (one in 2012–2013, four in 2014, 11 in 2015, and 12 from 2016 onward, except 10 in 2024).

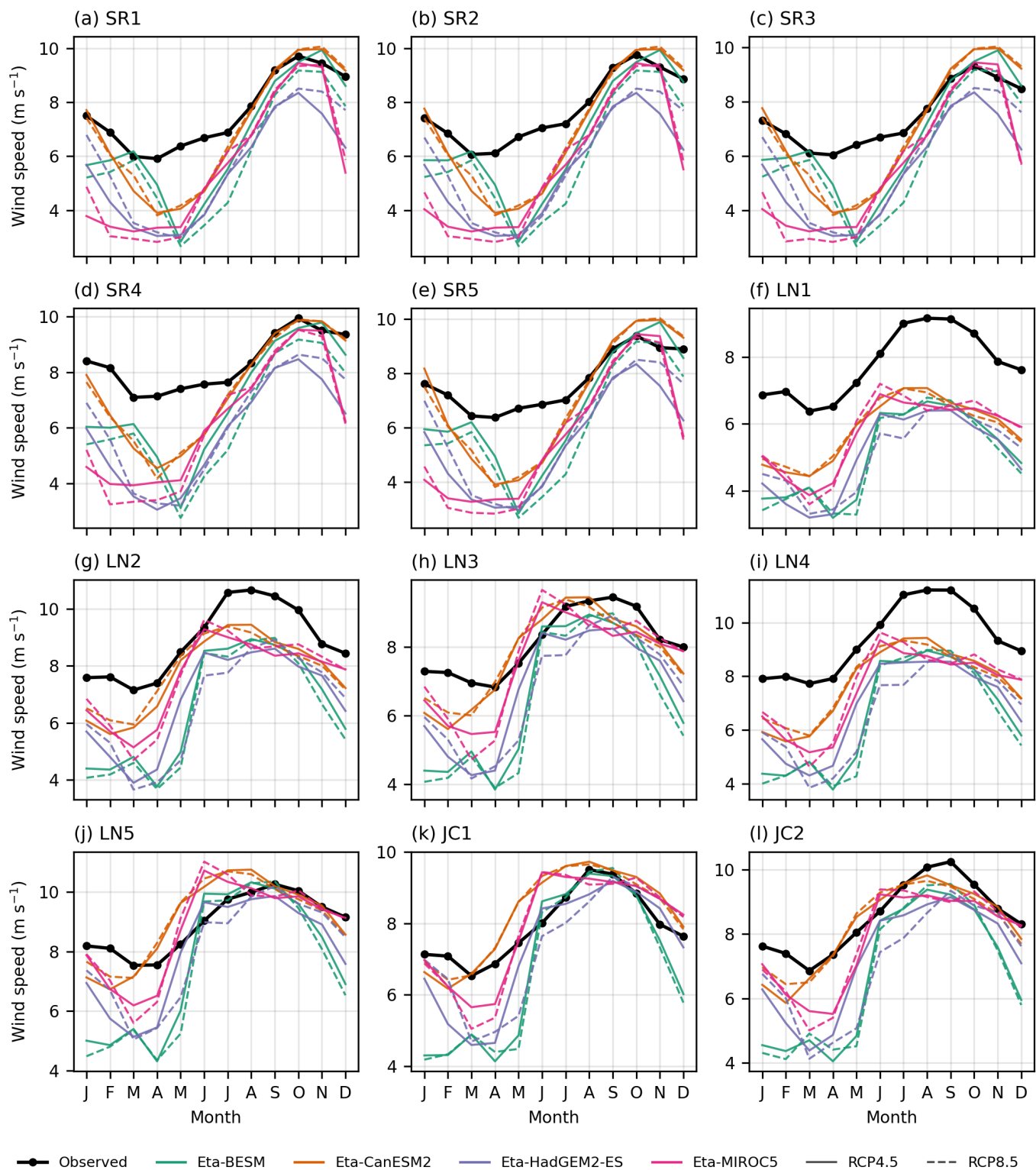


Figure 3

Monthly climatology of the observed wind speed (black) and of the raw W100 of each Eta-GCM (colors; RCP4.5 as solid lines and RCP8.5 as dashed lines), over the period of each station.

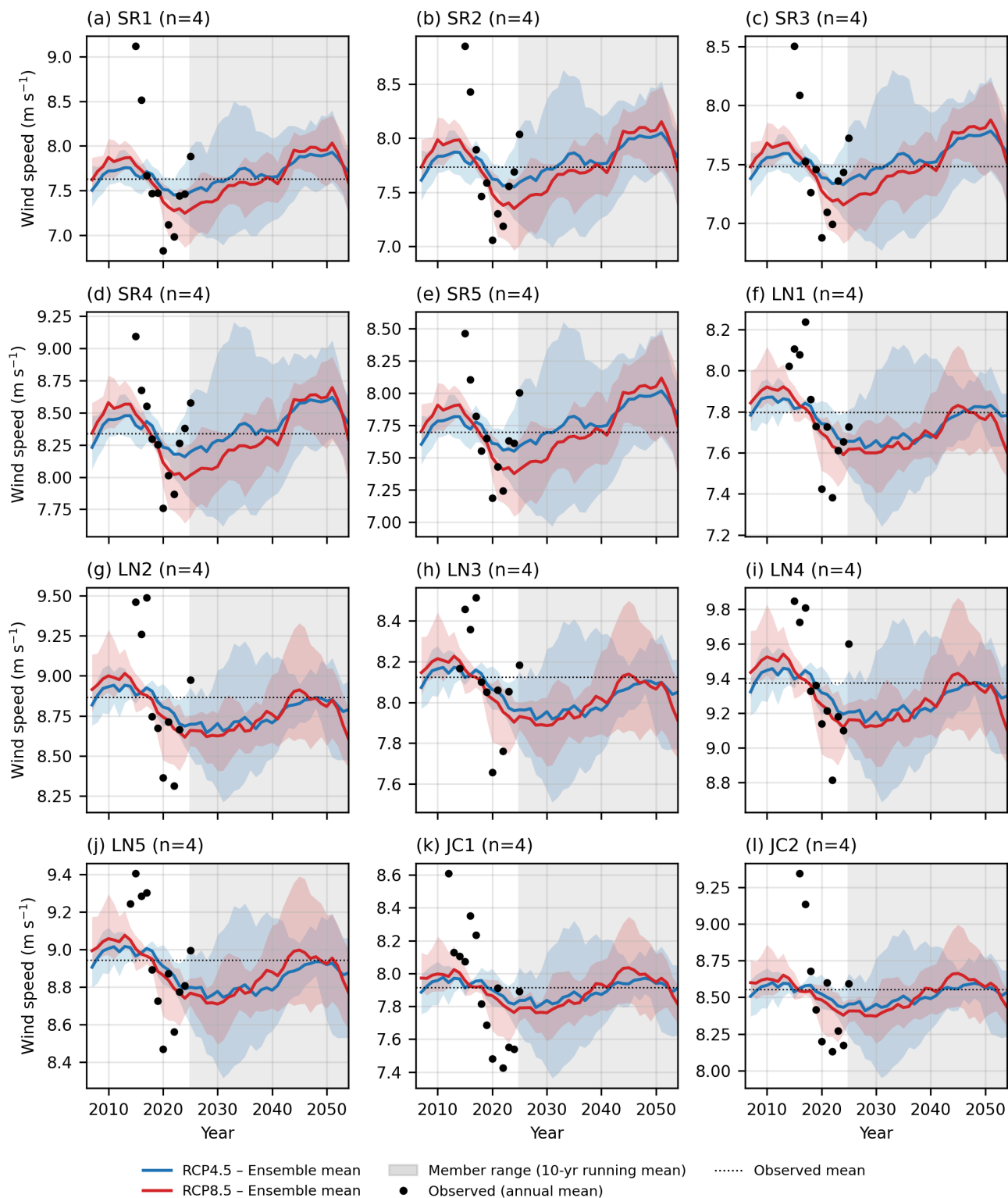


Figure 4

Annual series of the QDM-corrected W100, 2006–2054, per station, showing the ensemble mean (lines; RCP4.5 in blue and RCP8.5 in red) and the range across members (bands), as 10-year running means, together with the observed annual means (dots) and the observed period mean (dotted line). The shaded area indicates the projection horizon (2025–2054); n is the number of members

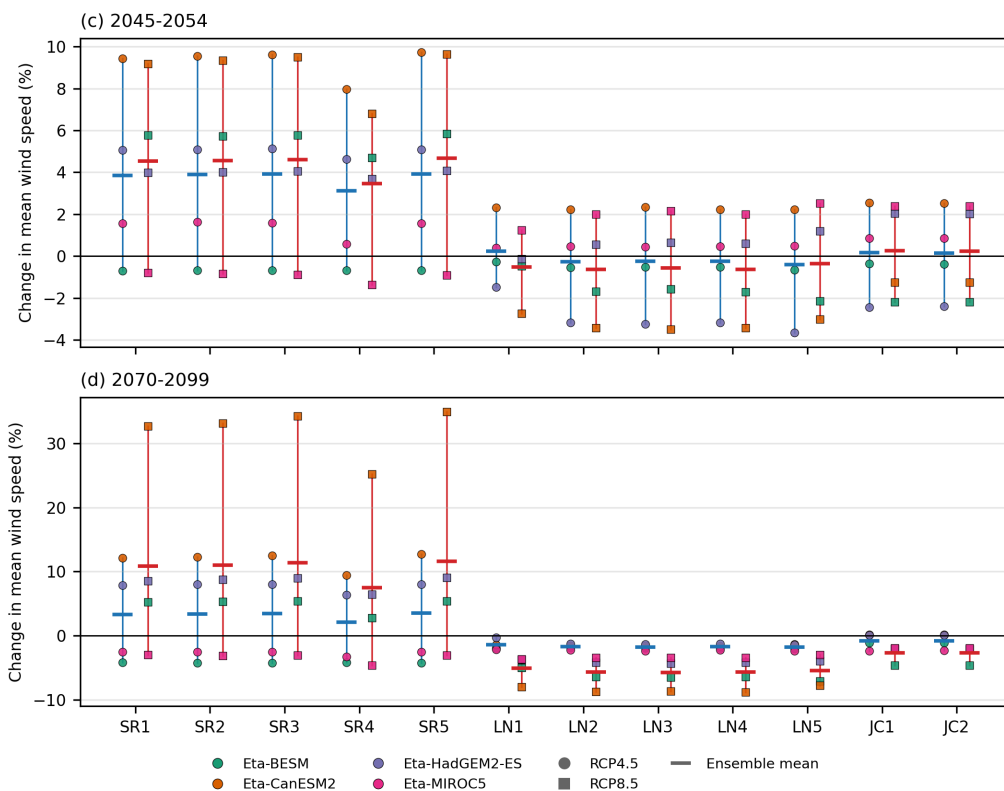
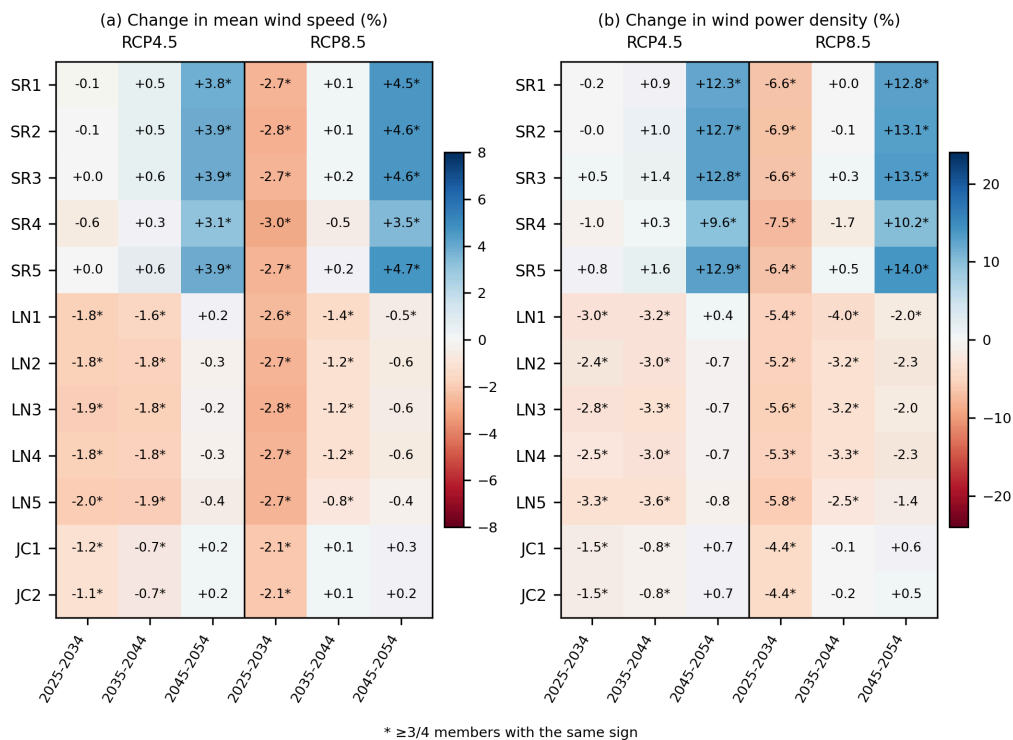


Figure 5

Projected percentage change (a) of the mean speed and (b) of the power density by the ensemble (mean of the four members; QDM) per decade and scenario, relative to the reference period, with an asterisk where at least three of the four members share the sign; and percentage change of the mean speed projected by each member (colors) and scenario (circles, RCP4.5; squares, RCP8.5) in (c) 2045–2054 and (d) 2070–2099, with the ensemble mean (horizontal tick) and the range across members (vertical line).

Supplementary Files

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