

Article

Quantifying Uncertainty in High-Resolution Near-Surface Wind Projections over Southeast Asian Seas

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Abstract

High-resolution projections of near-surface winds are crucial for ocean circulation and sea level studies in Southeast Asia, a region characterized by complex coastlines and monsoon variability. This study evaluates the added value of dynamical downscaling using the Weather Research and Forecasting (WRF) model at 9 km resolution, driven by two CMIP6 global climate models (EC-Earth3 and MPI-ESM1-2-HR), to simulate 10 m wind climatology over the Southeast Asian seas. Comparisons were made against ERA5 reanalysis and the parent CMIP6 GCMs, focusing on seasonal mean patterns, interannual variability, and the annual cycle. The WRF simulations demonstrate substantial improvement in capturing the spatial structures of monsoonal winds and regional circulation features. Future wind projections under SSP2-4.5 and SSP5-8.5 scenarios reveal seasonally and spatially heterogeneous trends. The downscaled models project strengthening of winter monsoon winds over the Southeast Asian seas and a weakening of summer monsoon flows, with implications for upper ocean dynamics and regional sea level patterns. The leading modes of variability from EOF analysis indicate basin-wide wind anomalies modulated by periodic signals at ~1 year and ~2–7 years, likely driven by ENSO and the Asian monsoon. The power spectra of principal components reveal that internal variability persists across scenarios, though with increased signal-to-noise ratios (SNRs) in the WRF projections toward the end of the 21st century.

Keywords: WRF model; Southeast Asian seas; near-surface wind; EOF analysis; signal-to-noise ratio

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1. Introduction

Near-surface wind fields play a critical role in modulating ocean circulation, wave dynamics, and sea level variability, especially in semi-enclosed tropical basins such as the Southeast Asian seas. In the Southeast Asian region, which encompasses the South China Sea (SCS), Sulu Sea, West Philippine Sea (WPS), and surrounding marginal seas, wind variability is especially important for modulating regional sea level through Ekman transport, wind-driven gyres, and boundary current dynamics [1–3]. These processes are sensitive not only to seasonal monsoonal shifts but also to intraseasonal-to-decadal modes

of climate variability, including the El Niño–Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the East Asian Winter Monsoon (EAWM) [4–7].

Under anthropogenic climate change, near-surface winds are expected to shift in both magnitude and spatial structure due to changes in radiative forcing, land–sea thermal contrast, tropical SST patterns, and shifts in atmospheric circulation regimes [8,9]. However, understanding how wind regimes will change, particularly in the tropics and monsoon-dominated regions, remains an open challenge due to model limitations and large internal variability [10–13]. Both CMIP5 and CMIP6 simulations suggest projected weakening of monsoon winds and zonal trade winds in many regions, particularly during boreal summer, due to a weakening Walker circulation and altered Hadley dynamics [6,11,13–16]. These global projections are typically based on coarse horizontal resolutions (100–250 km), which limit their ability to resolve fine-scale features of wind variability and monsoon flows over maritime Southeast Asia. As a result, it is a challenge to capture mesoscale processes, coastal wind gradients, orographic effects, land–sea breezes, and diurnally modulated circulations, all of which are essential for driving regional ocean dynamics and influencing sea level anomalies [17–20].

The uncertainty in future wind projections remains substantial, especially at regional scales. CMIP6 ensembles show large inter-model spread in the magnitude and even sign of projected wind changes over Southeast Asia, with ensemble-mean differences sometimes masking strong but localized signals present in individual models [13,21,22]. This uncertainty limits the ability to reliably assess future changes in low-level circulation systems, monsoon strength, and associated moisture transport. Variability in projected wind fields directly affects the simulation of convective organization, precipitation patterns, and the evolution of tropical disturbances, which are critical for understanding climate impacts in Southeast Asia. Moreover, poorly resolved wind gradients in coarse-resolution models hinder the representation of monsoon transitions, land–sea breeze dynamics, and sub-seasonal variability tied to phenomena such as the Madden–Julian Oscillation (MJO) [23–25]. Consequently, improving the spatial fidelity of wind projections is essential not only for ocean applications, but also for constraining atmospheric responses to climate forcing in one of the most dynamically complex regions of the tropics.

Regional climate downscaling has been increasingly used to improve climate information over Southeast Asia, particularly through initiatives such as SEACLID/CORDEX-SEA [26]. The CORDEX-SEA framework has provided coordinated regional climate simulations for assessing regional rainfall, temperature, and climate extremes over both mainland and maritime Southeast Asia. Previous CORDEX-SEA studies have shown that regional climate models can improve the spatial representation of climate features affected by complex terrain, land–sea contrast, and monsoon circulation, although substantial model spread remains across driving GCMs, regional models, and physics configurations. Therefore, improved spatial resolution alone is not sufficient to guarantee more reliable projections. Model uncertainty, boundary forcing uncertainty, internal variability, and regional model structural uncertainty must also be considered when interpreting downscaled climate information.

Previous regional climate studies over Southeast Asia have mainly focused on rainfall, temperature, and extremes, while fewer studies have examined near-surface marine winds in detail. Earlier WRF-based regional climate simulations demonstrated the usefulness of dynamical downscaling for representing Southeast Asian climate variability, but also highlighted persistent biases in monsoon rainfall and seasonal circulation [27]. WRF sensitivity studies over Southeast Asia and the Maritime Continent further show that rainfall, convection, and low-level circulation can be sensitive to cumulus and microphysics parameterization choices [28–30]. More recent studies on sea-

surface wind changes over Southeast Asia showed that dynamical downscaling can improve the representation of wind speed compared with coarse-resolution GCMs, particularly by reducing wind speed underestimation, although the magnitude and sign of future changes remain sensitive to the driving GCM, regional model, season, and subregion [31]. These findings motivate the present study, which focuses specifically on near-surface wind projections over the Southeast Asian seas and evaluates both the added value and uncertainty of high-resolution WRF downscaling.

To address these limitations, dynamical downscaling using regional climate models such as the Weather Research and Forecasting (WRF) and RegCM4 models offers a pathway to bridge the scale gap between GCMs and the physical processes governing local wind behaviour [31–33]. High-resolution regional simulations can better represent boundary-layer and mesoscale features, including coastal wind gradients, topographically influenced monsoon flows, land-sea interactions, and regional wind variability that are poorly resolved in coarse GCMs. Moreover, regional climate simulations provide an opportunity to assess the emergence of climate signals above internal variability, which is important for quantifying the robustness and detectability of future changes [34,35].

2. Materials and Methods

2.1. Dynamical Downscaling with WRF

This study employs the Advanced Research WRF model version 3.9.1 (ARW-WRF v3.9.1) [36] to dynamically downscale near-surface (10 m) wind fields over the Southeast Asian domain [90° E–144° E and 18° S–26° N], with 699×621 horizontal grid points at 9 km grid spacing. The WRF simulation domain covers maritime Southeast Asia, including the South China Sea, Gulf of Thailand, Java Sea, Sulu Sea, Celebes Sea, and surrounding marginal seas. Although the full model domain includes both land and ocean grid cells, the analysis was restricted to the Southeast Asian seas using an ocean-only land–sea mask (Figure 1). The model was configured at a horizontal resolution of 9 km, using a single domain covering the maritime Southeast Asia region, with 35 vertical levels and a model top at 50 hPa. A spin-up period of 1 month (December 1994 for historical simulation and December 2020 for future simulations) was excluded from the analysis. Physical parameterizations include the Yonsei University (YSU) planetary boundary layer scheme [37], the New Thompson microphysics scheme [38], the Rapid Radiative Transfer Model for both longwave and shortwave radiation (RRTMG) [39], and the Noah land surface model [40]. To allow explicit simulation of deep convection at this convection-permitting resolution, the cumulus parameterization was turned off. The cumulus parameterization was switched off in the main WRF configuration. We acknowledge that the 9 km horizontal grid spacing used here lies within the convective grey zone rather than the fully convection-permitting range. Therefore, the cumulus-off configuration should be interpreted as an explicit-convection grey-zone setup, rather than as a fully convection-resolving simulation. This configuration was selected because the primary objective of the study is to evaluate near-surface wind fields over the Southeast Asian seas, where mesoscale wind gradients, coastal effects, and monsoon flow structures are of central interest.

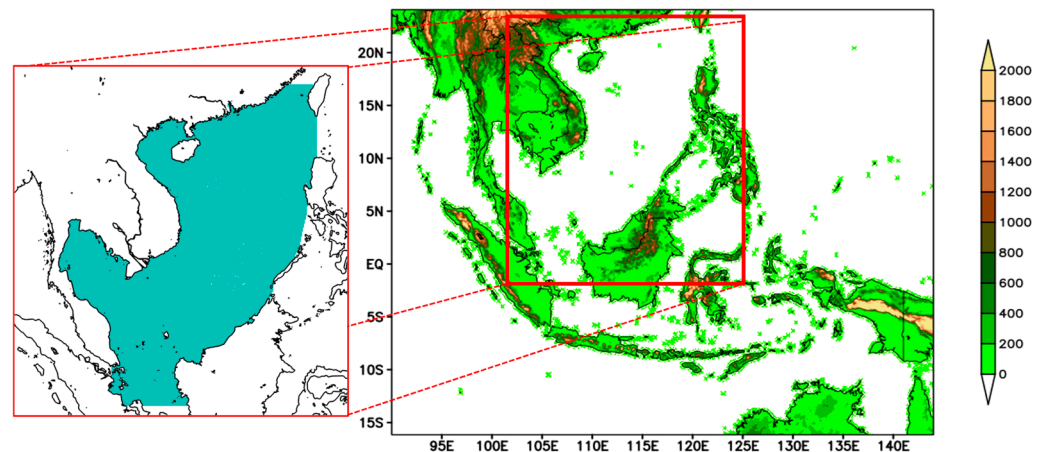


Figure 1. WRF model domain and analyzed Southeast Asian seas. The main panel shows the WRF simulation domain with terrain height shaded in metres. The red box indicates the subregion used for analysis, while the inset highlights the ocean-only mask applied to the Southeast Asian seas. All land grid cells were excluded from the statistical analysis, and only the masked marine grid cells were used for the analyses.

Two CMIP6 GCMs, EC-Earth3 (r1i1p1f1) and MPI-ESM1-2-HR (r1i1p1f1), were selected as boundary forcings based on their availability at high temporal resolution and their representation of monsoon variability in the region. Dynamical downscaling was performed for both historical (1995–2014) and future (2021–2099) periods under SSP2-4.5 and SSP5-8.5 scenarios. Lateral and surface boundary conditions were updated every 6 h and derived directly from the bias-uncorrected CMIP6 model output, consistent with recent high-resolution downscaling protocols (e.g., CORDEX-SEA, Singapore’s Third National Climate Change Study) [26,41].

This study focuses specifically on improving wind projections for the Southeast Asian seas, a region where fine-scale wind structures critically impact ocean surface forcing. The spatial domain evaluated excludes land regions to emphasize open-ocean and shelf seas where future wind forcing is most relevant for ocean modelling. This targeted approach follows the rationale of [20], who highlights the importance of resolving surface forcing over marginal seas and shelf systems for improving regional sea level simulations.

2.2. Observational Data for Evaluation

The ERA5 reanalysis from the European Centre for Medium-Range Weather Forecasts [42] was used as the reference observational dataset. ERA5 provides hourly global atmospheric reanalysis at ~31 km horizontal resolution. The ERA5 10 m wind data were accessed from the Copernicus Climate Data Store on 7 September 2025. For comparison with model output, ERA5 10 m wind speeds were temporally averaged to monthly means and bilinearly regridded to match the WRF and GCM grids where necessary.

2.3. CMIP6 Ensemble for Background Variability

To assess background internal variability and model spread, a 32-member ensemble of CMIP6 GCMs was compiled (Table 1). The historical and future 10 m wind data from these models were regridded to a uniform $1^\circ \times 1^\circ$ grid using bilinear interpolation and averaged to obtain the multi-model ensemble mean (MME). This ensemble was used for comparative diagnostics and as the reference spread for signal-to-noise ratio (SNR)

analysis. The ensemble standard deviation across models represents the magnitude of internal and structural variability in historical simulations.

Table 1. Availability of historical and future climate scenarios (SSP2-4.5 and SSP5-8.5) for selected CMIP6 models used in this study. A check mark (✓) indicates data availability for the specified experiment.

No.	Model	Historical	SSP 2-4.5	SSP 5-8.5
1	BCC-CSM2-MR	✓	✓	✓
2	BCC-ESM1	✓		
3	CAMS-CSM1-0	✓	✓	✓
4	CAS-ESM2-0	✓	✓	✓
5	FGOALS-f3-L	✓	✓	✓
6	CanESM5-CanOE	✓	✓	✓
7	CanESM5	✓	✓	✓
8	CNRM-CM6-1-HR	✓	✓	✓
9	CNRM-CM6-1	✓	✓	✓
10	CNRM-ESM2-1	✓	✓	✓
11	ACCESS-CM2	✓	✓	✓
12	ACCESS-ESM1-5	✓		✓
13	EC-Earth3-Veg	✓	✓	✓
14	EC-Earth3	✓	✓	✓
15	INM-CM4-8	✓	✓	✓
16	INM-CM5-0	✓	✓	✓
17	IPSL-CM6A-LR	✓	✓	✓
18	MIROC-ES2L	✓	✓	✓
19	MIROC6	✓	✓	✓
20	HadGEM3-GC31-LL	✓		
21	HadGEM3-GC31-MM	✓		
22	UKESM1-0-LL	✓	✓	✓
23	MPI-ESM1-2-HR	✓	✓	✓
24	MPI-ESM1-2-LR	✓	✓	✓
25	MRI-ESM2-0	✓	✓	✓
26	GISS-E2-1-G-CC	✓		
27	GISS-E2-1-G	✓		✓
28	GISS-E2-1-H	✓		✓
29	NorCPM1	✓		
30	KACE-1-0-G	✓	✓	✓
31	GFDL-ESM4	✓	✓	✓
32	NESM3	✓	✓	✓

2.4. Statistical and Diagnostic Methods

2.4.1. Taylor Diagram Analysis

Model skill in reproducing the observed seasonal climatology and interannual variability was evaluated using Taylor diagrams [43]. These diagrams simultaneously summarize the spatial correlation, normalized standard deviation, and centred root-mean-square difference between model output and ERA5 to evaluate across WRF simulations, driving GCMs, and the CMIP6 MME.

2.4.2. Empirical Orthogonal Function (EOF) Analysis

To isolate dominant modes of spatial and temporal wind variability, EOF analysis [44] was applied to monthly mean 10 m wind anomalies over the study domain. The

leading EOF patterns (EOF1 and EOF2) and their associated principal components (PC1 and PC2) were extracted separately for each model and scenario (2021–2099). Power spectral density (PSD) analysis was then performed on PC1 and PC2 to identify dominant periodicities.

2.4.3. Hybrid Signal-to-Noise Ratio (SNR) Analysis

To assess the reliability of future wind changes relative to internal variability, we computed the hybrid signal-to-noise ratio (SNR) following a methodology adapted from prior climate detection frameworks [34,35,45]. The hybrid SNR quantifies whether the projected change in wind fields from a high-resolution regional climate model (WRF) exceeds the ensemble spread of raw CMIP6 simulations, which serves as a proxy for internal variability.

The SNR was computed seasonally (DJF and JJA) using the following formulation:

$$SNR_{WRF} = \frac{|\mu_{WRF,fut} - \mu_{WRF,hist}|}{\sigma_{CMIP6}} \quad (1)$$

$\mu_{WRF,fut}$ is the seasonal mean of domain-averaged 10 m wind speed from the WRF simulation during the future period (2021–2099) under SSP2-4.5 or SSP5-8.5 scenarios.

$\mu_{WRF,hist}$ is the mean from the corresponding WRF simulation during the historical baseline (1995–2014).

σ_{CMIP6} is the inter-model standard deviation of the historical 10 m wind speeds from the full CMIP6 ensemble, calculated over the same baseline period (1995–2014).

This hybrid formulation leverages the forced signal from the high-resolution downscaling (WRF) while using the CMIP6 ensemble spread to represent background internal variability. The SNR was computed separately for each WRF configuration (WRF/ECE and WRF/MPI) and each scenario (SSP2-4.5 and SSP5-8.5). The analysis was conducted over a spatial domain covering the Southeast Asian seas, and the seasonal means were derived from monthly averaged data.

A higher SNR indicates a clearer emergence of climate change signals above natural variability. Specifically, $SNR > 1$ implies that the projected mean change is larger than the inter-model spread and thus potentially reliable or robust. This hybrid method provides a conservative yet informative estimate of signal emergence, accounting for both model uncertainty in WRF and internal variability represented by the CMIP6 ensemble.

3. Results

3.1. Mean Seasonal Climatology

Figure 2 presents the boreal winter (DJF) climatology of 10 m wind fields from ERA5, two CMIP6 GCMs (EC-Earth3 and MPI-ESM1-2-HR), their WRF-downscaled outputs (WRF/ECE and WRF/MPI), and the CMIP6 multi-model ensemble mean (MME/CMIP6). ERA5 exhibits a pronounced northeasterly monsoon flow over the northern portion of the Southeast Asian seas, which represents the influence of the East Asian Winter Monsoon (EAWM) and the enhanced meridional pressure gradient during the cold season. The reanalysis fields also show intensified near-surface winds associated with terrain-induced channelling and coastal zones.

The DJF bias maps show that the parent GCMs generally underestimate wind speed over several parts of the northern South China Sea and along coastal wind gradient regions, where ERA5 indicates stronger monsoon flow. This negative bias is particularly evident in areas affected by winter monsoon channelling and coastal acceleration. In contrast, the WRF simulations reduce part of this underestimation and better reproduce the spatial structure of the strong northeasterly flow. However, some regional biases remain, including local overestimation over parts of the southern and equatorial seas,

particularly in WRF/MPI. This indicates that dynamical downscaling improves several aspects of the DJF wind field but does not remove all systematic errors inherited from the driving GCMs or introduced by the regional model configuration.

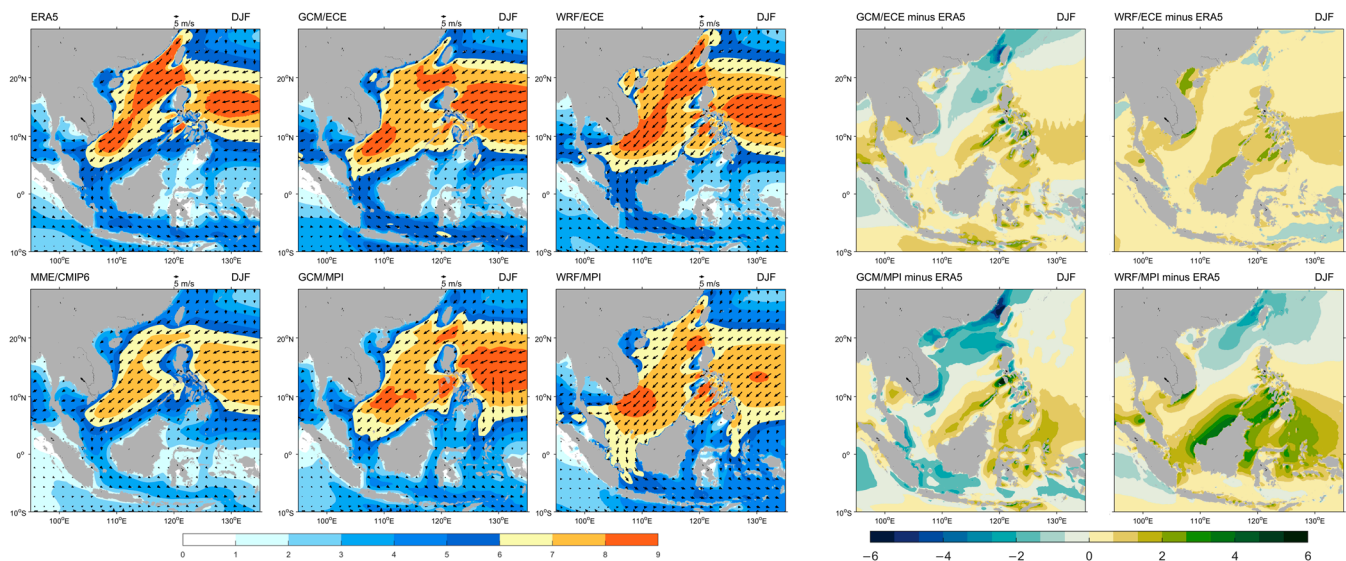


Figure 2. Boreal winter (DJF) climatology of 10 m wind speed and wind vectors over the Southeast Asian seas during the historical period 1995–2014. The first three columns show wind speed magnitude (shaded, m/s) and wind vectors from ERA5 reanalysis (**1st column**), the CMIP6 multi-model ensemble mean (MME/CMIP6 (**1st column**)), the parent GCMs (GCM/ECE and GCM/MPI (**2nd column**)), and their WRF-downscaled simulations (WRF/ECE and WRF/MPI (**3rd column**)). The last two columns show wind speed biases relative to ERA5 for the parent GCMs and WRF-downscaled simulations. Grey shading denotes masked land areas excluded from the ocean-only analysis.

While the two CMIP6 GCMs (GCM/ECE and GCM/MPI) reproduce the large-scale direction of the winter monsoon, they markedly underestimate wind magnitudes and weakly capture mesoscale features such as coastal intensification and wind gradients near complex land–sea interfaces. The WRF simulations demonstrate substantial added value in spatial fidelity. In particular, WRF/ECE enhances the representation of strengthened near-surface winds and better resolves localized wind-intensified zones. These improvements stem from WRF’s higher spatial resolution (9 km), which enables more accurate simulation of orographic blocking and land–sea thermal contrast that are poorly resolved or absent in the parent GCM.

Figure 3 shows the climatology for boreal summer (JJA), during which the prevailing surface winds reverse direction as the South Asian and western Pacific summer monsoons dominate the region. ERA5 captures strong southwesterly winds over the southern Southeast Asian seas, along with dynamically induced curvature and convergence zones associated with the northward shift in the Intertropical Convergence Zone (ITCZ). These features are consistent with the seasonal reversal of cross-equatorial flow and the strengthening of the Hadley circulation during the warm season.

The JJA bias maps reveal a more heterogeneous error structure than in DJF. The parent GCMs capture the broad monsoon reversal but show regional wind speed biases, including underestimation over parts of the northern South China Sea and overestimation across portions of the equatorial and southern maritime region. The WRF simulations reduce some of the large-scale underestimation and better represent regional flow curvature, but positive biases remain over parts of the Java Sea, southern South China Sea, and surrounding equatorial seas. These residual biases suggest that JJA winds are more

difficult to simulate than DJF winds, likely because summer monsoon flow is strongly affected by land–sea contrast, cross-equatorial flow, convection, and regional-scale circulation variability.

The GCMs capture the broad reversal in wind direction but significantly underestimate wind strength and fail to reproduce narrow wind jets and localized wind maxima across equatorial and strait-dominated areas. In contrast, the WRF downscaling, particularly WRF/MPI and WRF/ECE, exhibits superior performance in resolving zonally aligned flow structures and equatorially trapped circulations. These improvements reflect WRF's ability to resolve mesoscale dynamics, including enhanced horizontal pressure gradients, sea breeze interactions, and sub-grid coastal effects critical for accurate wind-driven surface forcing in regional ocean models.

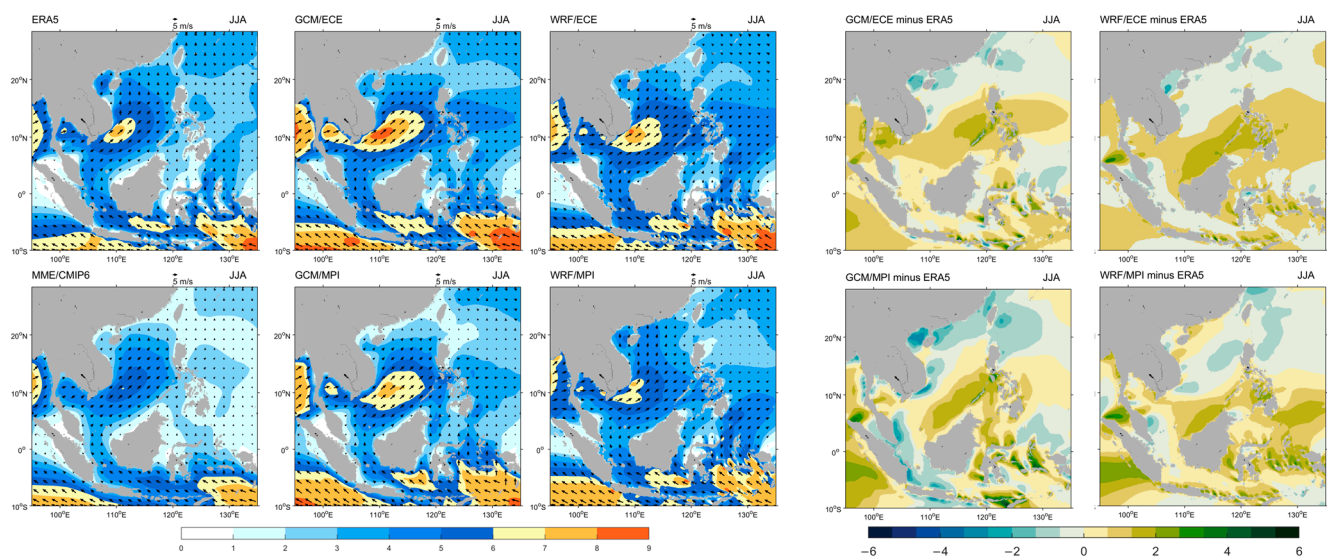


Figure 3. Similar to Figure 2, but for boreal summer (JJA).

3.2. Annual Cycle and Seasonal Reversal

Figure 4 illustrates the annual cycle of the domain-averaged 10 m zonal (u) and meridional (v) wind components over the Southeast Asian seas to represent the seasonal evolution of the regional monsoon system. The ERA5 reanalysis captures a well-defined monsoon circulation pattern, with strong westward flow (negative u -component) from January to May and again from October to December, with magnitudes up to -4 m/s. A reversal to eastward flow (positive u -component) occurs from June to September, which peaks near $+3$ m/s. This seasonal reversal reflects the shift from northeasterly winter monsoon to southwesterly summer monsoon circulation.

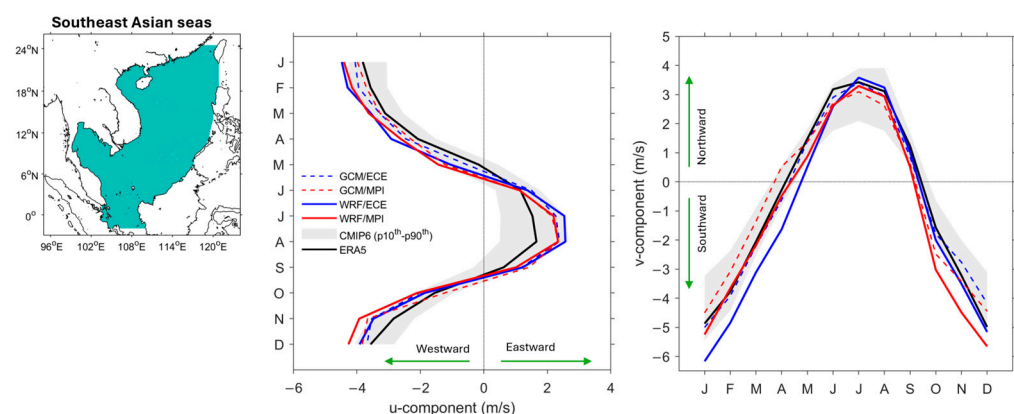


Figure 4. Annual cycle of 10 m wind components over the Southeast Asian seas during the historical period 1995–2014. The map on the left shows the grey-shaded ocean-only Southeast Asian seas mask, which was used to calculate the regional averages shown in the annual cycle plots. The middle panel shows the monthly mean zonal wind component, where negative values indicate westward flow and positive values indicate eastward flow. The right panel shows the monthly mean meridional wind component, where negative values indicate southward flow and positive values indicate northward flow. Solid and dashed lines represent simulations from the parent CMIP6 GCMs and their WRF-downscaled counterparts. ERA5 reanalysis is shown by the black line. The grey shaded envelope in the line plots represents the 10th–90th percentile range of the CMIP6 multi-model ensemble.

The meridional component (v) also exhibits a clear annual signal, with strong southward winds (negative values) prevailing from January to May and again from October to December, consistent with the EAWM and cross-equatorial flow. Northward winds (positive v -component), associated with the boreal summer monsoon inflow, dominate from May to September and peak around +4 m/s. Notably, the v -component reaches maximum southward values of −6 m/s in boreal winter, indicating the dominance of cold surge and monsoon-driven flow.

During July to September, all model configurations show a tendency to overestimate the zonal wind component relative to ERA5, which indicates overly strong eastward flow during the boreal summer monsoon phase. This bias may arise from several sources, including biases in the large-scale summer monsoon pressure gradient inherited from the driving GCMs. In the WRF simulations, the bias may also be influenced by boundary-layer mixing and convection-related circulation adjustments. Therefore, although WRF improves the spatial representation of monsoon-related wind structures, the zonal wind bias indicates that seasonal circulation errors remain and should be considered when interpreting the projected summer wind changes.

The raw CMIP6 GCMs (GCM/ECE and GCM/MPI) reproduce the broad seasonal pattern in both components but generally underestimate the magnitude of the peak winds, particularly in the v -component. This underestimation may be attributed to their coarse spatial resolution, which limits the ability to resolve sharp land–sea thermal gradients and topographically forced circulations.

The WRF downscaled simulations (WRF/ECE and WRF/MPI) show notable improvements. In the u -component, all models, including GCMs and WRF, closely follow the seasonal evolution captured by ERA5, with minimal differences in magnitude. However, in the v -component, WRF simulations better capture the amplitude and timing of monsoon transitions. Specifically, WRF/MPI aligns most closely with ERA5 from January to April (capturing the winter monsoon phase), while WRF/ECE performs better during the August–December period (reflecting improved representation of the late monsoon to post-monsoon transition). These enhancements in WRF simulations are likely due to improved representation of land–sea contrast, atmospheric boundary layer processes, and mesoscale circulations that modulate the seasonal wind response. The strong coherence between ERA5 and WRF outputs in both wind components highlights the added value of dynamical downscaling in capturing the intra-annual variability of near-surface winds in the SEA region.

3.3. Interannual Variability and Model Fidelity

Figures 5 and 6 present the interannual standard deviation of 10 m wind magnitude during DJF and JJA, respectively. These figures illustrate the models' ability to reproduce year-to-year variability, which is a crucial metric for evaluating their skill in simulating monsoon dynamics and regional wind variability over the Southeast Asian seas.

During DJF (Figure 5), ERA5 shows distinct variability hotspots over the northern, western, and southern flanks of the Southeast Asian seas with standard deviation values exceeding ~ 1.5 m/s, while the central Southeast Asian sea exhibits lower variability (~ 0.4 m/s). This spatial distribution is closely linked to the strength and position of the EAWM, cold surges funnelled through the Luzon Strait, and the variability of the Siberian High. The WRF simulations reproduce both the pattern and magnitude more accurately than their driving GCMs. Specifically, WRF/ECE aligns well with ERA5 in spatial structure and intensity, which shows enhanced fidelity over coastal zones and along monsoon wind flow. WRF/MPI also outperforms GCM/MPI, particularly in capturing enhanced variability along the Vietnamese coast and the southern Southeast Asian sea, where orographic and ocean feedback are significant [11,20].

In contrast, the GCMs and MME/CMIP6 largely underestimate interannual variability across the region. The MME/CMIP6 shows notably low standard deviation, limited to ~ 0.2 – 0.4 m/s, which is insufficient to represent key regional dynamics. This underestimation reflects coarse model resolution that fails to capture land–sea breeze interactions, orographic effects, and localized atmospheric instabilities critical in modulating surface wind variability.

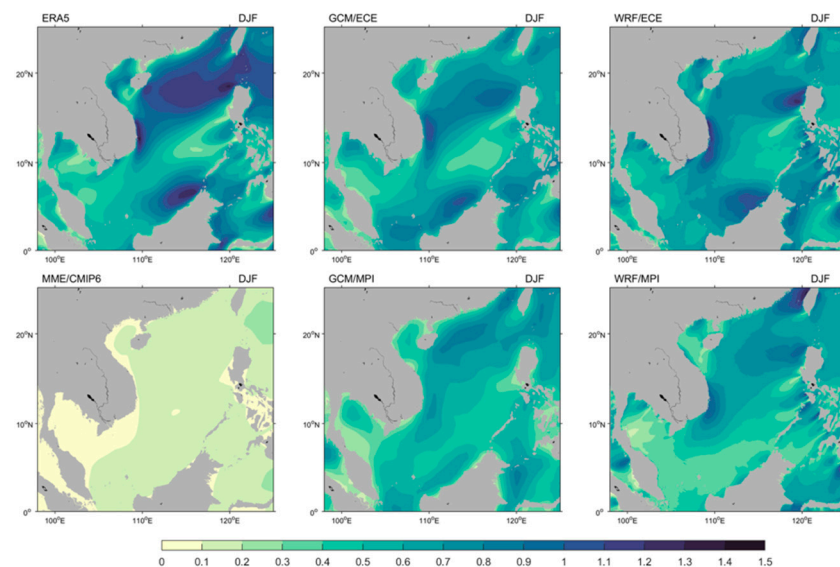


Figure 5. Spatial distribution of interannual standard deviation of 10 m wind speed (m/s) during boreal winter (DJF) over the Southeast Asian seas for the historical period 1995–2014, derived from ERA5 reanalysis, CMIP6 GCMs (GCM/ECE and GCM/MPI), their WRF-downscaled counterparts (WRF/ECE and WRF/MPI), and MME/CMIP6. The standard deviation represents wind variability over the DJF season across years.

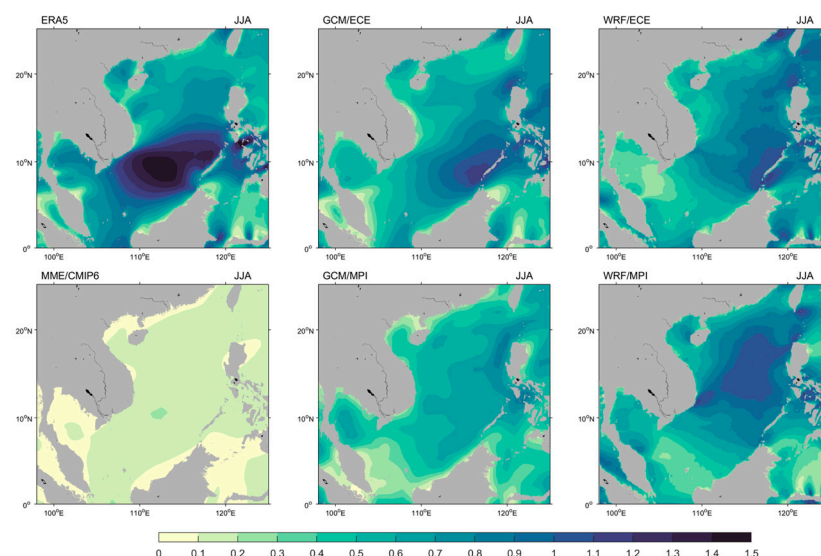


Figure 6. Similar to Figure 5, but for boreal summer (JJA).

During JJA (Figure 6), the highest interannual standard deviation in ERA5 is centred over the central Southeast Asian sea (~ 1.5 m/s), decreasing toward the northern basin (~ 0.6 m/s). Wind variability reflects the influence of the boreal summer monsoon, equatorial wave activity, and the convective response to SST gradients over the Maritime Continent [46,47]. Similar to DJF, WRF simulations better capture the magnitude and spatial extent of variability. WRF/MPI reproduces both the central maxima and spatial gradients, though with a slight northward displacement of peak variability. WRF/ECE also captures the spatial pattern reasonably well but slightly underestimates the standard deviation, particularly in the southern basin.

Figure 7 presents Taylor diagrams summarizing the spatial performance of the raw GCMs and corresponding WRF-downscaled simulations, MME/CMIP6, and individual CMIP6 models against ERA5 during DJF and JJA seasons. The diagram compares correlation coefficients, normalized standard deviations, and RMSD to provide an integrated evaluation of model fidelity in simulating the spatial structure of 10 m wind fields.

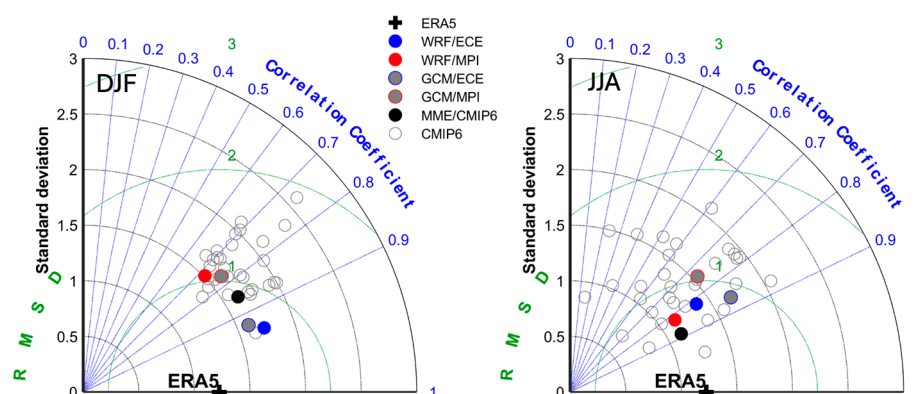


Figure 7. Taylor diagrams showing model performance for 10 m wind speed over the Southeast Asian seas during (left) boreal winter (DJF) and (right) boreal summer (JJA) for the historical period 1995–2014. The reference dataset (ERA5) is indicated by the black cross. Each marker represents the spatial pattern statistics of a model or ensemble mean.

In DJF, both WRF simulations exhibit enhanced skill relative to their GCM drivers, reflecting the added value of regional downscaling. WRF/ECE stands out with a

correlation exceeding 0.9 and a standard deviation near unity, which indicates good agreement with ERA5 in terms of both pattern and variability. This suggests that WRF/ECE captures the dominant structures of the EAWM with high spatial fidelity. In contrast, WRF/MPI shows minimal reduced skill, with correlation and variability metrics falling below those of GCM/MPI.

In JJA, the model spread increases substantially across all configurations, indicating that the boreal summer wind patterns are more challenging to simulate, likely due to complex land–ocean–atmosphere interactions. Despite this, both WRF/MPI and WRF/ECE show improved performance relative to their parent GCMs, with higher spatial correlation and better representation of variability. WRF/MPI, in particular, demonstrates strong agreement with ERA5, while WRF/ECE, despite its improvement over GCM/ECE, slightly underrepresents the amplitude of variability and exhibits lower correlation.

3.4. Emergence of Forced Signal Above Internal Variability

Figures 8 and 9 examine the time evolution of domain-averaged seasonal 10 m wind anomalies and their corresponding signal-to-noise ratios (SNR) under SSP2-4.5 and SSP5-8.5 scenarios from 2021 to 2099. These analyses assess the robustness of projected wind changes from 2021 to 2099 relative to internal variability derived from the CMIP6 ensemble. The boxplots, shown alongside each panel, summarize the distribution of wind anomalies and SNR values specifically for the end-of-century period (2080–2099). A direct comparison with 50–100-year observed marine wind trends is limited by the sparse and uneven distribution of long-term in situ observations over the Southeast Asian seas. Therefore, the projected changes are interpreted relative to the 1995–2014 baseline and alongside historical variability and model bias, rather than as a direct continuation of past observed trends.

In DJF (Figure 8), a coherent and progressively intensifying wind anomaly signal emerges, particularly under SSP5-8.5. The WRF/ECE simulation shows a marked strengthening of winter monsoon winds beginning around mid-century, with anomalies increasing steadily through the 2090s. The SNR associated with this signal exceeds 1 after ~2060, indicating that the magnitude of the forced signal surpasses the range of internal interannual variability. The boxplots for the end-century projection reinforce this emergence: median wind anomalies are clearly positive, and the interquartile ranges are narrow, demonstrating robust signal convergence.

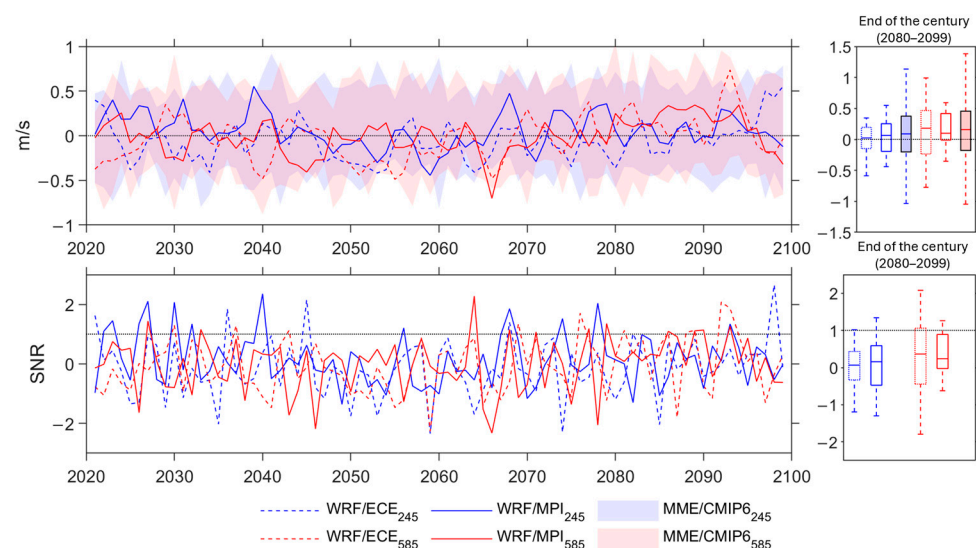


Figure 8. Time evolution of projected DJF 10 m wind anomalies (**top row**) and corresponding hybrid signal-to-noise ratio (SNR (**bottom row**)) over the Southeast Asian seas from 2021 to 2099.

Anomalies are computed relative to the baseline period (1995–2014), and shaded areas represent inter-model spread (10th–90th percentile) from the MME/CMIP6 under SSP2-4.5 (blue) and SSP5-8.5 (red). Dashed and solid lines denote WRF/ECE and WRF/MPI, respectively. Box plots on the right summarize the mean wind changes and SNR values at the end of the century (2080–2099).

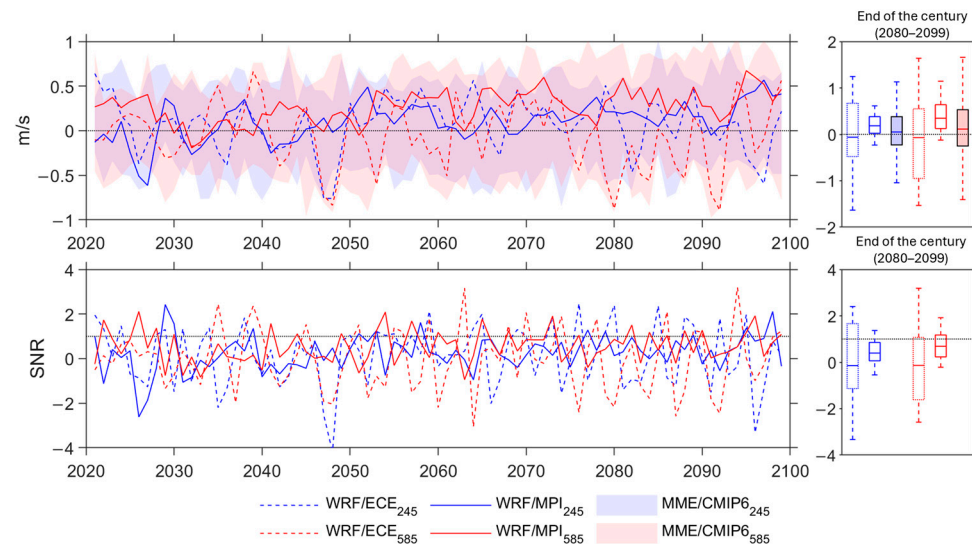


Figure 9. Similar to Figure 8, but for JJA.

In JJA (Figure 9), the time series of wind anomalies remain noisy and interannually variable across most configurations. However, under SSP5-8.5, both WRF/MPI and MME/CMIP6 show a statistically discernible positive trend in the latter half of the century. Their corresponding SNR values exceed 1 after ~2080, indicating the emergence of a forced signal above internal variability. This is supported by the end-of-century boxplots, which show a shift in the median and a reduction in the interquartile ranges for these configurations.

In contrast, WRF/ECE under both scenarios and WRF/MPI under SSP2-4.5 exhibit weak or inconsistent signals, with SNR values generally below 1, which suggests continued dominance of natural variability or conflicting model responses. Additionally, the opposite signal between WRF/ECE (negative median change) and WRF/MPI (positive) in JJA is linked to the choice of driving GCM and emission scenario. While WRF/MPI occasionally suggests slight strengthening in summer monsoon winds, WRF/ECE leans toward neutral or even weakening trends.

3.5. Dominant Modes of Future Variability and Associated Climate Oscillations

Figures 10 and 11 present an EOF analysis of projected 10 m wind variability over the Southeast Asian seas under SSP2-4.5 and SSP5-8.5 scenarios. The leading two EOF modes, EOF1 and EOF2, are computed using monthly wind anomalies from 2021 to 2099 derived from WRF/ECE, WRF/MPI, and the MME/CMIP6. The corresponding principal components (PC1 and PC2) are subjected to spectral analysis to identify dominant periodicities that modulate interannual and decadal wind variability.

EOF1 explains approximately 35–43% of the total variance across scenarios and models, with the highest variance contribution consistently observed in the MME/CMIP6 under SSP2-4.5. The spatial structure of EOF1 features anomalies across Southeast Asian seas. This large-scale monopolar pattern signifies domain-wide strengthening or weakening of near-surface winds and is indicative of modulation by global-scale climate modes, particularly ENSO. In positive phases, weakened trade winds and basin-wide

wind anomalies can be attributed to anomalous subsidence and suppressed convection during El Niño events.

The power spectral density (PSD) of PC1 reveals prominent peaks at ~1-year and 2–7-year periodicities, consistent with the annual cycle and ENSO bandwidth. The spectral peaks are more sharply defined in the WRF simulations compared to the MME/CMIP6, which suggests that WRF more accurately preserves the low-frequency modulation of wind variability, likely due to improved resolution of SST gradients and air–sea coupling in monsoon regimes.

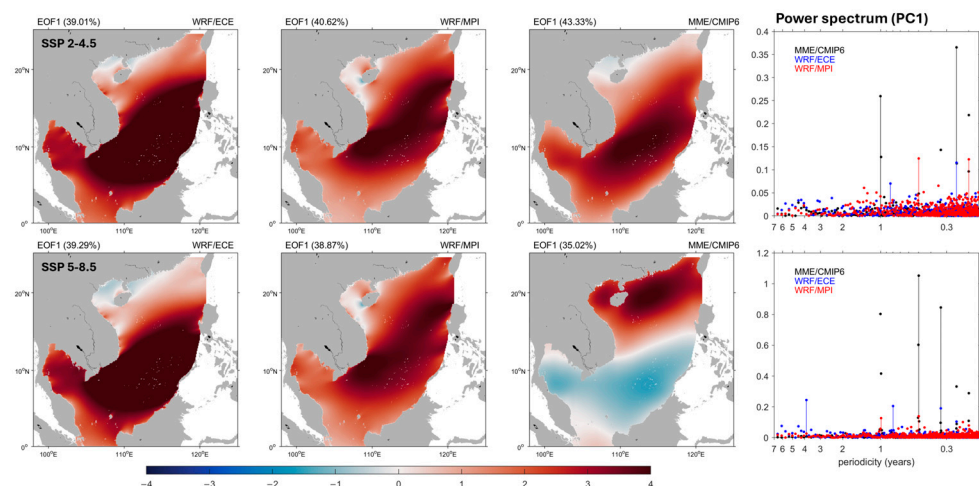


Figure 10. Leading EOF1 patterns of 10 m winds future anomalies (2021–2099) over the Southeast Asian seas and corresponding power spectral density (PSD) of the principal component (PC1) under SSP2-4.5 (**top row**) and SSP5-8.5 (**bottom row**) scenarios. Left to right: WRF/ECE, WRF/MPI, and MME/CMIP6. To facilitate visual comparison with the dynamically downscaled results, the EOF spatial pattern from MME/CMIP6 has been scaled by a factor of 3. The rightmost panels show the PSD of PC1.

EOF2 accounts for approximately 21–31% of the total variance and exhibits a meridional dipole structure, where wind anomalies in the northern Southeast Asian seas oppose those in the southern and equatorial regions. This spatial pattern is consistent with fluctuations in the EAWM and South China Sea anticyclonic anomalies, which are known to vary with the strength of cross-equatorial flow [48]. Additionally, this structure may reflect the influence of MJO events and their phase propagation across the Maritime Continent.

The spectral characteristics of PC2 show dominant periodicities around 2–3 years, which fall within the ENSO frequency bands. These signals indicate that regional wind anomalies in EOF2 are modulated by tropical Pacific SST variability, which has been shown to influence precipitation anomalies in Southeast Asia.

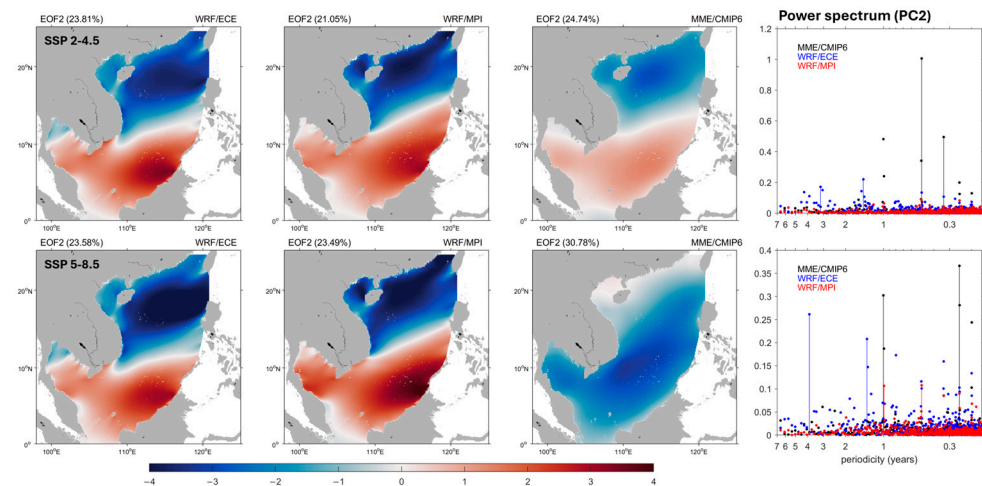


Figure 11. Similar to Figure 10, but for EOF2 and PSD of PC2.

The WRF simulations again exhibit stronger spectral signatures in these frequency bands compared to the MME/CMIP6, which tends to underestimate both variance and coherence. This implies that the downscaling process enhances the representation of seasonal-to-interannual variability.

A key distinction between SSP2-4.5 and SSP5-8.5 lies in the shift in dominant frequencies and the redistribution of power spectra. Under SSP2-4.5, wind variability remains primarily confined to seasonal and interannual timescales, with the signal dominated by the monsoon and only intermittent influence from ENSO. In contrast, SSP5-8.5, particularly in the WRF/ECE simulation, exhibits a broader spectral signal that includes enhanced intra-seasonal variability (e.g., MJO) and more persistent multi-year ENSO-like signals. This indicates a nonlinear response of wind variability to stronger greenhouse forcing, which likely suggests that intensified warming leads to more complex and temporally diverse atmospheric variability in the Southeast Asian region.

3.6. End-of-Century Projected Changes in Seasonal Winds (2080–2099)

Figures 12 and 13 present projected changes in 10 m wind magnitudes for DJF and JJA, respectively, under SSP2-4.5 and SSP5-8.5 at the end of the century. Figure 12 reveals that in DJF, both WRF/ECE and WRF/MPI under SSP5-8.5 project an intensification of northeasterlies across the northern Southeast Asian seas, with domain-mean increases of +0.14 to +0.15 m/s. Under SSP2-4.5, changes are more subdued (+0.03 to +0.04 m/s). The small values reported above the future change panels represent signed domain-averaged changes over the full Southeast Asian seas mask. These domain means can be small because positive and negative anomalies are averaged together; therefore, they do not necessarily represent the magnitude of local projected changes. The likely physical driver is a strengthened Siberian High and associated EAWM response under enhanced land–sea thermal contrast, consistent with future projections of stronger continental cooling relative to ocean warming. While the MME/CMIP6 range for DJF changes (−0.13 to +0.46 m/s) broadly encompasses these values, it lacks spatial coherence and underrepresents the narrow coastal winds in the WRF simulations, which could emphasize the importance of resolving regional dynamics that may be missed in coarser GCMs.

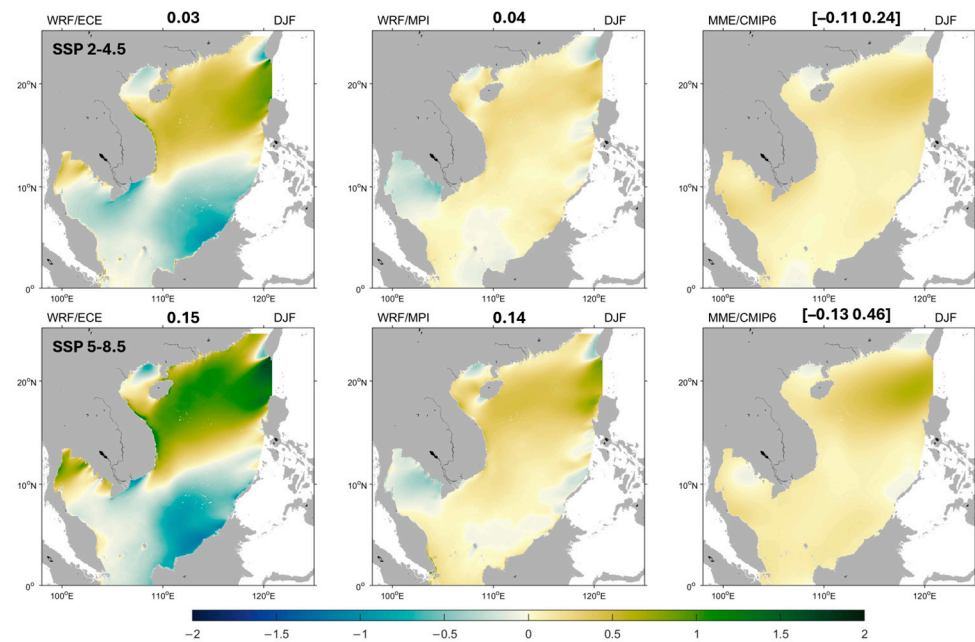


Figure 12. Projected changes in 10 m wind speed (m/s) during boreal winter (DJF) for the end-of-century period (2080–2099), relative to the historical baseline (1995–2014), under SSP2-4.5 (**top row**) and SSP5-8.5 (**bottom row**) from WRF/ECE, WRF/MPI and MME/CMIP6. The numbers above the WRF/ECE and WRF/MPI panels indicate the spatial domain-averaged mean change over the analyzed Southeast Asian seas, while the bracketed values above the MME/CMIP6 panels indicate the 10th–90th percentile range of domain-averaged changes across the CMIP6 ensemble.

By contrast, JJA projections (Figure 13) reveal more spatially heterogeneous and model-divergent responses. Under SSP5-8.5, WRF/ECE projects a weakening of summer monsoon winds over the southern basin and Java Sea (−0.18 m/s), while WRF/MPI projects a significant strengthening of up to +0.38 m/s in the same domain. These opposing responses reflect the strong sensitivity of regional monsoon dynamics to boundary forcing from the driving GCMs, particularly in how they simulate future SST warming patterns. The weakening in WRF/ECE may be attributed to a reduced land–sea thermal gradient or weakening of the Walker circulation, both of which are consistent with CMIP6 projections of a weakened monsoon under high-emission scenarios [49]. DJF wind signals appear more robust and spatially consistent across models and scenarios, while JJA projections exhibit higher inter-model spread.

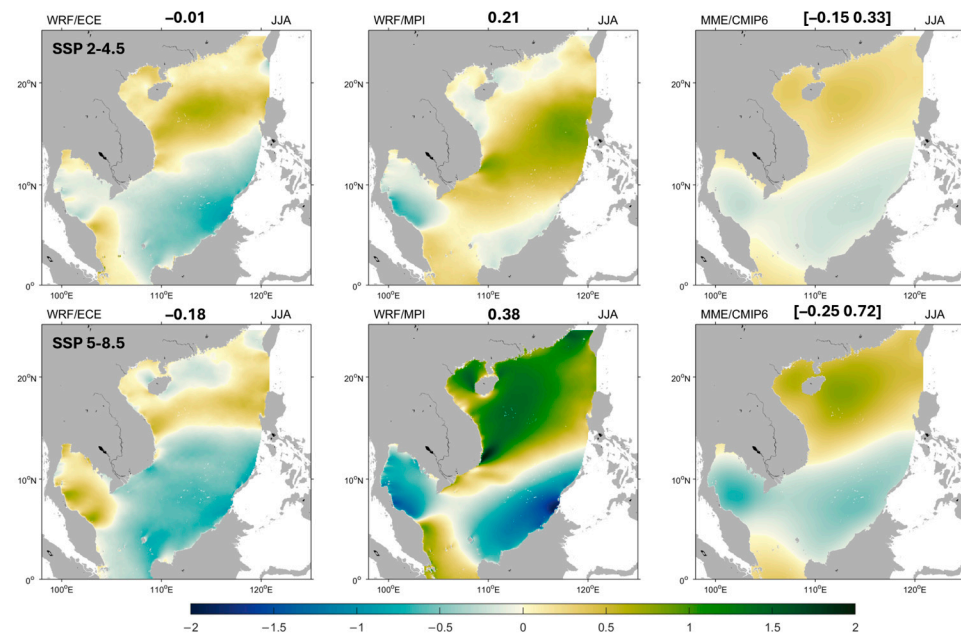


Figure 13. Similar to Figure 12, but for JJA.

4. Discussion

This study presents a detailed assessment of present and future near-surface wind characteristics over the Southeast Asian seas, using high-resolution WRF simulations driven by two CMIP6 GCMs: EC-Earth3 and MPI-ESM1-2-HR. The performance of the raw GCMs, WRF downscaling, and the CMIP6 multi-model ensemble mean (MME/CMIP6) is assessed compared to ERA5 reanalysis across multiple time scales: seasonal climatology, annual cycles, interannual variability, future projections, and modes of variability.

The WRF simulations significantly enhance the spatial fidelity of seasonal wind patterns, resolve coastal winds and enhance the representation of localized wind maxima. WRF models reproduce the annual cycle of zonal and meridional winds with higher accuracy than GCMs. Improvements are most notable in the meridional (v) component, where WRF simulations align more closely with ERA5 during seasonal transitions. Additionally, WRF outperforms GCMs in simulating the spatial patterns and magnitudes of interannual variability, with higher correlations and better standard deviation matching in Taylor diagrams. However, the added value is not spatially or seasonally uniform, and some systematic biases remain.

These findings are consistent with previous regional downscaling studies over Southeast Asia, which have shown that regional climate models can add value in areas where climate variability is strongly influenced by complex coastlines, topography, land–sea contrast, and monsoon circulation. CORDEX-SEA studies [26], for example, demonstrated that regional models can improve aspects of regional climate representation, although model spread remains substantial across different GCM-RCM combinations. For marine winds, [31,32] showed that dynamical downscaling can improve the representation of sea-surface wind speed over Southeast Asia, particularly by reducing the wind speed underestimation commonly found in coarse-resolution GCMs. Our results agree with these earlier findings because WRF improves the spatial structure of monsoon-related wind fields and coastal wind gradients in several diagnostics. However, our results also show that this added value is not uniform across all seasons and driving models. In particular, the divergent JJA responses between WRF/ECE and WRF/MPI are consistent with earlier studies showing that projected

Southeast Asian wind changes remain sensitive to the driving GCM, regional model configuration, season, and subregion.

Future projections indicate stronger and more coherent wind changes during DJF than JJA. Under SSP5-8.5, a clear signal emerges in DJF by mid-century, with SNR values exceeding 1, indicating that the projected strengthening of winter monsoon winds rises above the estimated background model spread. In contrast, JJA signals remain weaker and more model dependent, with only WRF/MPI and MME/CMIP6 showing late-century emergence. The contrasting JJA responses between WRF/ECE and WRF/MPI highlight the strong influence of driving-GCM uncertainty on future summer monsoon wind projections.

The EOF analysis further shows that the leading modes of future wind variability remain physically interpretable and linked to large-scale climate variability. EOF1 and EOF2 together account for more than 60% of the total future wind variance in the region, suggesting that dominant modes associated with monsoon variability, ENSO, and possibly MJO-related modulation continue to shape Southeast Asian wind regimes under future forcing. The WRF-downscaled simulations provide enhanced spatial detail in these modes compared with the coarser MME/CMIP6 fields, although attribution to specific climate drivers should be interpreted cautiously without additional index-based diagnostics.

The projected wind speed changes should be interpreted in relation to both historical model bias and background variability. The spatial maps indicate larger regional changes, particularly over the northern shelf and basin areas, where wind speed changes exceed 2 m/s in both DJF and JJA. Nevertheless, the projected changes should be interpreted cautiously where their magnitude is comparable to historical model bias or where the SNR remains below 1. More confidence is given to regions where the projected changes are spatially coherent and emerge above the estimated background model spread.

The added value of this work is not limited to the finer spatial resolution of WRF. The study provides a wind-focused, multi-diagnostic assessment of historical performance and future uncertainty over the Southeast Asian seas. This is important because marine near-surface winds provide a key forcing for ocean circulation and sea level modelling, and their future changes cannot be assessed reliably from spatial refinement alone. The results show that downscaling improves several aspects of regional wind structure, but also that projected changes remain sensitive to the driving GCM, season, and model configuration.

Several limitations should be considered when interpreting the projected wind changes. First, only two CMIP6 GCMs were dynamically downscaled; therefore, the WRF projections do not fully sample the broader range of GCM structural uncertainty. Second, only one WRF physics configuration was used for the main historical and future simulations. Although the ERA5-driven sensitivity experiment indicates that the 10 m marine wind diagnostics are not strongly affected by switching the cumulus parameterization on or off, the treatment of cumulus convection at 9 km resolution remains a source of structural uncertainty. Third, ERA5 was used as the sole reference dataset for model evaluation. While ERA5 provides a physically consistent and widely used reanalysis product, observational uncertainty may remain, particularly over data-sparse marine regions. Finally, the CMIP6 ensemble spread used in the hybrid SNR analysis should not be interpreted as pure internal variability alone, because it also contains inter-model structural differences. The SNR values therefore provide a practical measure of signal emergence relative to background model spread, rather than a complete partitioning of forced response, internal variability, and model uncertainty.

5. Conclusions

This study evaluates high-resolution near-surface wind simulations over the Southeast Asian seas using 9 km WRF dynamical downscaling driven by EC-Earth3 and MPI-ESM1-2-HR. The results show that WRF improves several aspects of the historical wind climatology compared with the parent GCMs, particularly the spatial structure of monsoon-related winds, coastal wind gradients, localized wind maxima, and the seasonal reversal of zonal and meridional wind components.

Future projections show a clearer strengthening of DJF near-surface winds, especially under SSP5-8.5, with the forced signal emerging above background model spread by mid-to late-century. In contrast, JJA projections are less certain and remain strongly dependent on the driving GCM, with WRF/MPI indicating strengthening and WRF/ECE showing weaker or neutral changes. This seasonal contrast indicates that winter monsoon wind changes are more robust than summer monsoon wind changes in the downscaled simulations.

The study demonstrates that high-resolution dynamical downscaling provides useful added value for marine wind assessment over the Southeast Asian seas, but it does not remove uncertainty associated with driving GCMs, regional model physics, reference data, and internal variability. The results provide regionally relevant wind-forcing information for future ocean circulation and sea level studies, while highlighting the need for larger multi-GCM and multi-physics downscaling ensembles to better constrain future near-surface wind projections.

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Data Availability Statement: The data used in this study were obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) archive. All CMIP6 model outputs analyzed in this research are publicly available through the Earth System Grid Federation (ESGF) data nodes. Information on data access procedures and usage policies can be found at the CMIP6 data portal: <https://esgf-node.llnl.gov/projects/cmip6/> (7 September 2025).

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