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Evaluating Hydrostatic vs. Non-Hydrostatic Dynamics in RegCM5: A 50-Year Simulation of Near-Surface Wind Speed over the Yellow River Basin

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Abstract

Accurate simulation of near-surface wind speeds over complex terrain is essential for wind energy assessment, ecological conservation, and hydro-climatic change studies. This study presents a 50-year (1971–2020) evaluation of the RegCM5 regional climate model over the Yellow River Basin, China. Three dynamical configurations are systematically compared: the traditional hydrostatic core (Model 1), the MM5-like non-hydrostatic core (Model 2), and the newly introduced Moloch non-hydrostatic core (Model 3). Driven by ERA5 reanalysis at a 25-km resolution, the simulations are validated against high-density observations (CN05.1). Results indicate that while all configurations capture the spatial climatology, they exhibit a systematic positive wind speed bias (+1.3 to +2.8 m s⁻¹), particularly in the rugged Upper Reaches due to sub-grid topographic smoothing. . However, Model 3 (Moloch) consistently outperforms the other configurations, achieving the lowest bias magnitude and the highest distributional fidelity (Perkins Skill Score). Regarding long-term trends, all models reproduce the interannual variability driven by large-scale circulation but fail to capture the magnitude of the observed "terrestrial stilling", highlighting a critical need to incorporate time-varying land use forcing in future multi-decadal experiments. Crucially, the study reveals a decisive disparity in computational efficiency. While the traditional non-hydrostatic core (Model 2) is computationally expensive due to strict CFL stability constraints (dt=25 s), the Moloch core (Model 3) maintains numerical stability with a significantly larger time step (dt=200 s). This capability results in a 58% reduction in total runtime compared to Model 2 and a 17% reduction compared to the hydrostatic baseline, without compromising physical accuracy. Consequently, the Moloch core emerges as the optimal configuration for long-term regional climate downscaling over complex terrains, effectively bridging the gap between high physical fidelity and numerical efficiency.

Keywords: RegCM5; Dynamical Cores; Wind Speed; Yellow River Basin; Computational Efficiency; Moloch

1. Introduction

Near-surface wind speed is a fundamental meteorological variable that governs land-atmosphere interactions, modulates evapotranspiration rates, and determines wind energy potential. In the context of global climate change, a widespread decline in surface wind speeds—known as "global terrestrial stilling"—has been observed over the past few decades, followed by a potential reversal in recent years (McVicar et al. 2012; Zeng et al. 2019). This phenomenon has profound implications for the hydrological cycle and renewable energy sectors, particularly in China, where wind power is a cornerstone of the national strategy to reach carbon neutrality (Ji et al. 2024).

The Yellow River Basin (YRB), revered as China's "Mother River" (Huang He) and northern China's "ecological shield", constitutes a critical region for hydroclimatic assessments (Li et al. 2024). Spanning from the rugged Tibetan Plateau through the highly erodible Loess Plateau to the eastern alluvial plains, the YRB features immense topographical complexity that has historically shaped Chinese civilization while presently sustaining over 12% of the national population and approximately one-third of China's grain production. In this socio-ecologically coupled system, near-surface winds are not merely a climatic resource but a pivotal driver of aeolian soil erosion, dust storm genesis, and air quality degradation (Yang et al. 2024), directly impacting the basin's ecological conservation strategies, renewable energy development, and sustainable water-soil-food resource management. Therefore, acquiring accurate, high-resolution, and long-term spatiotemporal distributions of wind speed is imperative for both regional climate resilience and national food security.

However, Global Climate Models (GCMs), with their coarse horizontal resolutions (typically > 100 km), struggle to resolve the intricate mesoscale topographic features and local land-surface processes that dominate near-surface wind regimes. Regional Climate Models (RCMs) have thus become indispensable tools for dynamically downscaling GCM outputs for bridging the gap between global forcing and local impact studies. Among these, the International Centre for Theoretical Physics (ICTP) Regional Climate Model (RegCM) has been extensively employed and validated over East Asia (Gao et al. 2006, 2017; Park et al. 2016; Gao and Giorgi 2017; Giorgi 2019; Xin et al. 2023; Wu et al. 2024). With the recent transition from RegCM4 to RegCM5, the model architecture has undergone significant updates. A pivotal development is the introduction of a new non-hydrostatic dynamical core alongside the traditional hydrostatic one, designed to enhance simulations at convection-permitting scales (Giorgi et al. 2023; Coppola et al. 2025). While the theoretical advantages of non-hydrostatic dynamics are clear at very high resolutions, their added value at mesoscale resolutions (e.g., 10–30 km)—which are computationally feasible for multi-decadal climatological runs—remains an open question (Prein et al. 2015a). However, the implementation of advanced non-hydrostatic physics typically incurs a prohibitive computational penalty. Consequently, the critical trade-off between simulation fidelity and efficiency is often overlooked in long-term climatological studies (Giorgi 2019; Coppola et al. 2020).

Existing studies evaluating RegCM over China have predominantly focused on temperature and precipitation (Gao and Giorgi 2017; Pan et al. 2020; Gao 2020; Gu et al. 2020; Nguyen-Xuan et al. 2021; Deng et al. 2023), with relatively less attention paid to the systematic evaluation of wind speed. Moreover, most comparative assessments of dynamical cores are restricted to short-term episodes or idealized experiments due to resource constraints (Prein et al. 2015a; Coppola et al.

2020). Few studies have conducted a long-term (multi-decadal) continuous evaluation of RegCM5's diverse dynamical configurations over complex terrains like the YRB. A 50-year simulation provides a robust observational baseline for climatological validation, enabling the assessment of models' fidelity in reproducing interdecadal variability and long-term trends such as the near-surface wind "stilling" phenomenon.

To address these gaps, this study presents a comprehensive evaluation of RegCM5 driven by the ERA5 reanalysis dataset (Hersbach et al. 2020) over the YRB for the period 1971–2020, with three primary objectives: (i) to evaluate the long-term performance of RegCM5 in reproducing spatiotemporal characteristics, interannual variability, and long-term trends (including the "stilling" phenomenon) of near-surface wind speed over complex terrain; (ii) to systematically compare the simulation capabilities of three distinct dynamical cores (one hydrostatic and two non-hydrostatic configurations) in capturing regional wind climatology; and (iii) to analyze the trade-off between model performance and computational cost, thereby identifying the optimal configuration that balances physical accuracy with computational economy for long-term climate downscaling. By providing a rigorous benchmark of RegCM5's performance versus efficiency, this study aims to offer practical guidance for future regional climate applications in the Yellow River Basin and analogous complex terrains globally.

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2. Data and Methods

2.1 Study Area

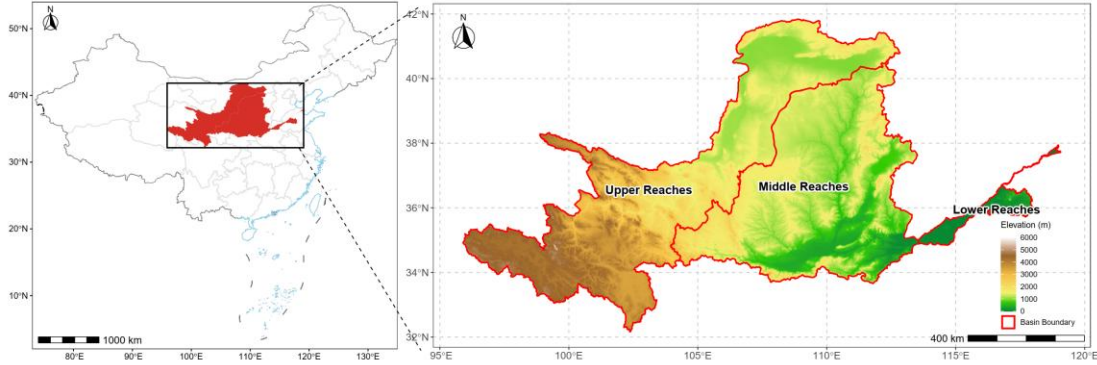


Figure 1 The Location of Study Area and Topography

This study investigates the YRB, the second-largest river basin in China, spanning approximately between 96°E–119°E and 32°N–42°N. The basin is characterized by a massive distinct three-step staircase topography, decreasing in elevation from west to east, which creates significant gradients in climate and surface roughness (Figure.1). Based on hydrological and topographical characteristics, the YRB is geographically partitioned into three distinct sub-regions:

- The Upper Reaches: Originating from the Bayan Har Mountains on the northeastern Qinghai-Tibet Plateau, this region is characterized by high elevation (mostly > 3000 m), complex alpine terrain, and permanent glaciers. It serves as the primary water source but poses significant challenges for terrain-following coordinates in climate models.
- The Middle Reaches: This section traverses the Loess Plateau, a region renowned for its fragmented gullies, fragile ecology, and highly erodible soil. The topography here is undulating with elevations ranging from 1000 to 2000 m.
- The Lower Reaches: Extending to the Bohai Sea, this region comprises the flat alluvial plain (North China Plain), characterized by low elevation (< 100 m) and high urbanization density.

2.2 Model Configuration and Experimental Design

In this study, we utilized the latest version of the Regional Climate Model (RegCM5.0), developed by the International Centre for Theoretical Physics (ICTP) (Giorgi et al. 2023; Coppola et al. 2025). The model was driven by the ERA5 reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF), which provided the initial and lateral boundary conditions (LBCs) updated every 6 hours with an exponential relaxation technique applied at the lateral buffer zone at a grid spacing of 1.5° (Hersbach et al. 2020). All necessary driving data, including the initial and boundary conditions and surface dataset, were retrieved from the ICTP data repository at <http://clima-dods.ictp.it/regcm4/>.

To assess the impact of dynamical formulations on wind speed simulation over complex terrain, three experimental simulations were designed using different dynamical cores available in

RegCM5, while keeping all other physical parameterizations identical. Based on pre-experiment sensitivity tests for numerical stability, the configurations and their corresponding time steps (dt , in seconds) are defined as follows:

- Model 1 (Hydrostatic Control): This configuration employs the standard MM4 hydrostatic dynamical core ($idynamic=1$) (Giorgi et al. 1993). It is based on the primitive equations with the hydrostatic assumption, which has been the workhorse of regional climate modeling for decades but theoretically limits the representation of vertical accelerations at high resolutions. For this simulation, the integration time step was set to ' $dt = 75$ '.
- Model 2 (MM5 Non-Hydrostatic): This configuration uses the MM5 non-hydrostatic dynamical core ($idynamic=2$) (Grell et al. 1994). It solves the fully compressible non-hydrostatic equations, allowing for a more realistic representation of vertical motion and gravity waves over steep topography. However, to satisfy the strict Courant-Friedrichs-Lewy (CFL) condition imposed by the explicit solving of fast acoustic modes, a restrictive time step of $dt = 25$ s was required, rendering this core computationally intensive.
- Model 3 (Moloch Non-Hydrostatic): This configuration utilizes the newly introduced Moloch non-hydrostatic core ($idynamic=3$) developed by the Institute of Atmospheric Sciences and Climate (CNR-ISAC) (Buzzi et al. 2014; Trini Castelli et al. 2020). This core is designed to be computationally efficient while maintaining non-hydrostatic physics. Leveraging its advanced time-splitting or semi-implicit numerical scheme, Model 3 operated stably with a significantly larger time step ($dt = 200$), offering a "fast" alternative for high-resolution simulations (Coppola et al. 2025).

For physical parameterizations, we adopted a configuration specifically tailored for the East Asian monsoon region. The Community Land Model version 4.5 (CLM4.5) was selected as the Land Surface Model (LSM), as it provides a more detailed representation of soil hydrology, vegetation dynamics, and land-atmosphere exchanges compared to the simpler BATS1e scheme (Oleson et al. 2013). The Planetary Boundary Layer (PBL) was parameterized using the Holtslag scheme, which is widely recognized for its robustness in wind field simulations (Holtslag and Boville 1993). Convective precipitation was treated using the Tiedtke scheme over both land and ocean grid points (Tiedtke 1989), while grid-scale moisture processes were handled by the Nogherotto-Tompkins explicit moisture scheme (Nogherotto et al. 2016). Air-sea fluxes were calculated using the Zeng scheme, with roughness lengths parameterized according to the specific formula option (Zeng et al. 1998).

The simulations were conducted at a grid spacing of 25 km for the continuous period from 1971 to 2020. The year 1970 was used as a spin-up period to allow the soil moisture and atmospheric fields to reach dynamic equilibrium, and not included in the analysis.

2.3 Observational Data

For model validation, we employ the CN05.1 observational dataset, a gridded climate product widely used in climate model evaluation and long-term climate analysis for China (Wu. and Gao. 2013; Wu et al. 2017; Chen et al. 2020; Miao and Wang 2020; Li et al. 2021). This dataset is constructed from daily observations at over 2,400 national-level meteorological stations, ensuring

high spatial density and quality control. The station data were interpolated onto a regular $0.25^\circ \times 0.25^\circ$ grid using the "anomaly approach" combined with thin-plate spline for climatology and angular distance weighting interpolation for the anomaly, which effectively retains spatial variability while minimizing interpolation errors over complex terrain. In this study, we utilize the daily mean near-surface (10-m) wind speed data spanning 50 years (1971–2020) as the ground truth for evaluating the RegCM5 simulations.

2.4 Evaluation Metrics

To ensure spatial consistency between the model outputs and observations, the RegCM5 outputs were bilinearly interpolated onto the regular $0.25^\circ \times 0.25^\circ$ grid as the CN05.1 dataset. The model performance was assessed using a comprehensive set of statistical metrics. The Mean Bias (MB), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were calculated to quantify the magnitude of simulation errors:

$$MB = \frac{1}{N} \sum_{i=1}^N (M_i - O_i) \quad (1)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |M_i - O_i| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (M_i - O_i)^2} \quad (3)$$

where M_i and O_i represent the simulated and observed values at the i -th time step or grid point, and N is the total number of samples.

To evaluate the temporal synchronization and phase consistency, the Pearson Correlation Coefficient (R) was employed:

$$R = \frac{\sum_{i=1}^N (M_i - \bar{M})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (M_i - \bar{M})^2} \sqrt{\sum_{i=1}^N (O_i - \bar{O})^2}} \quad (4)$$

where $\bar{M}$ and $\bar{O}$ denote the mean values of the simulation and observation respectively.

Given the importance of capturing the frequency distribution of wind speeds for wind energy and extreme event analysis, we utilized two advanced metrics: the Index of Agreement (IOA) (Willmott 1982), and the Perkins Skill Score (PSS) (Perkins et al. 2007). The IOA, proposed by Willmott, provides a standardized measure of the degree of model prediction error, varying between 0 (no agreement) and 1 (perfect match):

$$IOA = 1 - \frac{\sum_{i=1}^N (M_i - O_i)^2}{\sum_{i=1}^N (|M_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (5)$$

The metric PSS measures the overlap between the simulated and observed probability density

functions (PDFs):

$$PSS = \sum_{j=1}^m \min(Z_{M,j}, Z_{O,j}) \quad (6)$$

where m is the number of bins used to construct the PDF, $Z_{M,j}$ and $Z_{O,j}$ are the frequencies of the simulated and observed values in the j -th bin, respectively. The PSS measures the cumulative minimum value of the two distributions (model and observation, in this paper, which means RegCM5 output and CN05.1 respectively) across all bins. It ranges from 0 (no overlap) to 1 (perfect overlap), providing a robust metric for evaluating how well the model captures the full range of wind speed variability, including extremes.

Furthermore, Taylor diagrams were utilized to provide a concise statistical summary of how well the simulated patterns match observations in terms of their correlation, root-mean-square difference, and the ratio of their variances (Taylor 2001). Finally, to address the trade-off between performance and cost, computational efficiency was quantified by tracking the "Computation Time per Simulated Year" (hours) for each dynamical core configuration.

3. Results and Analysis

3.1. Climatological Characteristics

We first characterize the models' fidelity in reproducing the multi-decadal (1971–2020) mean wind speed climatology over the complex terrain of the Yellow River Basin (YRB). Figure 2 presents the spatial distribution of annual mean wind speeds from the CN05.1 observations and the three RegCM5 simulations. From a qualitative perspective, all dynamical configurations exhibit a high degree of spatial correlation with observations, successfully capturing the dominant northwest-to-southeast gradient. The models correctly identify the high-wind regimes over the northwestern highlands (e.g., the Inner Mongolia Plateau and the Ordos Plateau), driven by the strong pressure gradients associated with the East Asian Monsoon and the exposed terrain. Conversely, the models accurately reproduce the diminishing wind speeds towards the southeast, particularly in the sheltered basins (e.g., Weihe River valleys) and the lower alluvial plains.

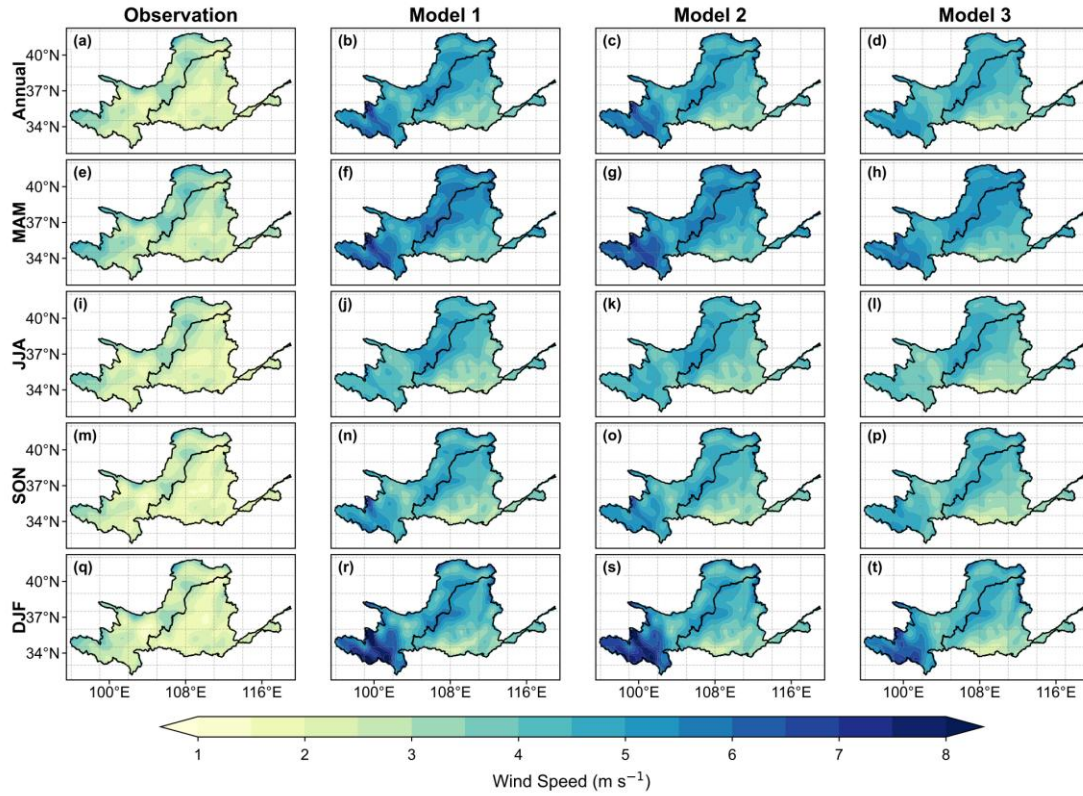


Figure 2 Spatial distribution of the multi-year mean (1971–2020) near-surface wind speed over the Yellow River Basin. Panels show the CN05.1 observations (a, e, i, m, q), and the corresponding simulations from Model 1(b, f, j, n, r), Model 2(c, g, k, o, s), and Model 3 (d, h, l, p, t). Rows represent the annual mean and seasonal means for Spring (MAM), Summer (JJA), Autumn (SON), and Winter (DJF), respectively.

However, quantitatively, a systematic positive bias is evident across the domain, as visualized in Figure 3 and quantified in Table 1. For the Whole Basin, the simulations systematically overestimate the observed annual mean wind speed (2.6 m s^{-1}), with Models 1 and 2 producing nearly identical values of 4.6 m s^{-1} (Bias: $+2.0 \text{ m s}^{-1}$). Model 3, however, effectively mitigates this systemic error, yielding a lower annual mean of 4.3 m s^{-1} (Bias: $+1.7 \text{ m s}^{-1}$). This overestimation is spatially heterogeneous: the Upper Reaches, characterized by rugged terrain, exhibit the largest biases (up to $+2.2 \text{ m s}^{-1}$ in Models 1 and Model 2), likely attributable to the smoothing of sub-grid topography at the 25-km resolution, which underestimates surface drag. In contrast, the biases are notably attenuated in the flatter Lower Reaches ($+1.3$ to $+1.5 \text{ m s}^{-1}$). Temporally, the bias follows the seasonal cycle of wind intensity, being most pronounced in spring (MAM) and weakest in autumn (SON). Across all seasons and sub-regions, Model 3 consistently maintains the lowest bias magnitude, suggesting that the Moloch core offers a superior representation of boundary layer momentum processes compared to the hydrostatic and MM5 cores.

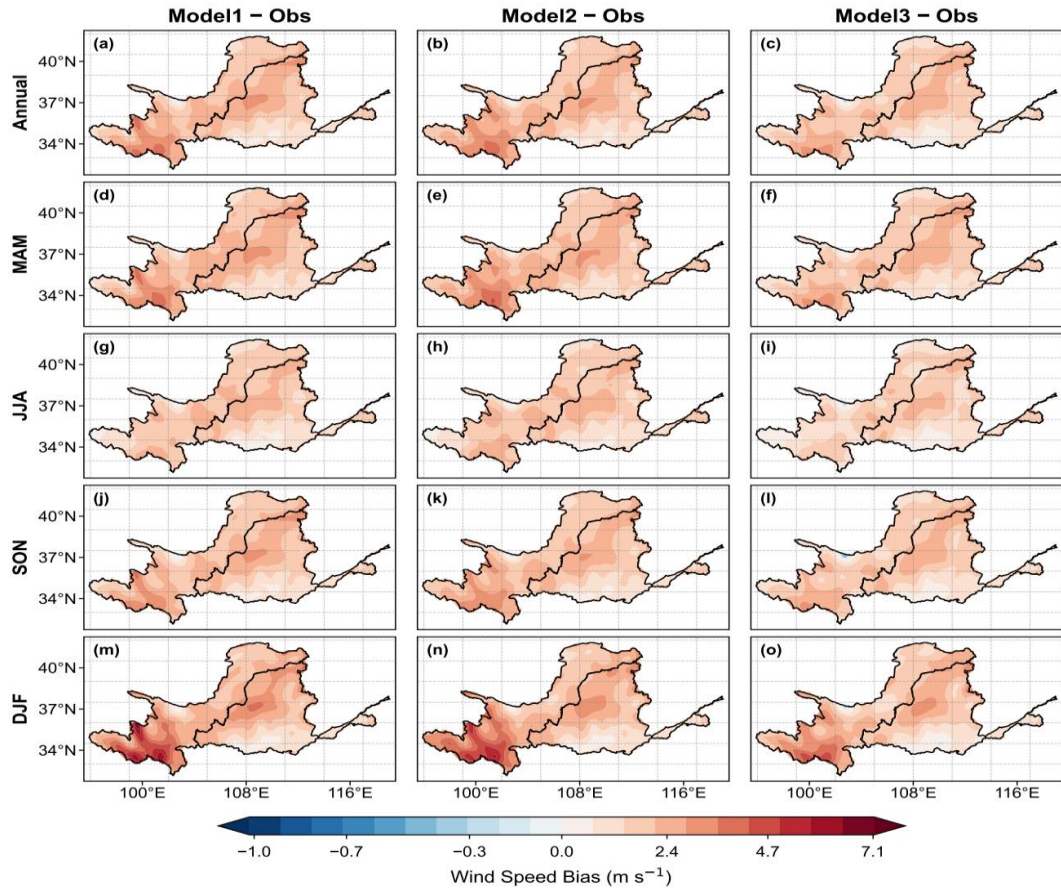


Figure 3 Spatial distribution of the wind speed bias (Model minus Observation) for the period 1971–2020. Columns represent the biases for Model 1 (left), Model 2 (middle), and Model 3 (right). Rows correspond to the Annual, MAM, JJA, SON, and DJF means. Red shades indicate overestimation, while blue shades indicate underestimation.

Table 1 Regional Mean Climatology Statistics

Region	Source	Annual	MAM	JJA	SON	DJF
Whole Basin	Obs	2.6	3.1	2.5	2.4	2.5
	Model 1	4.6 (+2.0)	5.1 (+2.1)	4.2 (+1.7)	4.3 (+1.9)	4.9 (+2.4)
	Model 2	4.6 (+2.0)	5.2 (+2.1)	4.2 (+1.7)	4.3 (+2.0)	4.8 (+2.4)
	Model 3	4.3 (+1.7)	4.8 (+1.8)	3.9 (+1.4)	4.0 (+1.7)	4.4 (+2.0)
	Obs	2.9	3.4	2.8	2.6	2.7
Upper Reaches	Model 1	5.1 (+2.2)	5.5 (+2.2)	4.5 (+1.7)	4.7 (+2.1)	5.5 (+2.8)
	Model 2	5.1 (+2.2)	5.6 (+2.2)	4.5 (+1.7)	4.7 (+2.1)	5.5 (+2.8)
	Model 3	4.7 (+1.8)	5.2 (+1.8)	4.2 (+1.4)	4.4 (+1.7)	5.0 (+2.2)
	Obs	2.3	2.7	2.3	2.1	2.1
Middle Reaches	Model 1	4.2 (+1.9)	4.7 (+2.0)	3.9 (+1.7)	4.0 (+1.9)	4.3 (+2.1)
	Model 2	4.2 (+1.9)	4.7 (+2.0)	3.9 (+1.7)	3.9 (+1.8)	4.2 (+2.0)
	Model 3	4.0 (+1.7)	4.5 (+1.8)	3.8 (+1.5)	3.7 (+1.7)	3.9 (+1.8)
	Obs	2.5	3.0	2.3	2.2	2.5
Lower Reaches	Model 1	4.0 (+1.5)	4.7 (+1.7)	3.9 (+1.6)	3.6 (+1.5)	3.8 (+1.3)
	Model 2	4.0 (+1.5)	4.8 (+1.8)	3.9 (+1.6)	3.6 (+1.5)	3.7 (+1.3)
	Model 3	3.8 (+1.3)	4.5 (+1.5)	3.8 (+1.6)	3.4 (+1.3)	3.5 (+1.0)
	Obs	2.5	3.0	2.3	2.2	2.5

*Values in parentheses denote the mean bias (Simulation minus Observation).

3.2. Statistical Evaluation

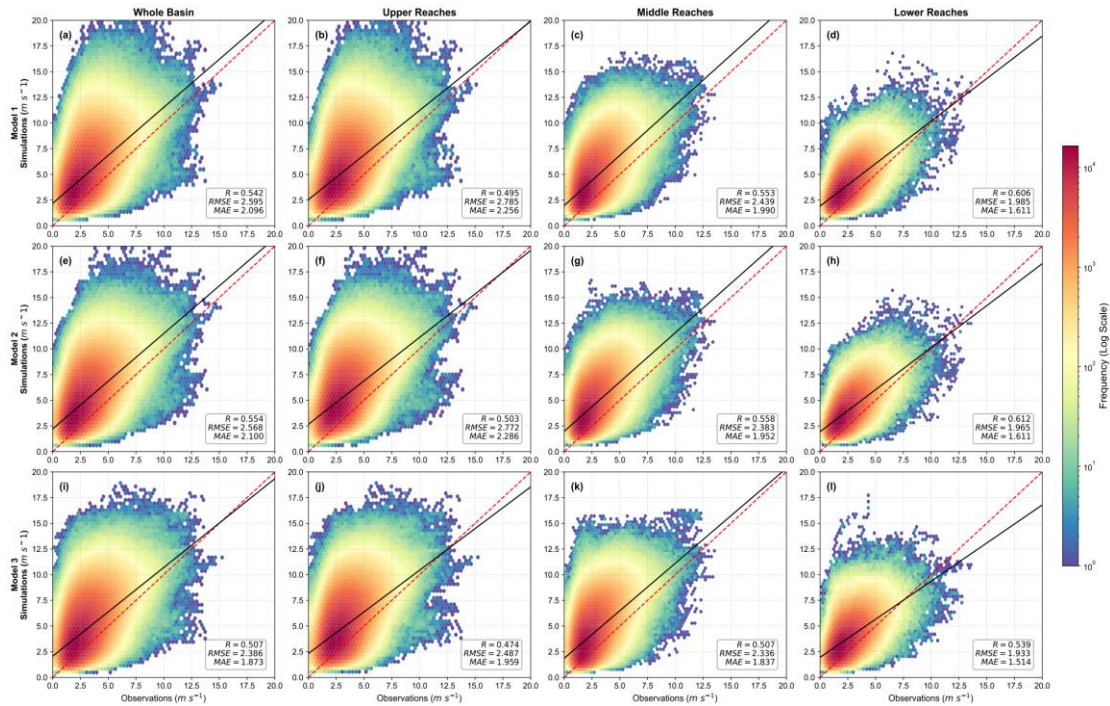


Figure 4 Joint probability density scatter plots of daily mean near-surface wind speed for the period 1971–2020. Panels are organized by Rows (Model 1, Model 2, and Model 3) and Columns (Whole Basin, Upper Reaches, Middle Reaches, and Lower Reaches). The red dashed line represents the 1:1 identity line, while the black solid line indicates the linear regression fit. The color scale represents the frequency of occurrence (log scale). Statistical metrics (R, RMSE, MAE) are embedded in each panel.

Figure 4 presents the joint probability density scatter plots of simulated versus observed daily wind speeds, illustrating the overall performance of the three RegCM5 configurations over the Yellow River Basin and its sub-regions. For the Whole Basin, Models 1 and 2 exhibit similar performance characteristics, sharing relatively higher correlations ($R=0.542$ and $R=0.554$, respectively) but notable errors ($RMSE = 2.595$ and 2.568 m s^{-1} ; $MAE = 2.096$ and 2.100 m s^{-1}). Model 3, in contrast, shows a slightly lower correlation ($R=0.507$) but achieves a superior performance in terms of error magnitude, with RMSE and MAE reduced to 2.386 m s^{-1} and 1.873 m s^{-1} , respectively.

Spatially, the model performance is distinct across different topographic units. The rugged Upper Reaches pose the greatest challenge, where all models show the lowest correlations and highest errors, likely due to the difficulty in resolving sub-grid orographic drag (Jiménez and Dudhia 2012). Moving to the flatter Lower Reaches, performance improves universally. Specifically, for Model 1, the MAE decreases sharply from 2.256 m s^{-1} in the Upper Reaches to 1.611 m s^{-1} in the Lower Reaches, accompanied by a rise in R from 0.495 to 0.606 . Similarly, Model 2 shows a parallel improvement (MAE drops to 1.611 m s^{-1} , R rises to 0.612). Model 3 follows this spatial trend (R improves from 0.474 to 0.539 ; RMSE drops from 2.487 to 1.933 m s^{-1}). Crucially, even in the "easiest" Lower Reaches, Model 3 achieves the lowest MAE (1.514 m s^{-1}) despite having a lower correlation ($R=0.539$) compared to the other two models ($R > 0.60$). This suggests that the performance advantage of the Moloch core may be primarily driven by its effective correction of wind speed magnitude (bias reduction) rather than an improvement in phase

301 synchronization.

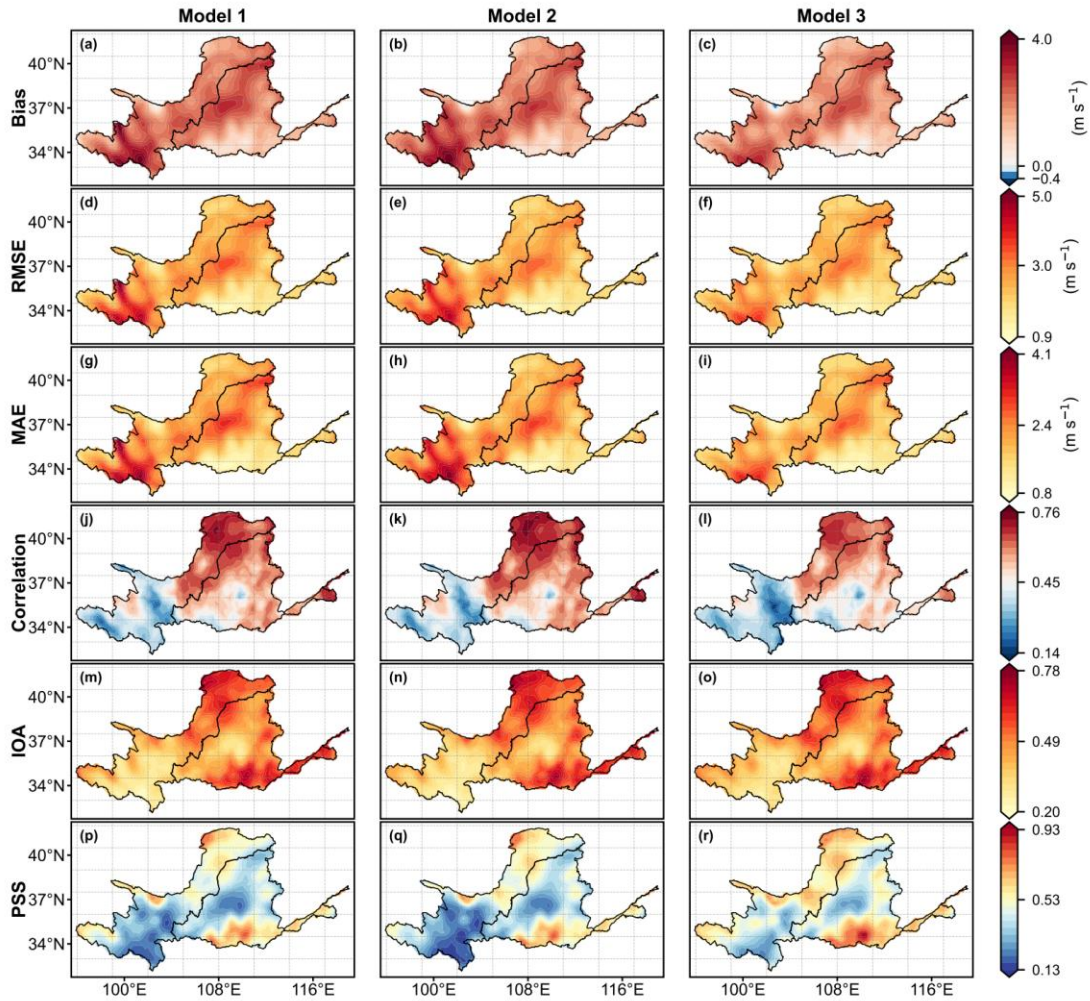


Figure 5 Spatial patterns of statistical evaluation metrics for the three RegCM5 configurations over the Yellow River Basin (1971–2020). Columns correspond to Model 1, Model 2, and Model 3. Rows display (a-c) Bias (m s^{-1}), (d-f) RMSE (m s^{-1}), (g-i) MAE (m s^{-1}), (j-l) Pearson Correlation Coefficient, (m-o) Index of Agreement (IOA), and (p-r) Perkins Skill Score (PSS).

Figure 5 explicitly characterizes the spatial heterogeneity of model performance, revealing a distinct west-to-east gradient in error magnitude that mirrors the underlying terrain complexity. The error metrics (RMSE, MAE) verify that the most significant deviations occur in the rugged Upper Reaches, where topographic forcing is strongest, while the best performance is consistently found in the flat Lower Reaches. Quantitatively, as detailed in Table 2, Models 1 and 2 exhibit nearly indistinguishable high-error patterns across the Whole Basin (Bias = $+2.0 \text{ m s}^{-1}$, RMSE = 2.50 m s^{-1}), indicating that the standard MM5 core provides no statistical advantage over the hydrostatic core at this resolution.

In contrast, Model 3 demonstrates a pervasive improvement in error reduction. Visually, this is evident in Figure 5 (c, f, i), where the deep red hues (indicating high Bias and RMSE) are noticeably lighter compared to Models 1 and 2. Statistically, Model 3 reduces the Whole Basin Bias to $+1.70 \text{ m s}^{-1}$ and RMSE to 2.33 m s^{-1} . More importantly, regarding the shape of the distribution, Model 3 achieves a superior Perkins Skill Score (PSS) of 0.52 (compared to 0.44 for Model 1), with the highest scores concentrated in the Lower Reaches (PSS = 0.62). This indicates

that while Model 3 may have a slightly lower correlation ($R=0.48$), it is significantly more effective at reproducing the probability density function (PDF) of the observed wind speeds, offering a more physically realistic representation of the regional wind climatology. The superiority of Model 3 is further underscored by the Index of Agreement (IOA), a composite metric that rigorously penalizes both phase shift and mean bias. By effectively mitigating the systematic overestimation, Model 3 achieves the highest IOA values, particularly in the challenging Upper Reaches (0.46 compared to 0.44 for Models 1 and 2).

Table 2 Regional Mean Metrics Summary

Region	Model	Bias	MAE	RMSE	Corr	IOA	PSS
Whole Basin	Model 1	+2.01	2.10	2.50	0.52	0.46	0.44
	Model 2	+2.02	2.10	2.49	0.53	0.47	0.43
	Model 3	+1.70	1.87	2.33	0.48	0.48	0.52
Upper Reaches	Model 1	+2.16	2.26	2.71	0.50	0.44	0.43
	Model 2	+2.21	2.29	2.70	0.50	0.44	0.41
	Model 3	+1.78	1.96	2.45	0.46	0.46	0.51
Middle Reaches	Model 1	+1.92	1.99	2.35	0.55	0.48	0.44
	Model 2	+1.89	1.95	2.31	0.55	0.49	0.44
	Model 3	+1.69	1.84	2.26	0.50	0.49	0.51
Lower Reaches	Model 1	+1.48	1.61	1.97	0.61	0.60	0.58
	Model 2	+1.49	1.61	1.96	0.62	0.60	0.57
	Model 3	+1.31	1.51	1.92	0.55	0.60	0.62

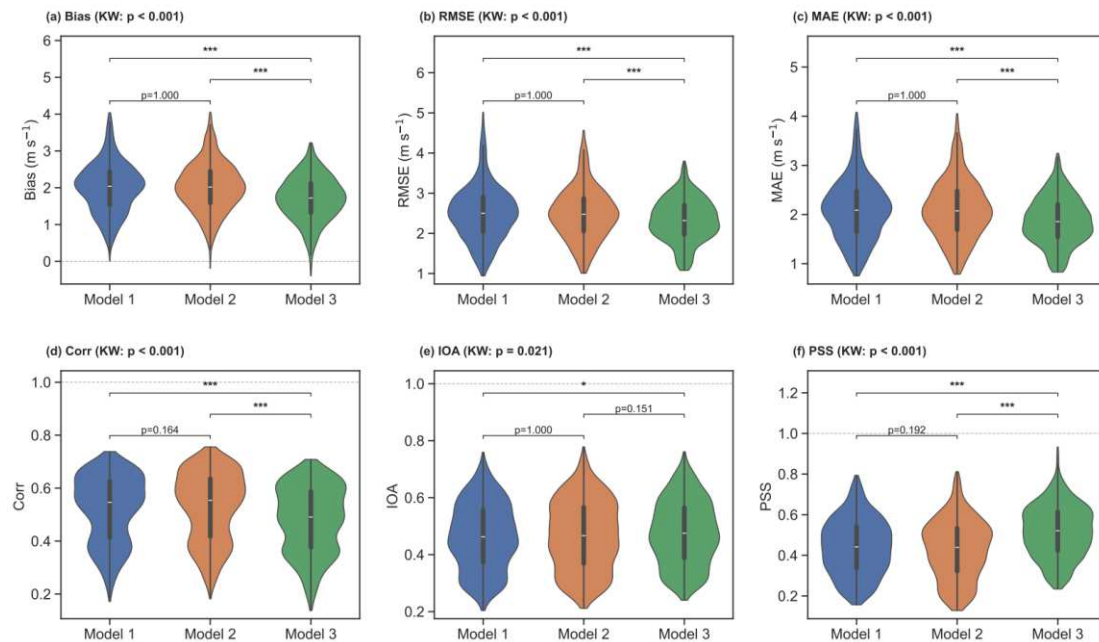


Figure 6 Violin plots of grid-point performance metrics over the Whole Basin: (a) Bias, (b) RMSE, (c) MAE, (d) Correlation, (e) IOA, and (f) PSS. Statistical significance was assessed using the Kruskal-Wallis (KW) test for global differences (p-values in headers) followed by pairwise Mann-Whitney (MW) tests. Brackets indicate pairwise significance results.

To rigorously assess the statistical significance of the inter-model discrepancies, Figure 6 presents the distribution of grid-point metrics analyzed via the non-parametric Kruskal-Wallis (KW) test, followed by pairwise Mann-Whitney (MW) comparisons to isolate specific model differences. The KW results confirm global heterogeneity across the three configurations for all

metrics ($p < 0.001$, except IOA at $p=0.021$). However, the pairwise connectivity analysis reveals a critical structural insight: Model 1 and Model 2 are statistically indistinguishable. As evidenced by the connecting brackets in Figure 6 (a-c, e), the differences between the hydrostatic (Model 1) and standard non-hydrostatic (Model 2) cores are non-significant ($p=1.000$) for Bias, RMSE, MAE, and IOA, implying that they belong to the same statistical population regarding error distribution.

In sharp contrast, Model 3 significantly diverges from this group, forming a distinct statistical entity. The MW tests confirm that Model 3 is significantly different from both Model 1 and Model 2 at the 99.9% confidence level ($p < 0.001$) for the majority of metrics. Specifically, Model 3 demonstrates a statistically significant reduction in error magnitudes (Bias, RMSE, MAE) and a substantial enhancement in distributional fidelity (PSS), as shown in Figure 6f. Although Model 3 shows a statistically significant decrease in correlation (Figure 6d), its superior performance in integrated error metrics and probability density matching highlights the Moloch core's unique capability to correct systematic biases.

3.3. Temporal Stability

To further investigate the robustness of the model performance over the multi-decadal period, we analyzed the temporal evolution of the IOA and PSS via monthly heatmaps (Figure. 7 and Figure. 8). These visualizations reveal a clear seasonal rhythm in simulation skill, with generally higher fidelity observed during the spring and summer transitions compared to the winter months across all configurations.

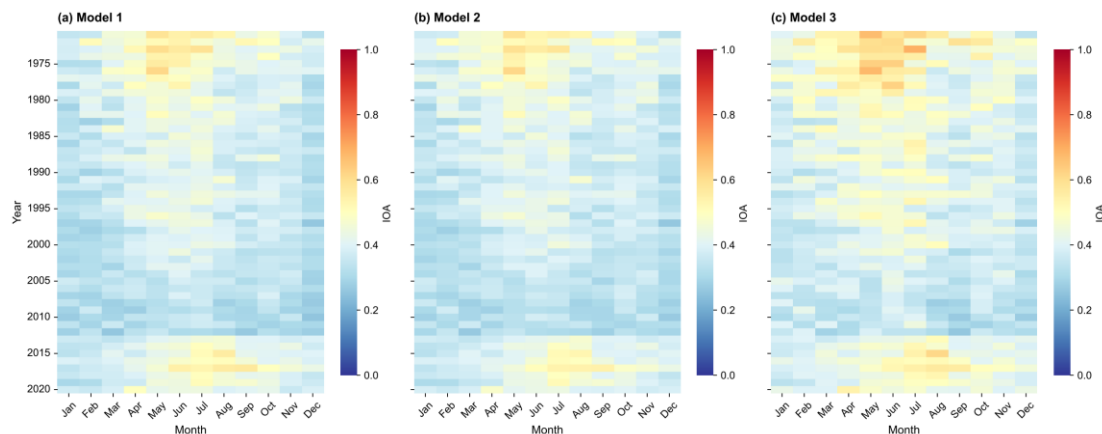


Figure 7 Temporal heatmaps of the monthly IOA for the Whole Basin from 1971 to 2020. Panels correspond to (a) Model 1, (b) Model 2, and (c) Model 3. The x-axis represents the calendar months (January to December), and the y-axis represents the years. The color gradient ranges from blue (low agreement) to red (high agreement).

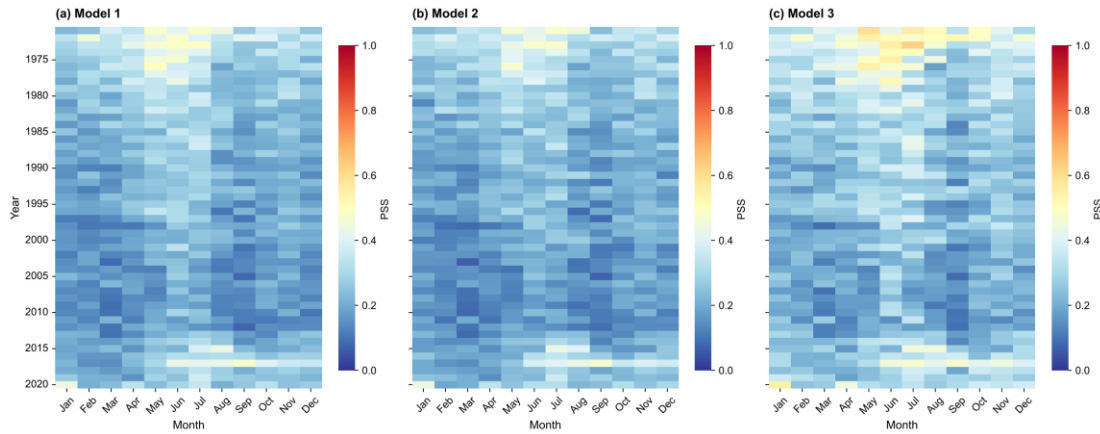
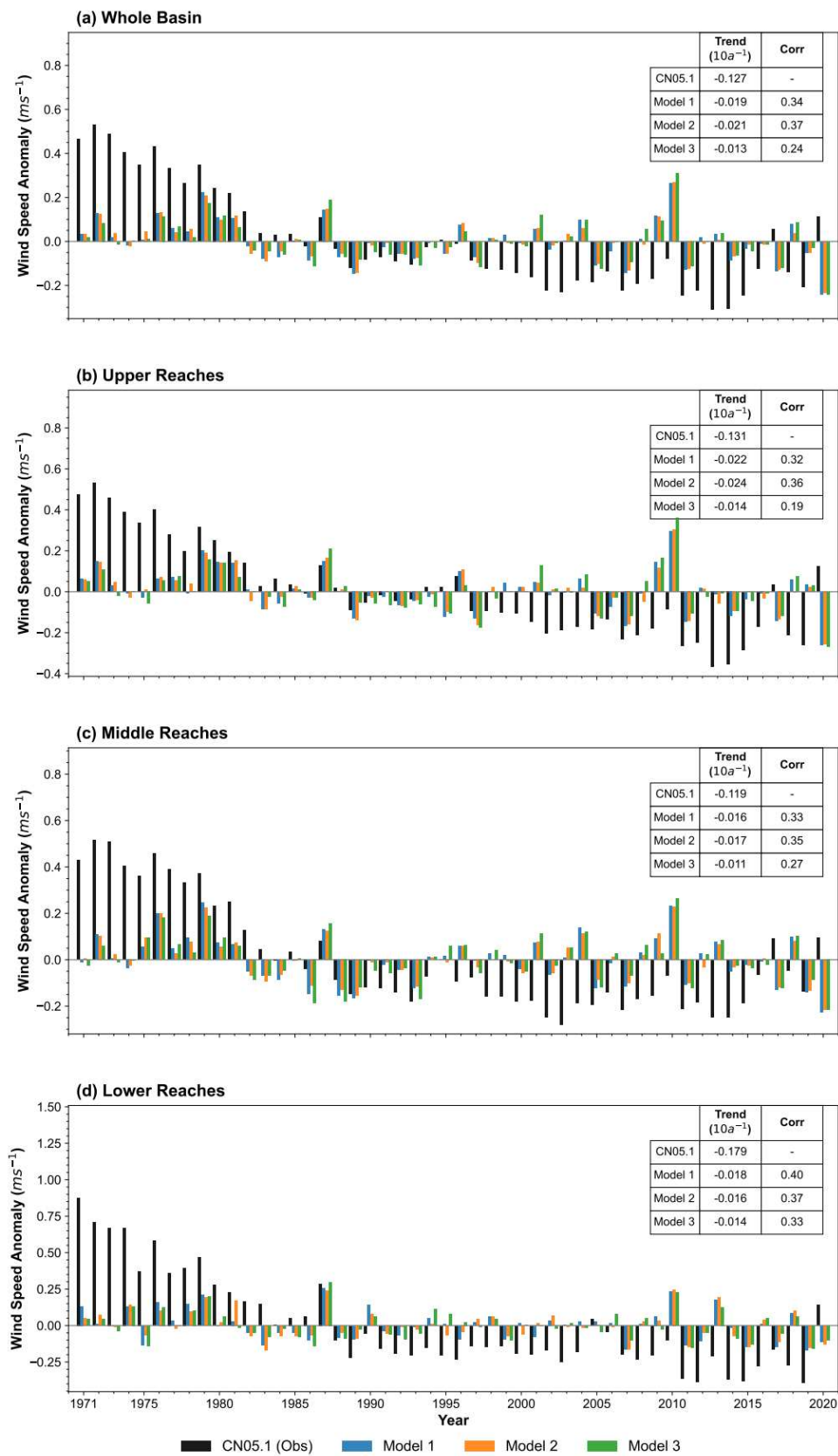


Figure 8 Same as Figure 7, but for PSS.

However, the inter-model comparison exposes a stark contrast in temporal stability. Models 1 and 2 are dominated by "cold" hues (blue shades) across the majority of the 1971–2020 timeline, particularly for the PSS metric (Figure. 8a, b), indicating a persistent struggle to capture the observed wind speed probability distributions. In contrast, Model 3 exhibits a pervasive "warming" of skill scores, characterized by the widespread emergence of yellow and orange tones (Figure. 7c, Figure. 8c). This improvement is not sporadic but systematic: Model 3 maintains high IOA and PSS values consistently across interannual variations, effectively mitigating the "performance dropouts" frequently observed in the hydrostatic and MM5 non-hydrostatic simulations. This confirms that the superiority of the Moloch core is temporally robust, stemming from a physically more consistent representation of the flow dynamics rather than a coincidental bias cancellation in specific years.

Figure 9 presents the time series of annual mean wind speed anomalies (relative to the 1971–2020 climatology) for the Whole Basin and its sub-regions. The observational record reveals a prominent and statistically significant "atmospheric stilling" phenomenon across the YRB. As quantified in the inset tables, the observed wind speed exhibits a robust downward trend of $-0.127 \text{ m s}^{-1}/10\text{a}$ for the Whole Basin, with the steepest decline occurring in the Lower Reaches ($-0.179 \text{ m s}^{-1}/10\text{a}$). However, the RegCM5 simulations struggle to capture this multi-decadal weakening signal. Regardless of the dynamical core, the simulated trends are essentially negligible, ranging from -0.011 to $-0.022 \text{ m s}^{-1}/10\text{a}$, which is an order of magnitude smaller than the observations. This distinct discrepancy suggests that the observed stilling is likely driven by external factors (e.g., urbanization or vegetation changes) that are not fully represented in the current experimental design, as the simulations utilized static land use (Vautard et al. 2010; Li et al. 2019), rather than being a deficiency unique to a specific dynamical core.

Despite the underestimation of the linear trend, the models show a reasonable capability in reproducing the interannual variability. The phases of simulated anomalies generally align with observations (i.e., capturing the correct "high" and "low" wind years). Notably, in terms of temporal correlation for these annual anomalies, Models 1 and 2 (Hydrostatic and MM5) actually outperform Model 3 (Moloch). For the Whole Basin, Model 2 achieves the highest correlation ($R=0.37$), followed by Model 1 ($R=0.34$), while Model 3 shows a weaker correlation ($R=0.24$). This indicates that while the Moloch core is superior in correcting the climatological mean bias (as shown in Section 3.1), it does not offer an advantage in capturing the low-frequency interannual fluctuations driven by large-scale circulation anomalies.



396

397 Figure 9 Time series of annual mean near-surface wind speed anomalies ($m s^{-1}$, relative to the 1971–2020 mean)
398 averaged over (a) the Whole Basin, (b) Upper Reaches, (c) Middle Reaches, and (d) Lower Reaches.

3.4. Taylor Diagrams

To provide a holistic synthesis of the models' ability to reproduce the spatiotemporal variability of the wind field, we employ Taylor Diagrams (Figure. 10 and Figure. 11) and the Taylor Skill Score (TSS) (Table 3). These diagnostics decompose the model errors into three components: the correlation coefficient (R), the normalized standard deviation (NSD), and the centered root-mean-square difference (CRMSD).

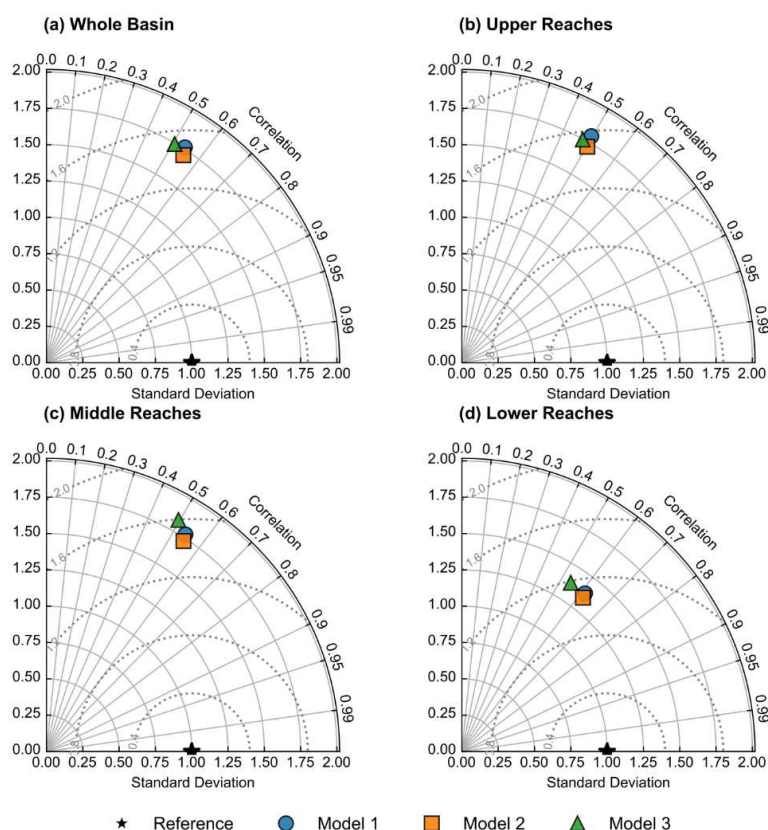


Figure 10 Taylor diagrams of the three RegCM5 models with respect to the CN05.1 observations for the period 1971–2020. Panels correspond to (a) Whole Basin, (b) Upper Reaches, (c) Middle Reaches, and (d) Lower Reaches.

Taylor diagrams (Figure. 10) highlight distinct performance characteristics among the dynamical cores. Models 1 and 2 generally exhibit higher temporal correlation coefficients but significantly overestimate the wind speed variance, as indicated by their NSD values exceeding 1.25. This implies that the hydrostatic and standard MM5 cores tend to simulate excessive fluctuation magnitudes. In contrast, Model 3 is situated much closer to the reference unit arc ($NSD = 1.0$), demonstrating that the Moloch core reproduces the observed variance with high fidelity. However, this improvement in variance comes with a slight reduction in temporal correlation compared to the other configurations.

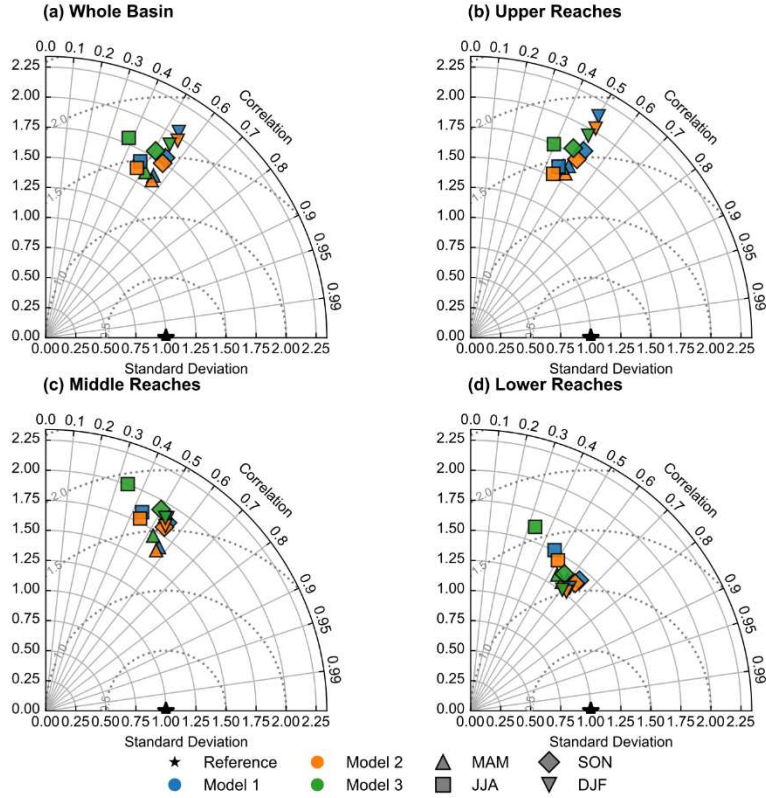


Figure 11 Seasonal Taylor diagrams of the three RegCM5 models with respect to the CN05.1 observations. Different shapes denote the seasons: Spring (MAM, squares), Summer (JJA, upward triangles), Autumn (SON, diamonds), and Winter (DJF, inverted triangles). Colors represent Model 1 (blue), Model 2 (orange), and Model 3 (green).

The seasonal dependence of these metrics is quantified in Table 3 and visualized in Figure 11. Since the Taylor Skill Score (TSS) formula places significant weight on the correlation coefficient (Taylor 2001), Model 2 consistently yields the highest scores across most seasons and sub-regions (e.g., Annual Whole Basin TSS: 0.59). However, a notable shift occurs during Winter (DJF), where Model 3 achieves comparable or superior scores (e.g., TSS = 0.52 for Model 3, and 0.48 for Model 1 in the Whole Basin). This suggests that the non-hydrostatic Moloch core provides a more robust representation of the flow field under stable boundary layer conditions, where the hydrostatic assumption often limits model performance.

Table 3 Taylor Skill Scores Summary

Region	Model	Annual	Spring	Summer	Autumn	Winter
Whole Basin	Model 1	0.57	0.62	0.57	0.56	0.48
	Model 2	0.59	0.64	0.59	0.58	0.51
	Model 3	0.56	0.61	0.50	0.54	0.52
Upper Reaches	Model 1	0.54	0.59	0.59	0.54	0.45
	Model 2	0.57	0.61	0.61	0.57	0.48
	Model 3	0.55	0.59	0.52	0.53	0.50
Middle Reaches	Model 1	0.56	0.61	0.51	0.54	0.52
	Model 2	0.58	0.63	0.53	0.55	0.55
	Model 3	0.53	0.58	0.43	0.50	0.52
Lower Reaches	Model 1	0.73	0.73	0.62	0.73	0.76
	Model 2	0.74	0.73	0.66	0.74	0.77
	Model 3	0.70	0.71	0.53	0.71	0.76

3.5. Numerical Efficiency

Beyond physical fidelity, computational cost is a critical constraint for multi-decadal high-resolution climate downscaling. All simulations were performed on identical Kunpeng 920 nodes (HiSilicon, 2.6 GHz; 192 cores/node, 4 sockets $\times$ 48 cores) to ensure unbiased intercomparison. Table 4 quantify the wall-clock time overhead: the standard non-hydrostatic MM5 core (Model 2) incurs the highest computational burden at 5.75 h/year (287.72 h total), approximately double the hydrostatic baseline (Model 1: 2.92 h/year). This aligns with the theoretical expectation that explicit treatment of vertical acceleration in non-hydrostatic solvers increases arithmetic intensity.

However, Model 3 (Moloch core) challenges this paradigm by demonstrating remarkable efficiency. Despite being a non-hydrostatic formulation, it achieves the lowest computational cost among all configurations, with an average of 2.42 hours per simulated year and a total runtime of 121.24 hours. This represents a 17% reduction compared to the hydrostatic Model 1 and a substantial 58% reduction compared to Model 2.

Table 4 Numerical Efficiency Statistics

Model	Avg Time/Year (h)	Total Time (h)	Time Step (s)
Model 1	2.92	146.18	75
Model 2	5.75	287.72	25
Model 3	2.42	121.24	200

Consequently, the Moloch core offers a "win-win" solution for regional climate modeling over complex terrain: it provides superior physical performance (as evidenced in Sections 3.2 and 3.4) while simultaneously minimizing the demand on high-performance computing resources.

4. Discussion

4.1. Mechanisms Behind the Systematic Wind Speed Overestimation

A pervasive feature across all three RegCM5 configurations is the systematic overestimation of near-surface wind speeds. This "positive wind bias" is a well-documented challenge in regional climate modeling, particularly over East Asia and complex terrains (Jiménez and Dudhia 2012). The magnitude of the bias is spatially correlated with topographic complexity, peaking in the Upper Reaches, as shown in Figure. 5. We attribute this primarily to the smoothing of topography at the 25-km simulation resolution. In reality, the Upper Yellow River Basin features rugged terrain with sub-grid orographic obstacles (e.g., ridges, valleys) that exert significant drag on the atmospheric flow (Yang et al. 2024). However, in the model's "envelope orography," these features are smoothed out, leading to an underestimation of the turbulent form drag and, consequently, an overestimation of surface momentum. Although the CLM4.5 land surface model improves surface heterogeneity representation, the standard parameterization of Sub-grid Scale Orography (SSO) in RegCM5 may still be insufficient to dampen the flow over the Tibetan Plateau margins. Future improvements could involve coupling more advanced SSO drag schemes or increasing the horizontal resolution to convection-permitting scales (< 5 km) to explicitly resolve these

topographic features (Prein et al. 2015b).

4.2. Numerical Stability and Time Step Constraints: The Efficiency Key

A critical finding of this study is the immense disparity in computational cost (Figure. 12), with Model 2 being significantly more expensive than Models 1 and 3. This efficiency gap is fundamentally rooted in the allowable integration time step (Δt) required to maintain numerical stability. The restrictive time step for Model 2 is characteristic of traditional compressible non-hydrostatic cores, which are strictly limited by the Courant-Friedrichs-Lewy (CFL) condition to resolve fast-propagating acoustic and gravity waves (Dudhia 1993). In contrast, Model 3 (Moloch core) employs advanced numerical techniques, such as semi-implicit time integration for vertical propagation of sound waves, that allow for a time step 8 times larger than that of Model 2 while preserving stability (Coppola et al. 2020, 2025). This capability to utilize large time steps is the primary physical reason behind the 58% reduction in simulation time. Our results demonstrate that for this scale (25 km) simulations, the Moloch core offers a decisive advantage by decoupling physical fidelity from the strict time-stepping penalties usually associated with non-hydrostatic dynamics.

4.3. The "Stilling" Paradox

While the models captured the interannual variability driven by large-scale circulation (e.g., variations in the East Asian Monsoon), they failed to reproduce the magnitude of the observed terrestrial stilling trend (Figure 9.). This discrepancy strongly suggests that the observed stilling in the YRB is driven by factors external to the standard RCM physics. The primary suspect is Time-Varying Land Use and Land Cover (LULC). Since the 1980s, China has implemented massive afforestation programs (e.g., the "Three-North Shelterbelt" and "Grain for Green") in the YRB, leading to a significant increase in vegetation coverage (Li et al. 2019). Additionally, rapid urbanization has increased surface roughness length (Vautard et al. 2010). Since our experiments utilized a static land cover climatology, this anthropogenic increase in surface drag was absent, leading to a flatter wind speed trend. This highlights the urgent need to incorporate dynamic vegetation and urbanization modules in multi-decadal RCM simulations to capture anthropogenic modification of the boundary layer, as suggested by McVicar et al. (2012) and Zeng et al. (2019).

4.4. Implications for Regional Climate Modeling Strategy

The trade-off analysis (Table 4.) provides a pragmatic guideline for the modeling community. In the era of high-resolution ensembles (e.g., CORDEX-Flagship Pilot Studies), computational resources remain a bottleneck (Coppola et al. 2020). Model 3 proved to be the "Goldilocks" configuration: it offers the advanced physics of a non-hydrostatic core but with the computational efficiency of a hydrostatic one (or better). By allowing a time step of 200 s, Model 3 enables researchers to generate decadal-scale simulations at less than half the cost of traditional non-

hydrostatic setups. This implies that for hydro-climate applications over complex terrain in the YRB, transitioning to efficient cores like Moloch yields a high return on investment, allowing resources to be reallocated towards generating larger ensembles to quantify uncertainty.

5. Summary and Conclusions

This study evaluates the multi-decadal performance (1971–2020) of three RegCM5 dynamical configurations in simulating near-surface wind speeds over the complex terrain of the Yellow River Basin. It is found that while all dynamical cores capture the spatial climatology, a systematic positive bias exists, particularly in the rugged Upper Reaches due to topographic smoothing; however, the Moloch non-hydrostatic core significantly mitigates this error and achieves superior distributional fidelity compared to the standard hydrostatic and MM5-like non-hydrostatic cores. Regarding long-term trends, the simulations reproduce the phase of interannual variability driven by large-scale circulation but universally fail to capture the magnitude of the observed "terrestrial stilling," indicating that this phenomenon is predominantly governed by external time-varying land surface forcings (e.g., urbanization and vegetation changes) rather than internal model dynamics. Furthermore, a decisive disparity in computational efficiency is identified: the Moloch core, leveraging semi-implicit time integration, maintains numerical stability with a time step eight times larger than the explicit MM5 core. This capability results in a 58% reduction in total runtime while maintaining or exceeding physical accuracy, thereby offering an optimal configuration that decouples high physical fidelity from prohibitive computational costs for long-term regional climate downscaling.

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Data availability

The RegCM5 model source code (version 5.0) is publicly available under the MIT license at <https://github.com/ICTP/RegCM>. All necessary driving data, including the initial and boundary conditions and surface dataset, were retrieved from the ICTP data repository at <http://climadods.ictp.it/regcm4/>. Due to the substantial volume of high-resolution model outputs, the simulation results are not deposited in a public repository but are available from the corresponding author upon reasonable request for research purposes.

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Declarations

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest