

~~An objective dynamic multivariable weighting method for reducing uncertainty in WRF parameterization scheme selection~~

A performance-based multivariable weighting framework for WRF parameterization-scheme selection

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Abstract. The selection of ~~optimal~~ physical parameterization schemes is a major source of uncertainty in WRF ~~model~~ simulations. A comprehensive evaluation of model performance requires the simultaneous consideration of multiple output variables. ~~However, existing multivariate approaches often rely on subjective or overly simplistic equal weighting strategies and lack an objective mechanism to quantify variable importance. Such limitations can obscure significant biases in poorly~~
5 ~~simulated variables. To overcome~~, but simple multivariable averaging can dilute the influence of variables that are difficult to simulate or that respond strongly to alternative physical-process options. To address this issue, this study proposes an
~~objective dynamic weighting method for multivariate~~ a performance-based multivariable weighting framework for WRF
parameterization-scheme evaluation. The ~~method employs a two-layer weighting framework based on two statistical metrics:~~
the framework combines two components: mean relative error, which ~~measures the simulation accuracy of a variable~~ represents
10 variable-level simulation difficulty quantified by relative simulation error, and the coefficient of variation of ~~the absolute~~
~~error, which reflects the sensitivity of a variable to the physical process under evaluation~~ absolute errors, which represents
the scheme-dependent response of each variable within the evaluated physical-process group. The approach ~~is applied and~~
~~validated~~ was applied and evaluated in assessing WRF parameterization schemes across two climatically distinct environ-
ments: the arid Northwest and the humid coastal Southeast of China. The results show that the method assigns greater weights
15 to ~~poorly simulated variables~~ variables that are difficult to simulate, such as precipitation and wind speed, thereby ~~enabling~~
the identification of more physically plausible and robust parameterization scheme combinations helping identify physically
interpretable and well-performing parameterization-scheme combinations under the prescribed evaluation framework. Com-
pared with ~~the equal weighting method, the scheme combinations obtained using this approach produce a lower Multivariate~~
~~Integrated Evaluation Index (MIEI), a higher correlation coefficient (R), a lower Root Mean Square Error (RMSE), and~~
20 ~~exhibit superior performance in independent equal weighting and established statistical weighting methods, the proposed~~
MRE $\times$ CV weighting helped identify parameterization-scheme combinations that achieved the lowest integrated cMIEI in
both representative screening years and in the independent 2010 extreme-year validations. By dynamically incorporating both

simulation performance and sensitivity specific to each variable, the method offers a more rigorous and objective framework for model evaluation and uncertainty reduction validation. These results indicate that jointly considering variable-level simulation difficulty and scheme-dependent response improves the diagnostic relevance of multivariable WRF parameterization-scheme evaluation.

1 Introduction

In the domains of climate change Earth system models (ESMs) support climate change detection and attribution, future climate projection, and adaptation research, Earth system models (ESMs) serve as indispensable tools (Reichler and Kim, 2008; Knutti et al., 2010). However, the reliability of these model-based studies is closely tied to the simulation performance of the models themselves (Knutti et al., 2010). With advancements in computational power and a growing understanding of Earth system dynamics, the range of physical process representations within models has expanded, and the interactions among these processes have become increasingly complex. Their reliability depends on systematic evaluation against observations, especially as model representations of physical processes become broader and more interconnected (Reichstein et al., 2019). As a result, there is a pressing need for more efficient and systematic evaluation approaches to accurately assess the consistency between model outputs and observational data, thereby offering a robust scientific foundation for future research endeavors (Eyring et al., 2019; Hausfather et al., 2020).

Given the extensive spatial and temporal variability in climate characteristics, the evaluation of Earth system models (ESMs) is a complex and challenging task. Current studies typically utilize Model evaluation commonly uses performance metrics to quantify a model's ability to how well simulations reproduce climate characteristics or processes (Baker and Taylor, 2016). For single variables, researchers assess the model's simulation capability by comparing the correlation, root mean square error, and variance ratio between the simulated and observed data are widely used, and the Taylor diagram combines these statistics into a compact graphical summary (Lambert and Boer, 2001). For example, the Taylor diagram (Taylor, Taylor, 2001) integrates these three metrics into a single graphical representation via geometric relationships. However, such methods are limited in their ability to comprehensively characterize the overall model performance single-variable or scalar summaries are insufficient when model performance must be assessed across multiple coupled variables (Pincus et al., 2008), particularly when addressing research questions involving multiple variables. Owing to the complex coupling and interactions between climate variables, achieving balanced simulation performance across different variables is often challenging. To evaluate the overall performance of the model (Gleckler et al., 2008), proposed the Multivariable metrics such as the Model Climate Performance Index (MCPI) which quantifies the model's overall bias by calculating the mean relative error across multiple variables and multivariate integrated evaluation (MVIE) therefore provide useful bases for integrated model assessment (Gleckler et al., 2008; Xu et al., 2017) introduced a multivariate integrated evaluation (MVIE) method that combines multiple scalar fields into a vector field to improve the overall assessment of climate models.

The Weather Research and Forecasting (WRF) model is a regional climate model utilized within the framework of the used within the Coordinated Regional Downscaling Experiment (CORDEX) under the World Climate Research Programme

(WCRP), is distinguished by its inclusion of It includes multiple parameterization schemes for ~~various physical processes, including~~ microphysics, land surface, planetary boundary layer, cumulus, and radiation processes (Skamarock et al., 2019). These schemes differ in complexity and in their representations of physical processes, and varying combinations can result in substantial disparities in the simulation of key Different schemes and combinations can produce large differences in simulated meteorological variables (Yu et al., 2022b).

However, due to the complex interactions among physical processes Because physical processes interact and individual schemes are region- and the varying adaptability of individual parameterization schemes variable-dependent, no universally optimal configuration exists that can consistently perform well across different spatial, temporal, and output variable contexts WRF configuration can be assumed (Fernández et al., 2007; Borge et al., 2008). The extensive range of freely selectable parameterization scheme combinations introduces significant uncertainty into the simulation performance of the WRF model This range of selectable schemes is a major source of WRF simulation uncertainty (Mooney et al., 2013). Consequently, identifying and evaluating the optimal combination of parameterization schemes tailored to a specific study region is a critical prerequisite for WRF-based research, making region-specific parameterization-scheme evaluation an important prerequisite for WRF applications (Chen et al., 2014; Ferreira et al., 2014).

Another major challenge stemming from the diversity of parameterization schemes is the substantial computational cost associated with model evaluation (Wang et al., 2021). For instance, in The size of the configuration space also creates a practical constraint. In WRF version 4.3, the model provides 28 microphysics schemes, 8 land surface schemes, 9 longwave radiation schemes, 8 shortwave radiation schemes, 13 planetary boundary layer schemes, 8 surface schemes, and 13 cumulus schemes—yielding a theoretical total of over available schemes yield a theoretical upper bound of more than 14.5 million possible combinations. Conducting an exhaustive evaluation of all these configurations would impose an immense computational burden, rendering such an approach practically unfeasible for most researchers. To address this, and to balance improvements in model performance with the efficient use of computational resources, researchers commonly employ sensitivity analyses of physical process parameterization schemes. By systematically varying the parameterization schemes for individual physical processes, they assess the corresponding effects on simulation outputs, thereby identifying the most suitable scheme for each physical process before physical compatibility constraints are considered (Wang et al., 2021). Exhaustive evaluation is therefore impractical, and sensitivity analyses that vary schemes process by process are commonly used to identify suitable configurations (Li et al., 2014; Yu et al., 2022a).

Although the WRF model generates A remaining difficulty is how to evaluate WRF configurations when several meteorological variables are considered together. WRF produces multiple output variables, researchers often prioritize the evaluation of but evaluations often emphasize key or difficult-to-simulate variables, such as precipitation. This univariate evaluation strategy may introduce biases in certain study regions, as it disproportionately emphasizes the accuracy of a single variable while neglecting the significant roles of other essential meteorological variables in Such univariate evaluation can bias model assessment by overlooking other variables that are important for regional climate dynamics (Lv et al., 2020). In response, the advancement of multivariate evaluation methodologies has prompted a shift toward more comprehensive assessments of the model's performance across multiple variables. This multidimensional approach facilitates a more objective and holistic

evaluation of simulation capabilities, while also enhancing the understanding and quantification of uncertainties associated with parameterization schemes. Multivariable evaluation has therefore been increasingly used to assess simulation performance more comprehensively and to represent parameterization-related uncertainty more transparently (Righi et al., 2020; Dai et al., 2021; Lu et al., 2021).

95 Although both univariate and multivariate integrated evaluation methods have contributed valuable insights into model comparison and simulation performance assessment, current multivariate approaches still exhibit notable limitations in objectively attributing sources of uncertainty. This is especially true for models like WRF that incorporate multiple physical process parameterization schemes, which exacerbates the uncertainty. First, this limitation is manifested in the averaging of simulation performance across different variables. Existing multivariate evaluation methods commonly allocate Yet many
100 multivariable approaches still assign equal weights to all variables or rely on subjective expert judgment for weighting. However, the model's simulation capabilities for various variables differ across regions. The overall uncertainty in model performance is not contributed equally by all meteorological variables but is instead dominated by large simulation biases in a few key limiting variables (e.g., precipitation, wind speed). This is typically because these variables involve more complex nonlinear physical processes. Traditional equal-weighting methods overlook these differences in simulation accuracy, allowing
105 variables with large biases to be masked by an averaging effect within the multivariate framework.

Second, the limitation is also evident in the neglect of the differential sensitivity of variables to various physical processes. In the sequential evaluation of individual physical processes, the optimal parameterization scheme selected for one process influences the evaluation of subsequent processes. This dependency can lead to the propagation and accumulation of errors, making the method highly reliant on the evaluation accuracy at each step. The influence of various physical processes on
110 different output variables in WRF is inherently uneven. weighting. These choices can dilute variables with large simulation errors, such as precipitation and wind speed, within an averaged multivariable score. They can also ignore the fact that variables respond unevenly to alternative physical-process schemes. For example, microphysics and cumulus parameterizations exert a greater influence on precipitation simulations. Hence, it is essential to apply differentiated weights to variables when evaluating the parameterization schemes of distinct physical processes. Existing studies tend to apply a uniform weight
115 setting across all physical processes, ignoring the coupled relationships and sensitivity differences of variables to different physical processes. Consequently, equal-weighting or subjective weighting methods cannot objectively reflect the simulation uncertainties associated with each variable and physical process, challenging the scientific validity and reliability of the evaluation results. How to objectively attribute the sources of model uncertainty and effectively integrate this attribution into the evaluation system has become a pressing challenge. schemes typically affect precipitation more strongly than some other
120 near-surface variables. Thus, WRF parameterization-scheme screening requires a weighting rule that can incorporate both variable-level simulation difficulty and scheme-dependent response.

To address the limitations outlined above this need, this study introduces an innovative dynamic weighting evaluation method, grounded in existing multivariate evaluation frameworks. This method aims to construct an evaluation framework that can objectively identify and quantify the uncertainty of each variable, dynamically amplify the influence of these variables during
125 the evaluation and select parameterization scheme combinations that are more physically sound and robust in independent

validations. The core of this method lies in a two-layer dynamic weighting mechanism: first, it assigns weights based on the model's varying simulation capabilities for different output variables to amplify the impact of key limiting variables; second, it dynamically adjusts these weights during the evaluation of different physical processes according to the sensitivity of each variable to those processes. As an objective weighting strategy based on the statistical characteristics of simulated variables, the dynamic weighting method provides substantial flexibility and adaptability. It enables real-time adjustment of weight distributions according to regional characteristics and the influence of various physical processes, thereby minimizing simulation errors arising from inappropriate or static weight assignments. This approach is particularly well-suited for evaluating complex models with multiple interacting physical processes, such as proposes a performance-based multivariable weighting framework for WRF parameterization-scheme evaluation. The proposed $MRE \times CV$ weighting combines two components: mean relative error (MRE), which represents variable-level simulation difficulty, and the coefficient of variation of absolute errors (CV), which represents the scheme-dependent response of each variable within the evaluated physical-process group. By combining these components, the framework gives greater influence to variables that are both difficult to simulate and informative for distinguishing candidate schemes. The method operates at the evaluation stage. It changes how variables contribute to the integrated score and can therefore affect which parameterization-scheme combination is selected, but it does not directly modify the WRF model. To validate the universality and robustness of the proposed method, we will conduct a comparative application of this method and the equal-weighting method in two distinct regions: physics or numerical simulations. We applied the method in two contrasting regions, the arid region of Northwest China and the coastal region of Southeast China. ~~Furthermore, we will use~~, and compared it with equal weighting, entropy weighting, coefficient-of-variation weighting, and CRITIC weighting. We further tested the selected configurations in an independent extreme climate year ~~for validation~~. This design aims to comprehensively assess the method's effectiveness under different dominant physical process backgrounds.

The remainder of this paper is organized as follows. Sect. 2 describes the study areas, model configuration, and data sources, as well as the proposed dynamic weighting evaluation method and its implementation. In datasets, and implementation of the proposed weighting framework. Sect. 3, ~~we systematically evaluate the performance of a large number of parameterization combinations and determine the regionally optimal physical parameterization scheme combination and compare the performance of the dynamic weighting method with the equal weighting method~~. An analysis of the robustness of the dynamic weighting method is further presented in Sect. 3.5. evaluates the parameterization combinations, identifies regionally optimal configurations, compares the proposed method with four alternative weighting strategies, and tests the selected schemes in an independent extreme climate year. Sect. 4 discusses the ~~weight allocation mechanism of the dynamic weighting method, along with its applicability and generalizability~~. Finally, weight-allocation mechanism, applicability, and generalizability of the framework. Sect. 5 summarizes the main conclusions ~~of this study~~.

2 Method

2.1 Study area

This study selects the arid region of Northwest China and the coastal region of Southeast China as its research areas. This choice is primarily based on the significant differences between the two regions in terms of climate background, underlying surface characteristics, and dominant physical processes. The two regions exhibit distinct hydro-thermal patterns but share similarities and complementarities in the frequency of extreme climate events and the complexity of climate dynamics. The arid region of Northwest China is characterized by extreme temperature fluctuations and dust weather, whereas the coastal region of Southeast China is marked by intense precipitation events and frequent typhoons. These extreme climatic conditions present substantial challenges to the accuracy and reliability of regional climate models, making them ideal testbeds for evaluating model simulation capabilities under extreme climate scenarios. By independently applying the same evaluation methodology to these two regions, this study aims not only to verify the method's general capability to stably identify optimal parameterization schemes across different climate backgrounds but also to provide a critical scientific basis for future research on water resource management in arid regions and the development of rainstorm and flood early warning systems in coastal urban clusters.

2.1.1 Arid region of Northwest China

The arid region of Northwest China (73°–106°E, 35°–50°N) lies at the core of the Eurasian continent, encompassing the entire Xinjiang region, the Hexi Corridor in Gansu Province, and parts of Inner Mongolia, as illustrated in Fig. 1(b). The region features complex topography, including prominent mountain ranges such as the Kunlun Mountains, Qilian Mountains, and Tianshan Mountains, as well as extensive inland basins like the Tarim and Junggar Basins. Its deep inland location, remote from maritime moisture sources, coupled with its position within a subsiding air divergence zone north of the Tibetan Plateau, severely limits moisture influx from the ocean, resulting in an extremely arid climate. Annual precipitation typically falls below 200 mm, with hyper-arid zones such as the Tarim Basin and Turpan receiving less than 50 mm per year, making this one of the driest regions globally. While a few southeastern subregions exhibit characteristics of a temperate monsoon climate, the vast majority of the area experiences a temperate continental or alpine climate, marked by cold, dry winters, hot summers, low precipitation, high evaporation rates, and significant diurnal temperature variation. Owing to its geographical position and distinctive climatic conditions, the region is highly sensitive to global climate change and regional anthropogenic activities—particularly regarding water cycle dynamics, temperature variability, and extreme climate phenomena such as droughts and heatwaves. This sensitivity underscores the region's importance for understanding climate impacts in inland arid zones and across the Tibetan Plateau (Fu et al., 2022). Furthermore, due to its extreme aridity and climatic complexity, existing climate models often face challenges in accurately simulating regional climate change patterns. A comprehensive assessment and study of climate simulation performance in this region holds immense value for predicting climate change in arid areas globally.

2.1.2 Coastal region of Southeast China

In contrast to the arid region of Northwest, the coastal region of Southeast China is among the most precipitation-abundant areas in the country. Situated at the convergence of tropical and subtropical climatic zones, the region features a diverse landscape of coastal plains, mountains, and hills. It is also one of China’s most densely populated and highly urbanized regions, as illustrated in Fig. 1(c), and serves as a major hub of economic activity. Heavily influenced by the southeast monsoon and frequent typhoons, the region benefits from a substantial influx of warm, moist air, resulting in annual precipitation exceeding 1,500 mm across most areas. The coastal region of Southeast is characterized by relatively high temperatures, minimal diurnal temperature variation, and a general equilibrium between precipitation and evaporation. This stands in sharp contrast to the arid, rainfall-deficient Northwest Arid Region, where large temperature fluctuations dominate. However, under the influence of global climate change and accelerated urbanization, the frequency and intensity of extreme climate events, such as typhoons, heavy rainfall, and droughts, have increased markedly in this region (Yang et al., 2015; Li et al., 2021), posing serious risks to both human populations and ecological systems. Accordingly, a comprehensive investigation into the regional climate system, particularly the coupled interactions among oceanic, atmospheric, and terrestrial components, is essential for enhancing climate prediction accuracy, mitigating the impacts of extreme events, and fostering sustainable regional development.

2.2 Model configuration and datasets

In this study, the Advanced Research WRF model version 4.3.3 was used for numerical simulations. Different model configurations were set for the two study regions (Table 1). For the arid region of Northwest China, the simulation domain covers 30°N to 52°N and 66°E to 114°E, with a horizontal grid resolution of 9 km and a total of 380 × 240 grid points. The model had 38 vertical levels, with the top of the model at 50 hPa. For the coastal region of Southeast China, the simulation domain covers 20°N to 29°N and 108°E to 120°E, with the same horizontal grid resolution of 9 km and a total of 120 × 105 grid points. The vertical configuration was identical to that of the arid region of Northwest.

Table 1: Overview of WRF model configurations.

	Northwest China	Southeast China
Model version	WRF/ARW (4.3.3)	WRF/ARW (4.3.3)
Horizontal resolution	9km	9km
Horizontal grid	380 (E–W) × 240 (S–N)	120 (E–W) × 105 (S–N)
Initial and boundary conditions	ERA5	ERA5
~~Simulation~~ <u>Evaluation</u> period	June 1st–Aug 31st, 2007	June 1st–Aug 31st, 2009
<u>Spin-up period</u>	<u>May 1st–May 31st</u>	<u>May 1st–May 31st</u>
Land-use data	GLC_FCS30D	GLC_FCS30D
Default parameterization schemes	Microphysics-Thompson	Microphysics-Thompson

PBL/surface layer scheme–MYJ	PBL/surface layer scheme–MYJ
Cumulus–Tiedtke	Cumulus–Tiedtke
Radiation–RRTMG	Radiation–RRTMG
LSM–Noah LSM	LSM–Noah LSM

For this study, the period from May 1 to August 31 was selected for 2007 in the arid region of Northwest China and 2009 in the coastal region of Southeast China to screen for optimal parameterization scheme combinations using both ~~dynamic~~the proposed MRE $\times$ CV weighting and equal weighting methods. ~~Consequently, simulations conducted from June to August were utilized~~The first month, from May 1 to May 31, was used as the model spin-up period, and only the June-August simulations were used to evaluate the performance of ~~various~~the physical parameterization scheme combinations. The selection of simulation years for the two study regions was based on ~~meteorological station data within each region. This involved comparing daily meteorological observations, including temperature, surface temperature, precipitation, pressure,~~
215 ~~evaporation, relative humidity, sunshine duration, and wind speed and direction, across eight meteorological variables for each year from long-term meteorological station observations from 1991 to 2020 with the corresponding 30-year climatological averages~~2020. For each candidate year, the observed multivariable meteorological conditions were compared with the corresponding 30-year climatological reference using centered multivariable integrated evaluation (MVIE) statistics, including the centered root-mean-square vector difference, vector similarity coefficient, standard deviation ratio, and cMIEI. The cMIEI
220 provides an integrated measure of the overall distance between each candidate year and the climatological reference, while the variable-level metrics were used to check whether the selected years were dominated by anomalous deviations in individual variables. The analysis ~~identified~~showed that 2007 and 2009 ~~as the year most representative of the climatological state over the past three decades for the arid region of Northwest and the coastal region of Southeast, respectively~~had the lowest cMIEI values in their respective regions and did not show pronounced outlying deviations among the seven variables evaluated in
225 the WRF assessment. Overall, these two years ranked among the candidate years closest to the long-term climatological state across the multivariable and variable-level metrics (see Tables ~~S1 and S2~~S2-S3 and Figs. ~~S1-S2~~S1-S2 in Supporting Information~~S1~~).
~~To evaluate the robustness of the proposed method~~As a single independent extreme-year validation, the year 2010, which was characterized by extreme climate events common to both study regions, was selected ~~as an independent validation period to examine whether the schemes obtained from the screening period retained their evaluated performance under a different climate~~
230 background. The optimal scheme obtained from the screening period was applied to the validation period for simulation, and its performance was subsequently evaluated. The year 2010 is a representative year of extreme climate in China, during which the arid region of Northwest ~~experiencing~~experienced drought and the coastal region of Southeast ~~suffering from~~was affected by severe flooding. From June to July in the Northwest, persistent high temperatures and markedly reduced rainfall, 30% to 80% below average, were observed. Concurrently, southern China experienced heavy rainfall in June and August, leading to
235 significant flooding in the coastal region of Southeast, with substantial loss of life and property. ~~Designating~~Therefore, the 2010 ~~as the validation period not only allows for an assessment of the method's robustness but also verifies its simulation capabilities~~

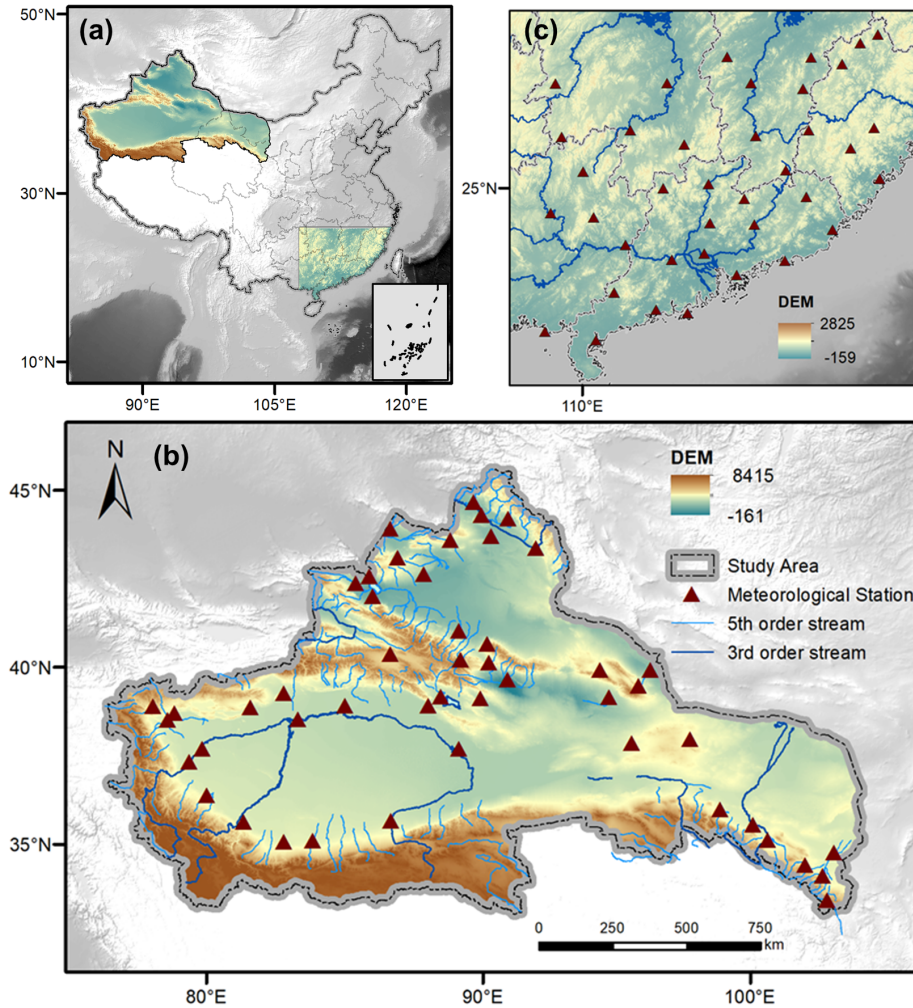


Figure 1. (a) Geographical location of the study area. (b) Overview of the arid region of Northwest China. (c) Overview of the coastal region of Southeast China.

~~under extreme climate conditions~~ experiment should be interpreted as an independent test under one extreme climate year, rather than as a temporal cross-validation or a proof of multi-year robustness.

~~This study follows the evaluation order suggested by existing research, namely, To reduce the computational burden~~ associated with the high-dimensional WRF physics-configuration space, this study adopted a pre-specified conditional screening strategy. The physical processes were evaluated sequentially in the order of microphysics, planetary boundary layer, cumulus, radiation, and land surface processes, and ~~sequentially selects the optimal parameterization scheme for each physical process to ultimately form the overall optimal combination (Dai et al., 2021; the best-performing parameterization scheme~~

selected at each step was carried forward as the background configuration for the subsequent step. This order follows procedural precedents in previous WRF parameterization sensitivity and physics-ensemble evaluation studies, including the stepwise decision approach of Stergiou et al. (2017), which begins with microphysics and then evaluates PBL, cumulus, radiation, and land surface scheme groups, and the WRF physics-ensemble evaluation of Dai et al. (2021). It is also consistent with empirical evidence from WRF ensemble evaluations and the present results that microphysics, planetary boundary layer, and cumulus schemes often exert strong influences on summer near-surface meteorological performance, particularly for precipitation, wind speed, temperature, and humidity, which are key variables in the present multivariable evaluation. Therefore, the prescribed sequence is used here as a computationally feasible stepwise screening heuristic, rather than as a theoretically unique physical hierarchy or a guarantee of global optimality. For this study, a near-complete ensemble of the parameterization schemes available within the WRF model was utilized, as presented in Table 2. The final number of scheme combinations was constrained by incompatibilities identified between certain physical process parameterizations. This resulted in 42 (the dynamic-proposed MRE $\times$ CV weighting method) / 43 (the equal weighting method) combinations for the arid domain in Northwest China and 54 (the dynamic-proposed MRE $\times$ CV weighting method) / 53 (the equal weighting method) combinations for the coastal domain in Southeast China (see Tables S3-S4 and S5-S6 S4-S5 and S6-S7 in Supporting InformationS1).

Table 2: Physics parameterization scheme assessed in this study.

	Microphysics	Planetary Boundary Layer/Surface Layer	Cumulus	Radiation	Land surface
1	8 Thompson	2 MYJ+2 MYJ	6 Tiedtke	1 RRTM+1 Dudhia	2 Noah LSM
2	1 Kessler	1 YSU+1 MM5	1 KF	3 CAM+3 CAM	1 SLAB
3	2 Lin	3 GFS+3 GFS	2 BMJ	5 New Goddard	4 NoahMP
4	3 WSM3	4 QNSE+4 QNSE	3 GF	99 GFDL+99 GFDL	5 CLM4
5	4 WSM5	5 MYNN2.5+1 MM5	5 Grell3		
6	5 Eta/Ferrier	5 MYNN2.5+2 MYJ	7 ZM		
7	6 WSM6	5 MYNN2.5+5 MYNN	11 MsKF		
8	9 Milbrandt	6 MYNN3+ 1 MM5	14 NSAS		
9	10 Morrison	6 MYNN3 + 2 MYJ	16 New Tiedtke		

10	11 CAM	6 MYNN3 + 5 MYNN	93 GD
11	13 Lin-SBU	7 ACM2+1 MM5	99 Old KF
12	14 WDM5	7 ACM2+7 Pleim-Xiu	
13	16 WDM6	8 BouLac + 1 MM5	
14	17 NSSL 2-17	8 BouLac + 2 MYJ	
15	18 NSSL 2-18	9 UW + 1 MM5	
16	19 NSSL 1-19	9 UW + 2 MYJ	
17	21 NSSL 1-21	11 Shin-Hong+1 MM5	
18	24 WSM7	12 GBM + 1 MM5	
19	26 WDM7	99 MRF+1 MM5	
20	28 Thompson aerosol-aware		
21	50 P3		

The model's initial and boundary conditions were provided by the ECMWF's fifth-generation atmospheric reanalysis dataset (ERA5), with a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and a temporal resolution of 6 h. The reanalysis dataset is available on the European Center for Medium-Range Weather Forecasting (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels> ; <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels>).

Owing to the lack of ground validation and limitations in spatial and temporal resolution, the default MODIS land use dataset in the WRF model exhibits discrepancies with actual land use results in the study areas. This study uses the 1985–2022 global 30-m land use product (GLC_FCS30D) developed by the Aerospace Information Research Institute, Chinese Academy of Sciences, as the surface input data (Zhang et al., 2024), available for download from <https://zenodo.org/records/8239305>. This dataset meets the requirements for continuous and consistent land use data in climate modeling, with a spatial resolution of 30 m and a time span from 1985–2022, making it suitable for more detailed regional simulation studies. The land use types in the dataset were reclassified according to the IGBP20 classification standard.

To comprehensively assess the performance of the WRF model, observational data from meteorological stations were used to validate the simulated variables. Daily meteorological observation data were obtained from the China Meteorological Data Service Centre (<https://data.cma.cn/en>). A total of 49 meteorological stations from the arid region of Northwest China and 38 from the coastal region of Southeast China, which provided long-term daily meteorological data from 1991–2020, were collected. The spatial distribution of the meteorological stations in the study area is shown in Fig. 1. These station-based observations underwent rigorous calibration and quality control, and thus provide a more accurate depiction of surface

275 meteorological conditions than gridded datasets. Based on the availability of meteorological variables at these stations, the output variables selected for evaluation in this study included 2-m air temperature (T2), ground surface temperature (GST), air pressure (PRS), precipitation (PRE), relative humidity (RH), meridional wind speed (U10), and zonal wind speed (V10).

2.3 Model evaluation and variable weighting method

2.3.1 Taylor diagram and related statistical metrics

280 This study utilizes several multivariate evaluation methods to describe the performance of the WRF model. The normalized Taylor diagram (Taylor, 2001) is used to assess the performance of different physical schemes in the sensitivity experiments to find the optimal combination of WRF schemes. The Taylor diagram simultaneously displays three complementary statistical metrics related to model performance: the center root mean square error (cRMSE), standard deviation (σ), and correlation coefficient (R). In addition, the vector statistical method (Xu et al., 2016) is employed, allowing the statistical metrics to reflect
285 the combined results of multiple variables.

$$\sigma_{fn} = \sqrt{\sum_{m=1}^M \omega_m \left(\frac{1}{T} \sum_{t=1}^T (f_{mnt} - \overline{f_{mn}})^2 \right)} \quad (1)$$

$$\sigma_r = \sqrt{\sum_{m=1}^M \omega_m \left(\frac{1}{T} \sum_{t=1}^T (r_{mt} - \overline{r_m})^2 \right)} \quad (2)$$

$$R_n = \frac{\sum_{m=1}^M \omega_m \left(\frac{1}{T} \sum_{t=1}^T (f_{mnt} - \overline{f_{mn}}) (r_{mt} - \overline{r_t}) \right)}{\sigma_{fn} \sigma_r} \quad (3)$$

$$cRMSE_n = \sqrt{\sum_{m=1}^M \omega_m \left(\frac{1}{T} \sum_{t=1}^T ((f_{mnt} - \overline{f_{mn}}) - (r_{mt} - \overline{r_t}))^2 \right)} \quad (4)$$

290 In the equation, m represents the output variable, and n represents the model's parameterization scheme. In the WRF parameterization-scheme evaluation, t denotes the valid daily station-level sample after pooling the station and day dimensions. The screening-year evaluations used 92 June-August daily values at 49 stations in Northwest China and 38 stations in Southeast China, after applying the common missing-value mask. The same daily station-level aggregation was used for R, cRMSE, MIEI, and the Taylor diagrams. These metrics were not calculated from monthly means, seasonal means, or climatological averages.
295 f_{mnt} represents the simulated value of the m variable at the t -th valid station-day sample for the model's n parameterization scheme, whereas r_{mt} represents the corresponding observed value. ω_m represents the weight of the m variable during the statistical calculation.

2.3.2 Model performance indicators

Although Taylor diagrams provide a multidimensional perspective on model performance through multiple statistical indicators, they are limited in their ability to fully quantify model superiority in complex evaluation scenarios. While it is widely recognized that a single performance metric cannot capture all aspects of model evaluation across multiple dimensions, the establishment of a unified evaluation standard is essential for this study to more intuitively illustrate the process of parameterization scheme selection. To this end, the multivariable integrated evaluation index (MIEI) (Zhang et al., 2021) is adopted as the primary metric for assessing model simulation performance.

MIEI integrates both the magnitude and pattern similarity of model-simulated variables and maintains a strictly monotonic relationship with overall model performance: the lower the MIEI value, the better the simulation accuracy. This makes MIEI particularly well-suited for ranking the comprehensive performance of models in multivariable simulations (Lv et al., 2020). A detailed description of the formulation and application of this method is provided in (Xu et al., 2016; Xu et al., 2017; Zhang et al., 2021). In the present WRF evaluation, MIEI and its component statistics were calculated from the same daily station-level June-August samples used in the Taylor diagrams; the 30-year climatological reference was used only for representative-year selection, not for ranking WRF candidate schemes.

$$MIEI_n^2 = \sum_m^M \omega_m (L_{mn}^* - 1)^2 + 2(1 - R_n) \quad (5)$$

$$L_{mn}^* = \begin{cases} \sigma'_{mn}, & \sigma'_{mn} \leq 1 \\ \frac{1}{\sigma'_{mn}}, & \sigma'_{mn} > 1 \end{cases} \quad (6)$$

$$\sigma'_{mn} = \frac{\sigma_{fmn}}{\sigma_{rm}} \quad (7)$$

In the equation, m represents the output variable, n represents the model's parameterization scheme. ω_m represents the weight of the m variable during the statistical calculation. σ'_{mn} represents the ratio of the σ value of the m variable in the n parameterization scheme of the model to the observed σ value. R_n represents the correlation coefficient between the simulated values and the observed values of the n parameterization scheme of the model.

2.3.3 ~~Dynamic weight evaluation approach~~ Performance-based multivariable weighting framework

The ~~dynamic weighting method~~ performance-based multivariable weighting framework proposed in this study is ~~mainly~~ used to calculate the variable weight ω_m in the evaluation metrics ~~mentioned above. This is an objective weighting method that is independent of the statistical indicators used, so that it can be applied to all multi-objective evaluation methods. The proposed dynamic weighting method is built upon a simple yet powerful principle: a variable should be given more importance in~~

the evaluation if (1) the model struggles to simulate it accurately, and (2) its simulation is highly sensitive to the choice of parameterization schemes for a given physical process. The foundation of this method is based on two statistical indicators: described above. The term performance-based is used because both weighting components are derived from the simulated performance of candidate WRF parameterization schemes against observations. This framework does not update weights online during WRF integration. Instead, the weights are recalculated after the simulations for each candidate physical-process group are completed and before the candidate schemes are ranked. The framework follows a simple evaluation principle: if a variable is difficult to simulate and its error responds strongly to the candidate schemes in the evaluated physical-process group, that variable should receive greater influence in the integrated evaluation. The two components are the mean relative error ($\overline{MRE}_m$) and the coefficient of variation of absolute errors ($CV_{|ME|m}$). The MRE and absolute-error CV components are therefore calculated on the same daily station-level model-observation pairs before being summarized across candidate schemes within each physical-process group.

The mean relative error ($\overline{MRE}_m$) represents variable-level simulation difficulty, quantified by the relative magnitude of simulation error across the candidate schemes in the evaluated physical-process group. Larger MRE values indicate variables for which the candidate schemes show weaker simulation ability and larger deviations from observations.

$$\overline{MRE}_m = \frac{1}{N} \sum_{n=1}^N MRE_{mn} \quad (8)$$

$$= \frac{1}{N} \sum_{n=1}^N \left(\frac{|ME|_{mn}}{\frac{1}{T} \sum_{t=1}^T |r_{mt}|} \right) \quad (9)$$

$$= \frac{1}{N} \sum_{n=1}^N \left(\frac{\frac{1}{T} \sum_{t=1}^T |f_{mnt} - r_{mt}|}{\frac{1}{T} \sum_{t=1}^T |r_{mt}|} \right) \quad (10)$$

In the equation, f_{mnt} represents the simulated values of the m variable at the t discrete points for the model's n parameterization scheme, while r_{mt} represents the observed values of the m variable at the t discrete points. $|ME|_{mn}$ represents the absolute error of the m variable in the n parameterization scheme of the model.

The coefficient of variation of the absolute error ($CV_{|ME|m}$) represents the degree of dispersion when a physical parameterization process simulates a specific variable scheme-dependent response of each variable within the evaluated physical-process group, quantified by the variability of absolute errors among candidate schemes. A larger value indicates that the variable is more useful for distinguishing alternative parameterization options in that evaluation stage. This indicates the sensitivity of the variable to the physical parameterization process.

$$CV_{|ME|m} = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^N \left(|ME|_{mn} - \overline{|ME|_m} \right)^2}}{\overline{|ME|_m}} \quad (11)$$

$$= \frac{\sqrt{\frac{1}{N} \sum_{n=1}^N \left(\frac{1}{T} \sum_{t=1}^T |f_{mnt} - r_{mt}| - \frac{1}{N} \sum_{n=1}^N \left(\frac{1}{T} \sum_{t=1}^T |f_{mnt} - r_{mt}| \right) \right)^2}}{\frac{1}{N} \sum_{n=1}^N \left(\frac{1}{T} \sum_{t=1}^T |f_{mnt} - r_{mt}| \right)} \quad (12)$$

In the equation, f_{mnt} represents the simulated values of the m variable at the t discrete points for the model's n parameterization scheme, whereas r_{mt} represents the observed values of the m variable at the t discrete points. $|ME|_{mn}$ represents the absolute error of the m variable in the n parameterization scheme of the model. $\overline{|ME|_m}$ indicates the absolute error of the m variable for all parameterization schemes of the model.

The base of the method is to assign higher weights to variables with larger relative errors (poor simulation performance) ~~or~~ and higher coefficients of variation (stronger scheme-dependent response within the evaluated physical-process group). We used the Softmax transformation to convert each statistical vector across variables into a set of positive weights that sum to one. This choice is consistent with the purpose of the proposed evaluation framework: variables that are difficult to simulate or whose errors respond strongly to alternative parameterization schemes should not be diluted in a multivariable average. At the same time, because Softmax assigns a positive value to every variable, no variable is removed from the integrated evaluation. The use of Softmax is therefore a methodological choice for balancing two requirements: preserving the multivariable nature of the evaluation while giving greater influence to limiting variables.

To make the normalization explicit, the two component weights are calculated over the M output variables as follows:

$$\omega_{m1} = \frac{e^{\overline{MRE_m}}}{\sum_{j=1}^M e^{\overline{MRE_j}}} \quad (13)$$

$$\omega_{m2} = \frac{e^{CV_{|ME|m}}}{\sum_{j=1}^M e^{CV_{|ME|j}}} \quad (14)$$

$$\omega_m = \frac{\omega_{m1}\omega_{m2}}{\sum_{j=1}^M \omega_{j1}\omega_{j2}} \quad (15)$$

In the equation, ω_{m1} and ω_{m2} represent the ~~weight values of component weights of~~ variable m derived from the ~~mean relative error and the~~ mean relative error and the coefficient of variation of the absolute error, respectively. The final variable weight ω_m is obtained by multiplying the two component weights and then normalizing the product across all variables. This second normalization ensures that $\sum_{m=1}^M \omega_m = 1$, as required by the multivariable evaluation metrics.

To examine whether the weight distribution depends on the specific normalization function, we also conducted a sensitivity analysis using linear normalization and temperature-scaled Softmax transformations. The temperature-scaled Softmax is defined as $w_m(\tau) = \exp(s_m/\tau) / \sum_{j=1}^M \exp(s_j/\tau)$ for a statistical score s_m . The original formulation corresponds to $\tau = 1$; smaller values of τ produce more concentrated weights, whereas larger values produce smoother weight distributions. As a separate sensitivity test of the component-combination rule, we also calculated an equally weighted additive alternative:

$$\omega_m^{add} = \frac{\alpha\omega_{m1} + (1 - \alpha)\omega_{m2}}{\sum_{j=1}^M [\alpha\omega_{j1} + (1 - \alpha)\omega_{j2}]}, \quad \alpha = 0.5. \quad (16)$$

This additive formulation has a compensatory interpretation, because a large value in one component can partly offset a smaller value in the other component. It was therefore used as a deliberately more permissive alternative to the proposed multiplicative rule, which gives the largest final weights to variables supported by both the MRE and CV components. The selected-scheme consequences of this alternative rule are reported in Table S10.

Together, the selection of the MRE and CV components, the Softmax transformation, and the multiplicative combination define a reproducible evaluation rule under explicit methodological choices. The framework is therefore intended to make variable weighting transparent and testable, rather than to claim a unique objective set of variable weights.

We further evaluated whether the derived weights were sensitive to the station sample, the summer time period, or the evaluated variable set. For each region and physical-process evaluation stage, stations were resampled with replacement 500 times while retaining all summer days. Temporal stability was evaluated using 500 moving-block bootstrap samples composed of contiguous 14 d blocks, together with separate June, July, and August subsets. The MRE component, absolute-error CV component, and final normalized weights were recalculated for every resample. Each resulting weight vector was compared with the full-sample vector using the Spearman rank correlation, maximum absolute weight difference, and retention rates of the highest-weight variable and the two highest-weight variables. Variable-set stability was evaluated analytically and numerically by deleting each variable group in turn and comparing the recomputed weights of the retained variables with their theoretical renormalization. Full definitions and results are provided in Fig. S6 and Tables S8-S9.

We also examined the ranking stability of the selected stage-level parameterization schemes. For each region-stage comparison, 500 station-bootstrap samples and 500 14 d moving-block-bootstrap samples were used to recalculate the proposed weights, cMIEI values, and candidate-scheme rankings. The selected scheme was compared with nearby competitors using 95% bootstrap intervals of Δ cMIEI, and its top-1, top-2, and top-3 rank retention rates were summarized in the Supporting Information (Fig. S8 and Table S13). Because physically related meteorological variables can carry overlapping information, we also diagnosed inter-variable dependence in two data views. Pearson correlation matrices were calculated from the observed daily station series and from the scheme-level standardized-error matrices used in the proposed screening workflow. We then performed a targeted no-GST sensitivity test while retaining TEM as the standard near-surface air-temperature variable, to examine whether the strongest temperature-related dependence dominated the selected stage-level schemes. These diagnostics are reported in Fig. S7 and Table S11.

The specific application process of this method in WRF model evaluation includes the following steps:

Step 1: Run all the parameterization schemes in the first physical parameterization process (e.g., microphysics schemes) and calculate the absolute and relative errors of the simulation results for different variables compared with the observed values.

Step 2: Calculate the mean relative error and the coefficient of variation of the absolute error for the simulation results of each parameterization scheme for different variables to quantify the degree of error and sensitivity of different variables each variable

to quantify variable-level simulation difficulty and the scheme-dependent response of variable errors within the evaluated physical-process group.

410 Step 3: Use the Softmax function to convert the two statistical indicators (mean relative error and coefficient of variation) into two ~~sets of weights, which serve as the importance measure for each variable in the simulation process~~ component weights, multiply the two components, and normalize the product across variables to obtain the final variable weights used in the parameterization-scheme evaluation.

Step 4: Based on the obtained weights, further calculate the statistical indicators for each scheme, such as the RMSE, R , σ ,
415 and MIEI, to determine the best scheme for the first physical parameterization process.

Step 5: Use the best scheme identified in Step 4, continue simulating the next physical parameterization process and repeat the above steps until the best scheme for all physical parameterization processes is determined.

2.3.4 Benchmark weighting methods

To examine how the proposed weighting scheme differs from established statistical weighting approaches, we included entropy
420 weighting, coefficient-of-variation weighting, and CRITIC weighting as benchmark methods. Equal weighting was retained as a simple reference baseline. All five methods used the same candidate WRF parameterization outputs, the same station observations, the same evaluation variables, and the same MVIE/MIEI evaluation framework. All evaluation metrics in this comparison were calculated from daily station-level June-August model-observation pairs. Therefore, differences among the methods mainly reflect differences in how the variable weights were calculated, rather than differences in model input data or
425 evaluation metrics.

Entropy weighting assigns larger weights to variables that contain more discriminating information across the candidate schemes. For each variable, the scheme-level error values were first converted into normalized proportions, and the entropy value was then used to measure the degree of dispersion in the error distribution. Variables with lower entropy provide stronger differentiation among candidate schemes and therefore receive larger weights after normalization. Coefficient-of-variation
430 weighting uses the ratio between the standard deviation and the mean error across candidate schemes. This method also emphasizes variables with larger relative dispersion, but its weighting response is directly controlled by the ratio of the spread to the mean error. CRITIC weighting combines two components: the contrast intensity of a variable, represented by the standard deviation of the normalized error values, and the conflict among variables, represented by the correlation structure among the variables. A variable receives a higher CRITIC weight when it varies strongly among candidate schemes and contributes
435 information that is less redundant with other variables.

The proposed $MRE \times CV$ weighting differs from these general statistical weighting methods in its evaluation target. It is designed for WRF parameterization-scheme screening, where a variable should receive greater influence when it is both difficult to simulate and responsive to alternative parameterization choices within the evaluated physical-process group. The MRE component therefore represents variable-level simulation difficulty, whereas the absolute-error CV component represents
440 the scheme-dependent response of that variable within a given physical-process group. The final weight combines these two

components and can therefore be interpreted as a performance-based multivariable evaluation weight rather than only a measure of statistical dispersion. A conceptual comparison of the five weighting strategies is provided in Table S1.

3 Result

3.1 Optimal parameterization scheme combination for the arid region of Northwest

445 Figure 2 shows the weights assigned to variables in the WRF simulations of different physical processes for the arid region of Northwest using the ~~dynamic-proposed~~ $MRE \times CV$ weighting method. Figure 2(a) shows the weights ω_{m1} assigned based on the mean relative error ($\overline{MRE}_m$), where wind speed and precipitation received average weights of 0.45 and 0.24, respectively, while all other variables had weights below 0.01. The higher weights for wind speed and precipitation indicate that all physical processes in the WRF model have significant errors in simulating these variables, reflecting the model's weaker simulation capability for these variables. Therefore, more attention needs to be given to these variables in the model.

Figure 2(b) shows the weights ω_{m2} assigned based on the coefficient of variation ($CV_{|ME|m}$) of the absolute error, where the weights for different variables showed considerable variation during the simulation process, reflecting ~~significant~~ differences in the ~~sensitivity-of-the-variables-to-different-physical-processes~~ scheme-dependent response of variable errors within each physical-process evaluation stage. Precipitation and temperature were the variables exhibiting the most pronounced variability. Precipitation carried weight values of 0.17 and 0.18 in the microphysics and cumulus processes, respectively, indicating ~~its~~ high-sensitivity-to-these-two-physical-processes a strong response to alternative schemes in these two physical-process groups. In contrast, temperature ~~demonstrated-greater-sensitivity-to~~ showed a stronger response in the radiation and land surface processes, with corresponding weight values of 0.184 and 0.201. Relative humidity showed a more pronounced response during the planetary boundary layer process, with a weight value of 0.176.

460 Figure 3(a) displays the standardized MIEI results for evaluating WRF parameterization schemes in the arid region of Northwest, providing an assessment of simulation performance across various output variables and in the overall integrated evaluation. Analysis of the simulation results for individual variables revealed substantial variability in precipitation simulation performance among different parameterization schemes. Notably, the P3 and MYJ schemes exhibited superior performance in simulating precipitation, as indicated by their lower MIEI values, which reflected greater accuracy. In contrast, the Kessler and CLM schemes yielded higher MIEI values, suggesting larger simulation errors. Although CLM, as a land surface model, does not directly govern precipitation-related processes, its influence on the hydrological cycle and land-atmosphere interactions significantly affects precipitation outcomes. In the simulations of surface and air temperature, the impact of specific physical processes on these variables is more direct. For example, the Noah-MP and CLM4 schemes achieved the lowest and highest MIEI values, respectively, for land surface processes, underscoring the critical role of land surface parameterizations in air temperature simulation. Additionally, the YSU scheme demonstrated strong performance in simulating wind speed within the planetary boundary layer process and was subsequently selected as the optimal scheme for further assessment. Consequently, the subsequent parameterization schemes for cumulus, radiation, and land surface processes also demonstrated good performance for wind speed.

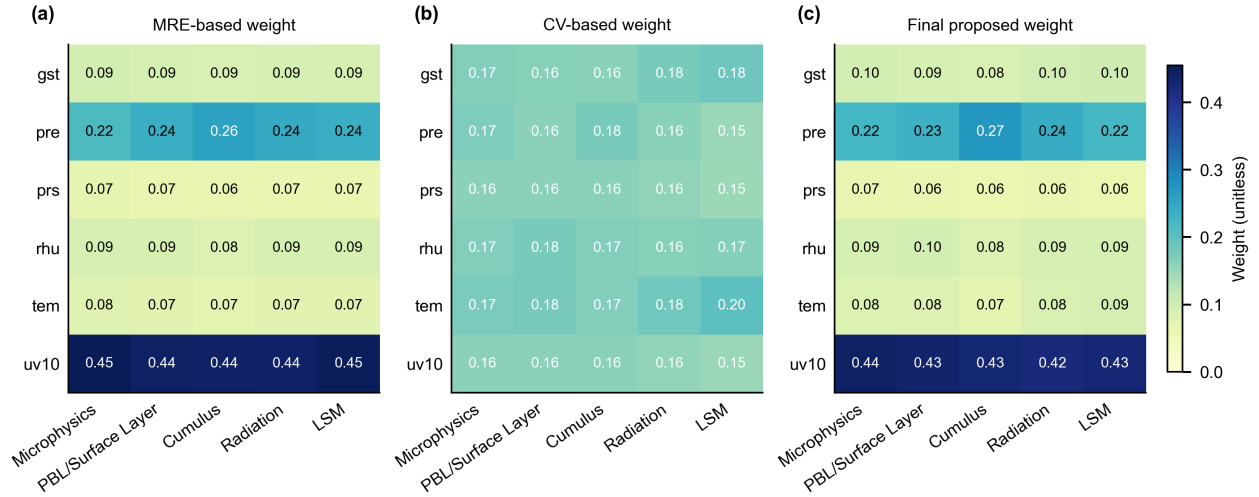


Figure 2. Weight distributions of the variables associated with the different physical processes of the WRF simulation in the arid region of Northwest. (a) Based on the mean relative error MRE-based weight, (b) Based on the coefficient of variation of the absolute error CV-based weight, and (c) final proposed weight. Weights are unitless.

In the multivariate integrated evaluation (rightmost column), the MIEI value serves as the primary criterion for selecting parameterization schemes in this study. As the evaluation of physical processes advances, a progressive decrease in MIEI values was observed, reflecting a corresponding improvement in model simulation accuracy indicating that the sequentially selected configurations achieved lower integrated evaluation scores. The integrated evaluation identified the P3 (microphysics), YSU (planetary boundary layer), Tiedtke (cumulus), GFDL (radiation), and Noah LSM (land surface) schemes as the optimal choices indicating that their combination yielded the most suitable configuration for the arid region of Northwest. However, it is important to note that the optimal parameterization scheme does not necessarily deliver the best performance across all individual variables. For instance, within the radiation process, the GFDL scheme exhibited slightly inferior performance compared to the RRTMG scheme in simulating relative humidity and precipitation. Nonetheless, its superior simulation results stronger evaluated performance for wind speed and temperature led contributed to a lower overall MIEI value, establishing GFDL as the relatively best-performing scheme in the integrated evaluation.

Compared to MIEI, the Taylor diagram offers a more comprehensive statistical evaluation of model performance, highlighting the discrepancies between different parameterization schemes and observational data. Figure 3(b-f) present the centered root mean square error (cRMSE), standard deviation (σ), and correlation coefficient (R) for each scheme across the various physical processes. In the microphysics process, the optimal parameterization scheme, P3, exhibited a relatively low RMSE of 1.232 and the highest correlation coefficient of 0.321. Most microphysics schemes demonstrated elevated standard deviation ratios (ranging from 1.156 to 1.205), indicating a tendency to overestimate the amplitude of anomalies in the simulated fields. For the planetary boundary layer process, the YSU scheme emerged as optimal, with the highest R value (0.346). Although

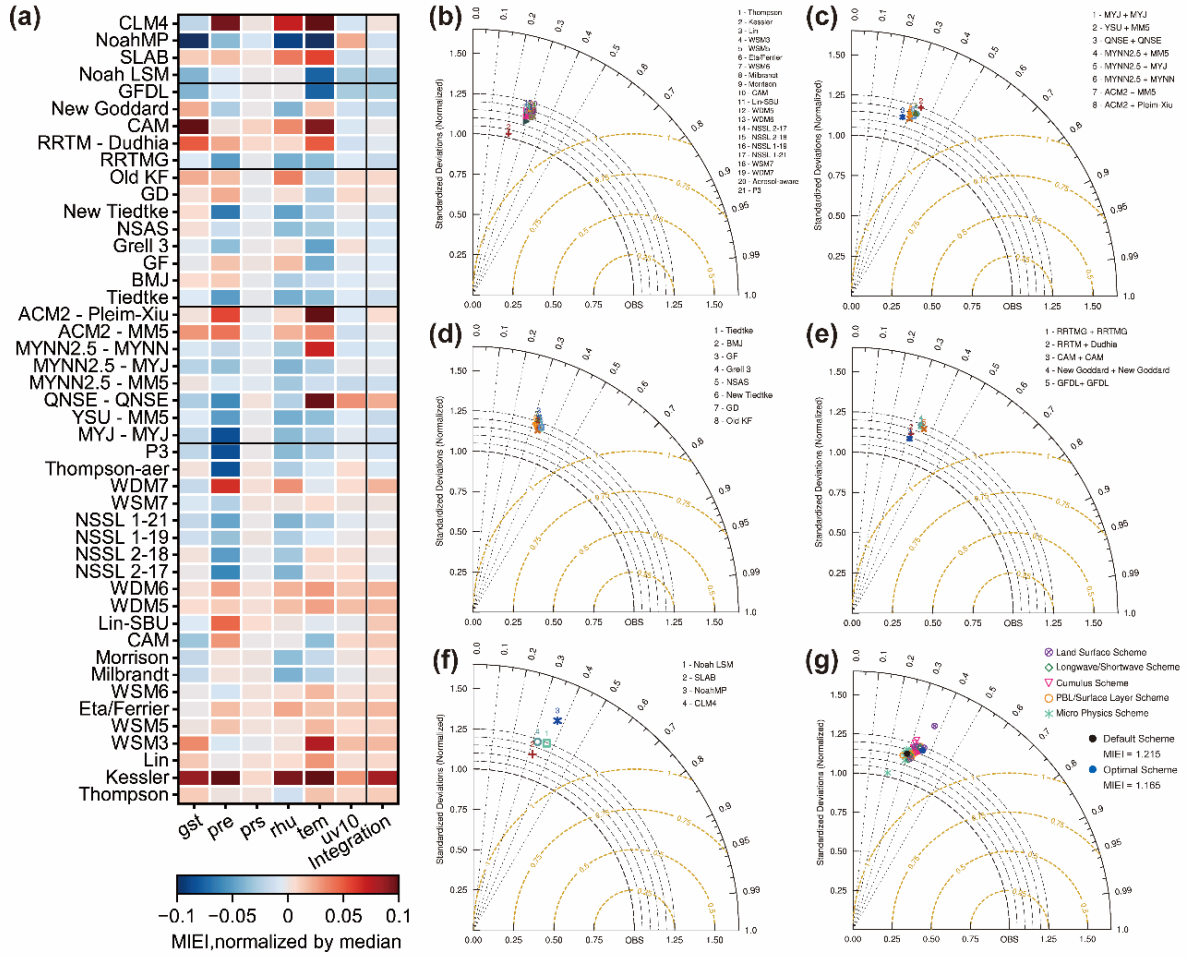


Figure 3. Evaluation results of parameterization schemes in the arid region of Northwest. (a) Normalized MIEI, with MIEI values normalized by the median MIEI value of the corresponding ensemble, and (b-f) Taylor diagrams of different physical processes. (b) Microphysics, (c) Planetary boundary layer, (d) Cumulus, (e) Radiation, (f) Land surface, and (g) Taylor diagrams of a total of 44 combinations of parametric schemes for all physical processes. All MIEI and Taylor-diagram statistics were calculated from daily station-level June-August values.

YSU performed well in terms of correlation, it still overestimated the amplitude of anomalies, as reflected in the standard deviation. In the cumulus process, the Tiedtke scheme demonstrated superior performance, with the lowest RMSE (1.277). For the radiation process, the GFDL scheme yielded the highest correlation coefficient (0.363). Although the CAM scheme showed better performance in terms of RMSE and standard deviation, its lower correlation coefficient (0.312) led to a lower integrated evaluation score compared to GFDL. In the land surface process, although the Noah LSM scheme did not achieve the best results in RMSE (1.282), correlation coefficient (0.365), its overall balanced performance across all indicators rendered it the most suitable parameterization scheme in the integrated evaluation.

The bootstrap ranking analysis supported this interpretation for Northwest China (Fig. S8 and Table S13). The selected stage-level schemes had median top-three retention rates of 0.974 in station-bootstrap samples and 0.984 in time-block-bootstrap samples. The 95% Δ cMIEI intervals were positive for several nearest-competitor comparisons, especially in the land-surface and radiation stages, indicating stable separation from close alternatives in those cases.

Figure 3(g) presents the Taylor plot for the combined simulations of all 44 parameterization scheme combinations. Each color denotes a different physical process option, with the blue symbol representing the optimal scheme and the black symbol indicating the default scheme for the study area. The plot revealed a clear separation in the statistical outcomes associated with different physical processes. Following the systematic selection of parameterization schemes across five physical processes, both the RMSE and R showed marked improvement. Notably, the optimal combination of parameterization schemes significantly outperformed the selected configuration showed a higher R and a lower RMSE than the default configuration. In the full-sample evaluation, the selected configuration performed better than the default configuration. The optimal scheme achieved a higher correlation coefficient ($R = 0.364$) compared to the default ($R = 0.295$), and a lower RMSE (1.277 versus 1.300), demonstrating its superior capacity to reproduce showing better evaluated agreement with the observed meteorological variables in the WRF model for the arid region of Northwest. A detailed analysis of individual physical processes indicated that microphysical, cumulus, and land surface schemes primarily contributed to reducing RMSE and enhancing overall simulation accuracy under the present evaluation metrics, though they exerted limited influence on the correlation coefficient. The planetary boundary layer process and the radiation process mainly affected the correlation coefficient and had a relatively weak influence on the root mean square error.

3.2 Comparison of dynamic-proposed $MRE \times CV$ weighting and equal weighting methods in the arid region of Northwest

In addition to employing the dynamic-proposed $MRE \times CV$ weighting method to determine the optimal parameterization scheme for the arid region of Northwest, this study also applies an equal-weighting approach, maintaining a consistent evaluation framework for both methods. Figure 4 presents the simulation results for various output variables obtained using the two weighting strategies.

Figure 4(a) displays the Taylor plots for the optimal parameterization schemes derived from the dynamic-proposed $MRE \times CV$ weighting and equal-weighting methods, providing a visual comparison of their respective performances. The optimal scheme identified through dynamic-the proposed $MRE \times CV$ weighting achieved a lower MIEI value (1.165) compared to that derived from the equal-weighting method (1.184). More specifically, the dynamic-proposed weighting approach yielded a higher correlation coefficient ($R = 0.364$) versus the equal-weighting method ($R = 0.323$).

Figure 4(b-h) shows scatter plots of the optimal parameterization schemes obtained via dynamic-proposed $MRE \times CV$ weighting and equal weighting methods, which present a comparison of the monthly mean values (where precipitation is the monthly cumulative value) and the observed values of the two optimal parameterization schemes at different stations. These monthly summaries are used only for the scatter-plot visualization and are not the temporal aggregation used for the Taylor-diagram or MIEI statistics. Among all the variables, air pressure performed the best. Both schemes showed extremely

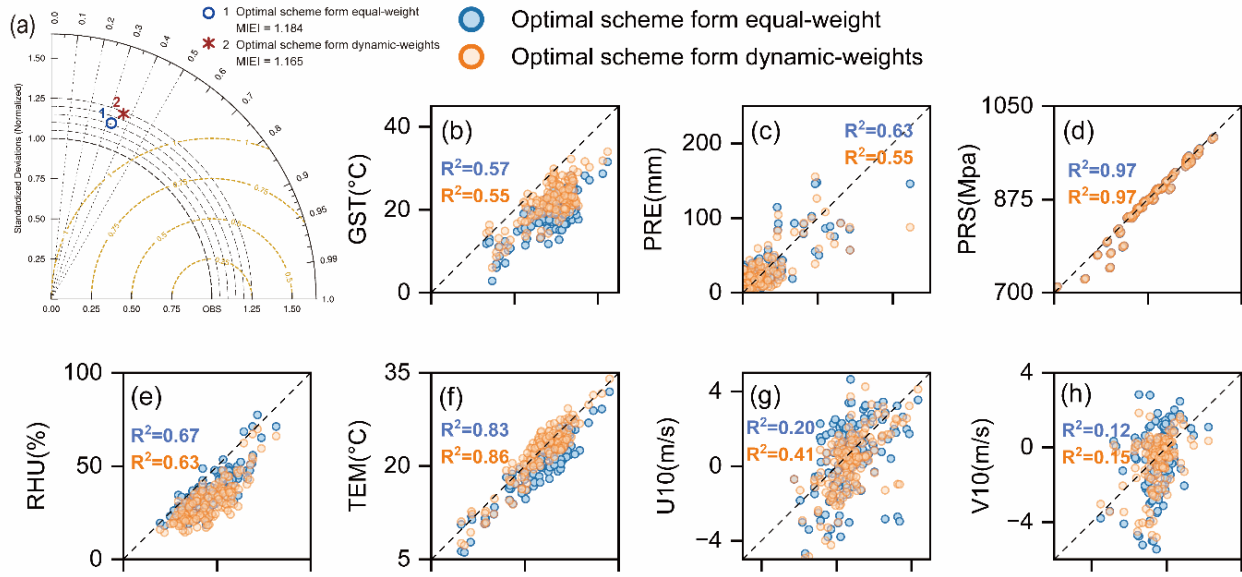


Figure 4. Comparison of simulation results obtained from the optimal parameterization schemes using the dynamic-weight-proposed MRE × CV weighting and equal weight methods. (a) Taylor plots of the optimal parameterization schemes obtained by different methods. (b-h) Scatter plots of the optimal parameterization schemes obtained via different methods for different meteorological elements. (b) Surface temperature, (c) precipitation, (d) Air pressure, (e) Relative humidity, (f) Air temperature, (g) Zonal wind, (h) Meridional wind. Panel (a) uses Taylor-diagram and MIEI statistics calculated from daily station-level June-August values; panels (b-h) use monthly station summaries only for visual comparison, with monthly means for non-precipitation variables and monthly totals for precipitation.

high fitting degrees and simulated the changing trend of air pressure relatively accurately. For the simulation results of surface temperature and relative humidity, the dynamic-configuration selected by the proposed weighting scheme yielded a slightly lower R^2 -compared to the equal weighting scheme. During the temperature simulation process, the dynamic-configuration selected by the proposed weighting scheme demonstrated superior performance under high-temperature scenarios, achieving an R^2 -of 0.86. In contrast to the air temperature results, the dynamic-configuration selected by the proposed weighting scheme performed relatively poorly in the precipitation simulation, and R^2 -decreased to 0.55. For the simulation of wind speed, neither scheme performed well in representing the zonal and meridional components. However, the R^2 -values of the dynamic-weight configuration selected by the proposed weighting scheme reached 0.41 and 0.15, which were significantly higher than those of the equal weight scheme (0.20 and 0.12), improving-the-simulation-of-the-indicating better evaluated agreement for wind speed. Although the simulation performances of some variables have slightly decreased, on the whole, the combination-of-the optimal-parameterization-schemes-with-dynamic-weights-simulated-the-changes-in-meteorological-elements-parameterization combination selected by the proposed MRE × CV weights showed better overall agreement with observed meteorological

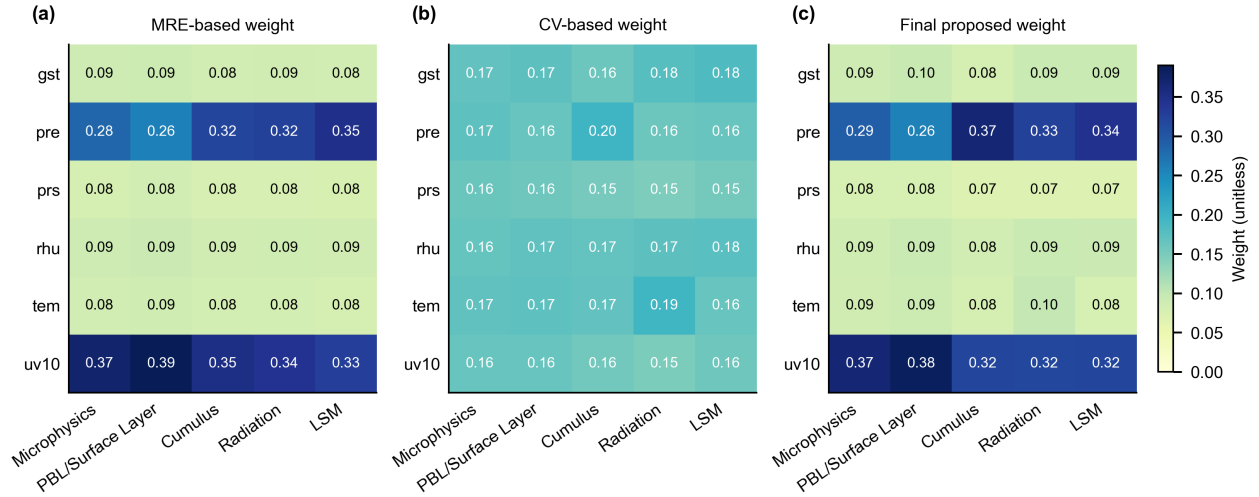


Figure 5. Weight distributions of the variables in the WRF simulations of the different physical processes in the coastal region of Southeast. (a) Mean relative error and MRE-based weight, (b) coefficient of variation of the absolute error CV-based weight, and (c) final proposed weight. Weights are unitless.

545 variability in the arid region of Northwest China ~~better than the optimal parameterization schemes obtained via~~ than the combination selected by the equal-weight method.

3.3 Optimal parameterization scheme combination for the coastal region of Southeast

Figure 5 shows the weight distributions of different variables across physical processes in the WRF simulations for the coastal region of Southeast, as determined by the ~~dynamic-proposed~~ MRE $\times$ CV weighting method. Figure 5(a) represents the weights ω_{m1} calculated on the basis of the mean relative error ($\overline{MRE_m}$). The simulation weights for wind speed and precipitation remained the highest, with average weights of 0.36 and 0.31, respectively. Compared with those of the arid region of Northwest, the weights of the other variables were generally greater. The weight for the wind speed has decreased noticeably, indicating that the WRF model has reduced the disparity between the wind speed simulation and other variables in the coastal region of Southeast, suggesting a more balanced simulation capability across different variables in this region.

555 Figure 5(b) represents the weights ω_{m2} calculated on the basis of the coefficient of variation ($CV_{|ME|m}$) of the absolute error. There was substantial variability in the weights assigned to different variables throughout the simulation process, reflecting ~~marked differences in their sensitivity to various physical processes~~ differences in the scheme-dependent response of variable errors within each physical-process evaluation stage. Precipitation exhibited the greatest variation in weight across physical processes, with a maximum value of 0.194 in the cumulus process, highlighting ~~the direct influence of cumulus on~~ precipitation simulation that precipitation errors responded strongly to alternative cumulus schemes. In contrast, air temper-

560

ature and surface temperature ~~demonstrated higher sensitivity to~~ showed stronger responses in the radiation process, with corresponding weight values of 0.194 and 0.177, respectively.

Figure 6(a) presents the standardized MIEI results for the evaluation of WRF parameterization schemes in the coastal region of Southeast. Analysis of the simulation performance across different variables revealed substantial variability in precipitation simulation across physical processes, with the microphysics process generally exhibiting the lowest performance. This outcome reflected the ~~high sensitivity of precipitation to microphysical processes~~ strong response of precipitation errors to alternative microphysics schemes. Within this category, the WDM6 scheme was identified as the optimal parameterization scheme and was subsequently incorporated into the following stages of evaluation. As a result, the parameterization schemes for the remaining physical processes demonstrated ~~improved performance in precipitation simulation~~ lower evaluated precipitation errors within
the sequential screening framework. For wind speed, the planetary boundary layer and land surface processes exerted a more direct influence, yielding superior simulation results relative to other physical processes. Surface temperature, air temperature, and relative humidity exhibited significant fluctuations and variability in MIEI values throughout the evaluation. These variations were attributed to the complex influence of multiple physical processes and the dominant role played by previously selected optimal parameterization schemes.

The MIEI values derived from the multivariate integrated evaluation showed a consistent decline as the assessment progresses, indicating ~~incremental improvements in overall model performance with each stage of physical process evaluation~~ that the selected configurations achieved progressively lower integrated evaluation scores at successive physical-process stages. Based on the multivariate evaluation, the optimal combination of parameterization schemes for the coastal region of Southeast included WDM6 (microphysics), Shin-Hong-MM5 (planetary boundary layer), Grell 3 (cumulus), GFDL-GFDL (radiation), and Noah LSM (land surface). As with the arid region of Northwest, the optimal combination does not guarantee superior simulation performance for all variables. For instance, in the cumulus process, the Grell 3 scheme performed exceptionally well in simulating precipitation and relative humidity but was slightly less effective for air temperature and wind speed. Nevertheless, due to the higher weight assigned to precipitation in the cumulus evaluation, Grell 3 remained the preferred scheme in the integrated analysis.

Figure 6(b-f) present Taylor diagrams for different physical process parameterization schemes. In the microphysical process, the optimal parameterization scheme, WDM6, had a relatively small RMSE (1.042), demonstrating good consistency between the simulated and observed values of anomalous fields. The correlation coefficients for all parameterization schemes within the microphysics process ranged from 0.42 to 0.47, exhibiting only minor variation, which suggested that the microphysics process exerted limited influence on the model's correlation performance. In contrast, within the planetary boundary layer process, the optimal scheme demonstrated a well-balanced simulation capability, with an RMSE of 1.066 and a correlation coefficient (R) of 0.488, both ranking among the highest across evaluated schemes. In the cumulus category, the Grell 3 scheme emerged as the optimal choice, yielding the lowest RMSE (1.032) and a relatively high correlation coefficient (0.478), while also effectively capturing the amplitude of anomalous field variations. For the radiation and land surface processes, the GFDL and Noah LSM schemes, respectively, achieved superior correlation coefficients compared to other schemes. Although their RMSE

595 were relatively elevated, these schemes were nonetheless regarded as optimal due to their overall strong performance in the integrated evaluation.

For Southeast China, the selected schemes also generally remained in the leading group under resampling (Fig. S8 and Table S13). The median top-three retention rates were 0.822 in station-bootstrap samples and 0.944 in time-block-bootstrap samples. The lower retention in the PBL/surface-layer stage reflects the close performance of adjacent schemes, whereas the radiation and land-surface stages showed stronger top-three retention.

Figure 6(g) presents the Taylor diagram summarizing the combined simulation results of all 54 parameterization scheme combinations. Following the sequential selection of optimal schemes for the five physical processes, ~~both RMSE and R exhibited notable improvements~~ the selected configuration achieved a lower RMSE and a higher R than the default configuration. Compared with the default scheme, the optimal configuration achieved a higher R value (0.502 versus 0.470) and a lower RMSE (1.039 versus 1.067), ~~underseering its enhanced ability to reproduce various~~ showing better evaluated agreement with the observed meteorological variables in the ~~WRF model for the~~ coastal region of Southeast. Independent analysis of each physical process revealed that microphysical, cumulus, and planetary boundary layer processes primarily contributed to reducing RMSE ~~and enhancing overall simulation accuracy~~ under the present evaluation metrics. In contrast, the radiation and land surface processes mainly influenced the correlation coefficient, with comparatively limited effects on the root mean square error.

3.4 Comparison of ~~dynamic-weight~~ proposed $MRE \times CV$ weighting and equal weight methods in the coastal region of Southeast

Figure 7 compares the performance of the optimal parameterization schemes derived using the ~~dynamic~~ proposed $MRE \times CV$ weighting method and the equal-weighting method in simulating various output variables. Figure 7(a) displays the Taylor plots corresponding to each method. The optimal scheme obtained through ~~dynamic~~ the proposed $MRE \times CV$ weighting exhibited a lower MIEI value (1.011) than that derived from the equal-weighting method (1.020). Specifically, the ~~dynamic~~ configuration selected by the proposed weighting scheme achieved a higher correlation coefficient ($R = 0.502$) compared to the equal-weighting scheme ($R = 0.499$), and a smaller RMSE (1.039 vs. 1.106), indicating ~~superior overall simulation accuracy~~ stronger evaluated performance under the Taylor and MIEI metrics.

Figure 7(b-h) present scatter plots comparing the observed and simulated results for each output variable using the respective optimal parameterization schemes. ~~As in Fig. 4, these scatter plots use monthly station summaries for visualization and do not define the temporal aggregation of the Taylor-diagram or MIEI statistics.~~ In the simulation of surface temperature, the ~~dynamic~~ configuration selected by the proposed weighting scheme yielded an R^2 -value of 0.24, slightly lower than that of the equal-weighting method. However, it performed better in capturing high-temperature scenarios. For precipitation, both schemes showed comparable correlation, with no significant difference in performance. Air pressure emerged as the best-simulated variable under both schemes, with extremely high levels of agreement. The ~~dynamic~~ configuration selected by the proposed weighting scheme achieved an R^2 -value of 0.92, effectively capturing the variability in air pressure. In the case of relative humidity, the ~~dynamic~~ configuration selected by the proposed weighting scheme outperformed the equal-weighting approach,

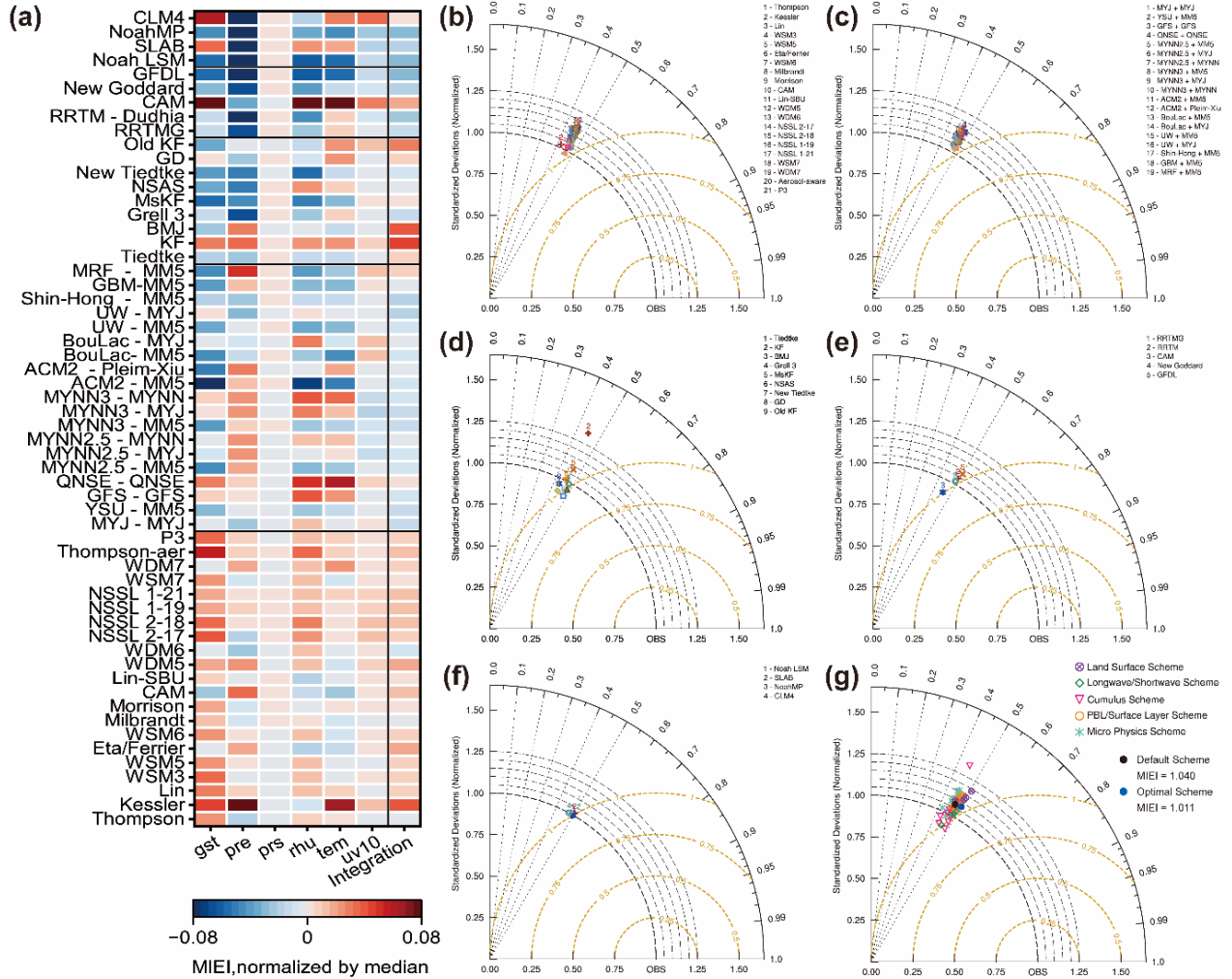


Figure 6. Evaluation results of parameterization schemes in the coastal region of Southeast. (a) Normalized MIEI, with MIEI values normalized by the median MIEI value of the corresponding ensemble, and (b-f) Taylor diagrams of different physical processes. (b) Microphysics, (c) Planetary boundary layer process, (d) Cumulus, (e) Radiation, (f) Land surface, and (g) Taylor diagrams of a total of 54 combinations of parametric schemes for all physical processes. All MIEI and Taylor-diagram statistics were calculated from daily station-level June-August values.

with R^2 -values of 0.86 and 0.82, respectively. The simulation of air temperature further highlighted the advantage of the dynamic configuration selected by the proposed weighting approach, which yielded a substantially higher correlation and an R^2 of 0.85. For wind variables, the dynamic configuration selected by the proposed weighting scheme also demonstrated superior performance. The R^2 -values for zonal and meridional wind were 0.54 and 0.44, respectively, compared to 0.11 and 0.36 under the equal-weighting scheme. Notably, the equal-weighting method exhibited a relatively large deviation in simulating zonal

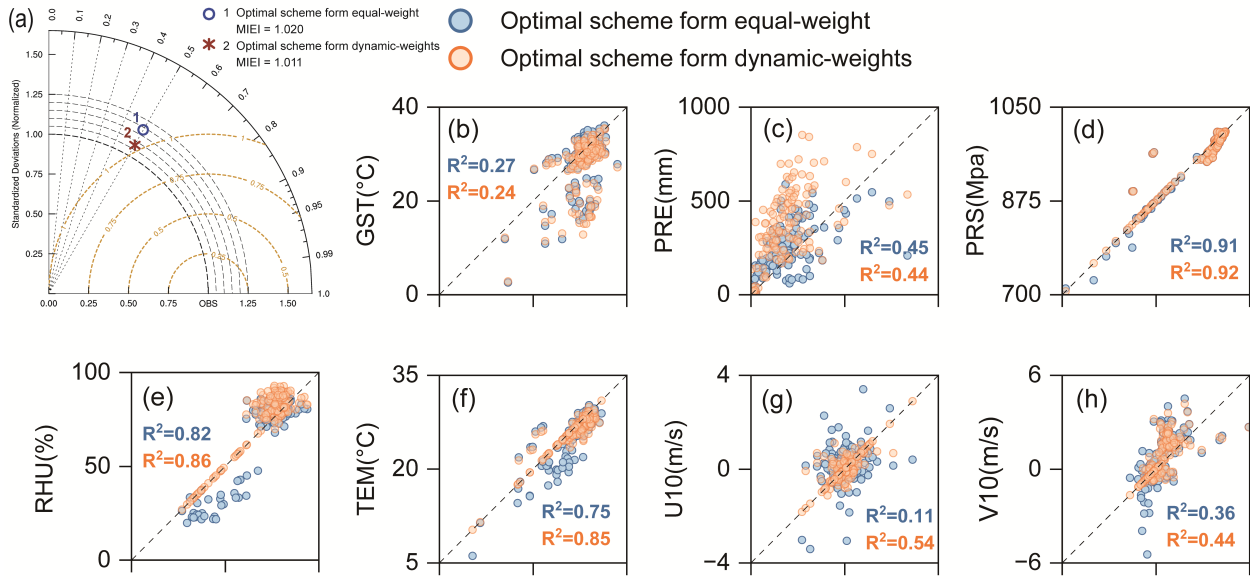


Figure 7. Comparison of simulation results obtained from the optimal parameterization schemes using the **dynamic-weight-proposed MRE** × **CV weighting** and equal weight methods. (a) Taylor plots of the optimal parameterization schemes obtained by different methods. (b-h) Scatter plots of the optimal parameterization schemes obtained via different methods for different meteorological elements. (b) Surface temperature, (c) precipitation, (d) Air pressure, (e) Relative humidity, (f) Air temperature, (g) Zonal wind, (h) Meridional wind. Panel (a) uses Taylor-diagram and MIEI statistics calculated from daily station-level June-August values; panels (b-h) use monthly station summaries only for visual comparison, with monthly means for non-precipitation variables and monthly totals for precipitation.

wind. Overall, the **optimal-parameterization-scheme-derived-from-the-dynamic-weighting-method-more-accurately-simulated-the**
 635 **variability-of-meteorological-elements-parameterization-combination-selected-by-the-proposed-MRE × CV weighting method**
showed better overall agreement with observed meteorological variability in the coastal region of Southeast than the **scheme**
obtained-through-combination-selected-by the equal-weighting approach.

Comparison of dynamic weight and equal weight methods for parameterization schemes in extreme climate years To
 evaluate the robustness of the **dynamic-weighting-method**, this study applied the optimal parameterization schemes, derived
 640 **from-the-year-most-representative-of-the-climatological-mean-for-the** To further clarify how the proposed MRE × CV weights
 changed the scheme-selection pathway relative to equal weighting, Table S12 summarizes the highest-weight variables, Top-1
 scheme changes, and variable-level contribution terms for rank-reversal cases. Across the ten region-stage evaluations, the
 Top-1 scheme changed in three stages: the Northwest PBL/surface-layer stage from MYJ + MYJ to YSU + MM5, the Northwest
 radiation stage from RRTMG to GFDL, and the Southeast cumulus stage from New Tiedtke to Grell 3. In all three cases, the
 645 **pairwise MIEI difference between the MRE × CV-weight winner and the equal-weight winner changed sign, from positive**

under equal weighting to negative under $MRE \times CV$ weighting ($D_{eq} = 0.0047, 0.0074$, and 0.0013 ; $D_{dyn} = -0.0056, -0.0119$, and -0.0059 for B1-B3, respectively). The variable-level contribution terms show that the higher UV10 weight promoted the selection of YSU + MM5 and GFDL in Northwest China, whereas the higher PRE weight promoted the selection of the Grell 3 cumulus scheme in Southeast China. Thus, the proposed $MRE \times CV$ weighting did not uniformly rescale all candidate schemes; it changed the integrated ranking when high-weight variables favored a different candidate scheme, preserving information on limiting variables and stage-specific scheme-dependent responses in the final screening pathway.

3.5 Comparison with established statistical weighting methods

To examine how the proposed method differs from established statistical weighting approaches in both weight structure and parameterization-scheme selection, we compared equal weighting, entropy weighting, coefficient-of-variation weighting, CRITIC weighting, and the proposed $MRE \times CV$ weighting. The comparison was conducted for the two representative screening years: 2007 in the arid region of Northwest China and ~~the southeastern coastal region, to a 2010 validation period.~~ ~~The aim is to assess the robustness and adaptability of each scheme under differing climatic scenarios~~ 2009 in the coastal region of Southeast China. All methods used the same candidate schemes, observations, variables, and MIEI evaluation framework. For each method, cMIEI, cVSC, cRMSL, R, and RMSE were computed from the same daily station-level June-August samples.

Figure 8 ~~compares the simulation performance of different meteorological variables using both weighting methods~~ shows that the five weighting methods produced different average variable-weight structures. Equal weighting assigned the same value to each of the six evaluated variable groups. The CRITIC weights were also close to a uniform distribution, with average weights ranging from 0.145 to 0.185 in Northwest China and from 0.142 to 0.199 in Southeast China. Although CRITIC explicitly includes an inter-variable conflict/non-redundancy term (Table S1), its final weights remained relatively close to equal weighting in this dataset.

Entropy weighting and coefficient-of-variation weighting showed more concentrated and mutually similar patterns because both methods primarily respond to the dispersion of variable errors across candidate schemes. In Northwest China, both methods assigned high average weights to TEM, reaching 0.448 for entropy weighting and 0.356 for ~~the year 2010. Figure 8(a) illustrates the comparison for the arid region of Northwest. The results indicated that the dynamic weighting scheme yielded superior performance relative to the equal-weighting approach. Specifically, the dynamic weighting method achieved a lower RMSE (1.372) compared to the equal-weighting method (1.437), and a lower MIEI value (1.310 vs. 1.313), reflecting greater simulation accuracy under extreme climatic conditions.~~ coefficient-of-variation weighting, while assigning low weights to PRS and UV10. In Southeast China, both methods gave relatively high weights to GST, TEM, and PRE. These similarities indicate that entropy weighting and coefficient-of-variation weighting identified broadly similar discriminating variables in the present error matrices, although their numerical differences were sufficient to change some scheme-ranking outcomes.

The proposed $MRE \times CV$ method produced a different weight structure. It consistently assigned larger weights to PRE and UV10, with average weights of 0.240 and 0.431 in Northwest China and 0.317 and 0.342 in Southeast China, respectively. This pattern reflects the purpose of the method: variables that are both difficult to simulate and responsive to alternative parameterization choices within the evaluated physical-process group retain greater influence in the multivariable score. The

complete process-level weight matrices for the five methods are provided in Figs. S3-S4, and the sensitivity of the proposed weights to the normalization function is shown in Fig. S5. The resampling analyses showed that the dominant weight structure was stable to station and intra-seasonal temporal sampling (Fig. S6 and Table S8). Across the ten region-stage combinations, the mean Spearman correlation with the full-sample weights ranged from 0.947 to 1.000 for station bootstrap samples and from 0.944 to 1.000 for 14 d block bootstrap samples. The lowest lower-tail or monthly-subset correlation was 0.886. PRE and UV10 formed the set of the two highest-weight variables in every station bootstrap, time-block bootstrap, and monthly subset. Their first and second positions occasionally interchanged in several Southeast China stages, most clearly in the radiation stage, but the identity of the dominant two-variable set was unchanged. For variable deletion, the recomputed retained-variable weights agreed with the theoretical renormalization to a maximum absolute residual of 2.22×10^{-16} , and their ordering was preserved in all region-stage cases (Table S9). The inter-variable dependence diagnostics showed that the strongest positive dependence occurred between GST and TEM. Their Pearson correlations were 0.930 in Northwest China and 0.847 in Southeast China for the observed daily station series, and 0.960 and 0.974, respectively, for the proposed scheme-level standardized-error matrices (Fig. S7). Removing GST while retaining TEM left the selected stage-level scheme unchanged in 8 of the 10 region-stage comparisons. The two changes occurred in the Southeast China PBL/surface-layer stage and land-surface stage (Table S11). Because the evaluated variable set differs between the original and no-GST analyses, the absolute cMIEI values are not interpreted as direct cross-set comparisons; the relevant evidence is the stability and physically interpretable sensitivity of the selected schemes.

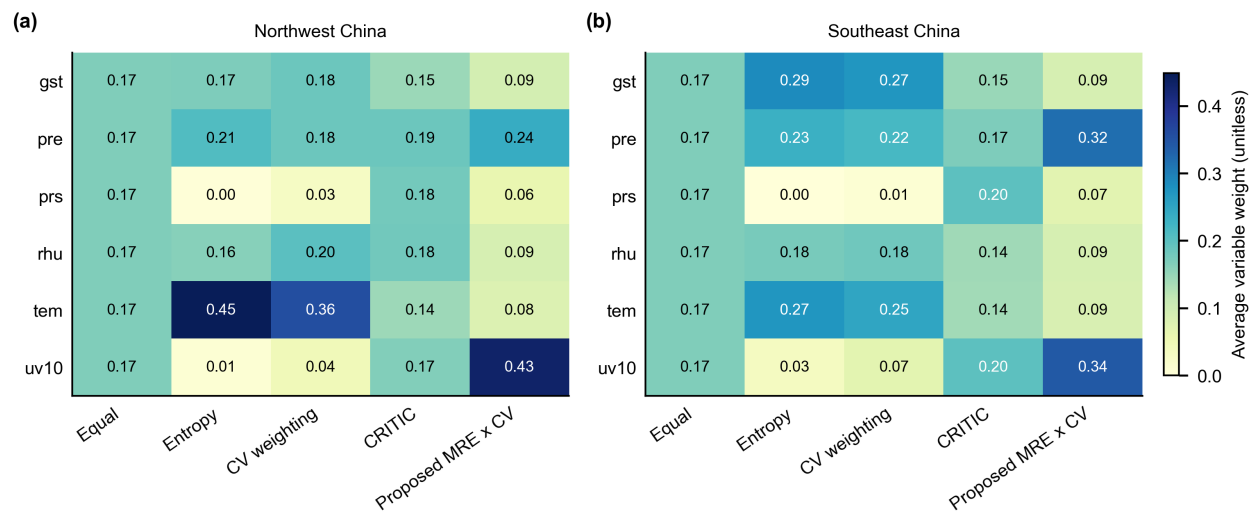


Figure 8. Comparison of average variable weights derived from equal weighting, entropy weighting, coefficient-of-variation weighting, CRITIC weighting, and the proposed MRE × CV weighting. Values represent averages across the five physical-process evaluation stages. (a) Arid region of Northwest China; (b) coastal region of Southeast China. Weights are unitless.

The different weight structures led to different integrated rankings of the selected configurations (Table 3). In Northwest China, the proposed $MRE \times CV$ method achieved the lowest cMIEI (1.166), compared with 1.186 for equal weighting and CRITIC, 1.198 for entropy weighting, and 1.207 for coefficient-of-variation weighting. In Southeast China, the proposed method also achieved the lowest cMIEI (1.008), slightly lower than coefficient-of-variation weighting (1.009), equal weighting and CRITIC (1.017), and entropy weighting (1.020). These results indicate that jointly considering variable-level simulation difficulty and scheme-dependent response produced the most favorable integrated ranking in the present cMIEI-based screening experiment.

Table 3: Comparison-Performance comparison of the optimal-parameterization schemes obtained via the dynamic weight and equal-weight configurations selected by five weighting methods in the 2010-simulation-results screening years. (a) The selected configuration is identified by the arid-region-of Northwest; (b) weighting method used in the coastal-region-of Southeast stepwise parameterization-screening workflow. Lower cMIEI indicates better integrated performance. The cMIEI, cVSC, and cRMSL values were calculated from daily station-level June-August values.

Region	Screening year	Weighting method	cMIEI	cVSC	cRMSL	Rank by cMIEI
Northwest China	2007	Equal weighting	1.186	0.321	1.167	2
		Proposed $MRE \times CV$	1.166	0.365	1.250	1
		Entropy weighting	1.198	0.365	1.428	4
		CV weighting	1.207	0.355	1.443	5
		CRITIC weighting	1.186	0.321	1.167	2
Southeast China	2009	Equal weighting	1.017	0.503	1.186	3
		Proposed $MRE \times CV$	1.008	0.505	1.086	1
		Entropy weighting	1.020	0.495	1.081	5
		CV weighting	1.009	0.505	1.008	2
		CRITIC weighting	1.017	0.503	1.186	3

Figure 8(b) shows the performance of the two schemes in the coastal region of Southeast . In this area, We further tested whether the selected configurations were sensitive to the way in which the two proposed weight components were combined. The equally weighted additive alternative ($\alpha = 0.5$) selected the same stage-level schemes as the proposed multiplicative rule in all five Southeast China evaluation stages. In Northwest China, it selected the same schemes in four of the five stages, with a change only in the cumulus-stage scheme. The full stage-level results are provided in Table S10. Because the additive and multiplicative rules selected the same final configuration in Southeast China, no duplicate 2010 simulation was required for that region. In Northwest China, where the additive rule produced a different final configuration, the independent 2010 validation gave cMIEI = 1.313 for the additive-rule configuration, close to but slightly higher than the proposed multiplicative-rule

configuration (cMIEI = 1.310). These results indicate that the simulation effect of the dynamic weight scheme had a higher correlation coefficient R (0.508; that of the equal weight method was 0.504) and a lower RMSE (1.028; that of the equal weight method was 1.030), with an MIEI value of 1.008, which was lower than the MIEI of main scheme-selection outcome was largely stable to this compensatory alternative, while the Northwest cumulus-stage difference shows that the multiplicative rule imposes a distinct joint-constraint interpretation rather than behaving as a simple additive average.

3.6 Independent 2010 validation of the five weighting methods

To examine the performance of the selected configurations outside the representative screening years, we further used 2010 as an independent extreme climate year for validation. This year was not used to calculate the weights or select the optimal configurations, and it therefore provides an out-of-screening test under an extreme climate background.

The 2010 validation results are summarized in Table 4. In Northwest China, the proposed $MRE \times CV$ method retained the lowest cMIEI (1.310), slightly lower than equal weighting and CRITIC (1.313), entropy weighting (1.324), and coefficient-of-variation weighting (1.322). In Southeast China, the proposed method again produced the lowest cMIEI (1.008), compared with 1.017 for the equal-weight scheme. This result indicated that the dynamic weight method had greater simulation accuracy when simulating meteorological variables in years with extreme climates and could better reflect meteorological changes under extreme climate conditions equal weighting and CRITIC, 1.017 for entropy weighting, and 1.034 for coefficient-of-variation weighting. This independent extreme-year test provides additional evidence that the proposed weighting strategy can retain its integrated performance advantage outside the screening year.

Table 4: Independent 2010 validation performance of the configurations selected by five weighting methods. Lower cMIEI indicates better integrated performance. The cMIEI, cVSC, and cRMSL values were calculated from daily station-level June-August values.

Region	Validation year	Weighting method	cMIEI	cVSC	cRMSL	Rank by cMIEI
Northwest China	2010	Equal weighting	1.313	0.190	1.239	2
		Proposed $MRE \times CV$	1.310	0.181	1.137	1
		Entropy weighting	1.324	0.225	1.404	5
		CV weighting	1.322	0.219	1.392	4
		CRITIC weighting	1.313	0.190	1.239	2
Southeast China	2010	Equal weighting	1.017	0.504	1.065	3
		Proposed $MRE \times CV$	1.008	0.508	1.067	1
		Entropy weighting	1.017	0.500	1.063	2
		CV weighting	1.034	0.486	0.988	5

4 Discussion

~~The dynamic weighting method~~

4.1 Evaluation meaning and weight-allocation mechanism

~~The performance-based multivariable weighting framework proposed in this study—based on the average relative error and the coefficient of variation of the absolute error across different output variables—introduces a more refined study~~
~~introduces a two-component~~ mechanism for assigning ~~weights in the evaluation of multiple physical processes. This approach~~
~~substantially enhances the accuracy of the WRF model in multivariable meteorological simulations~~variable weights during
WRF parameterization-scheme evaluation. It does not directly modify the WRF physical parameterizations; instead, it changes
how different variables contribute to the integrated evaluation and thereby affects which scheme combinations are selected.
Accordingly, lower cMIEI, RMSE, or higher R values should be interpreted as better evaluated performance of the selected
configurations, ~~not as direct improvement of WRF physics by the weighting method itself.~~ As demonstrated in Figs. 2 and
5, the ~~dynamic weighting method~~proposed framework identifies precipitation and wind speed as key constraining variables
in two climatically distinct regions. This finding aligns with previous evaluation studies that have highlighted precipitation
as a particularly challenging target variable (Yu et al., 2022b; Wang and Tan, 2023). This suggests that despite the different
prevailing climate backgrounds, the WRF model may face common physical process challenges in accurately simulating pre-
cipitation associated with local strong convection and the near-surface wind field related to surface friction. In multivariable
simulation studies, as the number of variables increases, those that are more difficult to simulate are often underrepresented in
the evaluation process. The ~~dynamic weighting method~~proposed framework addresses this issue by ensuring that critical ~~and~~
~~sensitive variables~~variables with large simulation errors or strong scheme-dependent responses consistently receive appropriate
weighting, thereby maintaining their influence and visibility throughout the model evaluation.

~~Through temporal cross-validation, this study confirms that the optimal combination of schemes selected by the dynamic~~
~~weighting evaluation method exhibits robustness across different years. Furthermore, the successful application of this method~~
~~in two climatically distinct areas—the arid region of Northwest China and the coastal region of Southeast China—verifies~~
~~its potential for broad applicability across different climatic regions. This demonstrates that the method serves as a general~~
~~paradigm broadly applicable to model evaluation in different regions. Under any specific regional climate background, it~~
~~can effectively capture the key constraining variables of a simulation, thereby enabling a more precise assessment of~~
~~parameterization schemes~~The comparison with entropy weighting, coefficient-of-variation weighting, and CRITIC further
clarifies the evaluation meaning of the proposed weights. Entropy weighting and coefficient-of-variation weighting both
emphasize dispersion among candidate schemes, which explains their similar weight patterns in the present experiments.
CRITIC additionally considers inter-variable conflict, but the contrast and conflict components together produced only
moderate departures from equal weighting in the present error matrices. By contrast, the proposed $MRE \times CV$ weighting is

760 designed to address a specific scientific problem in WRF parameterization screening: key variables with large simulation errors may be diluted in a multivariable average, and different variables respond unevenly to alternative parameterization choices within each physical-process group. The MRE component represents variable-level simulation difficulty, and the absolute-error CV component represents the scheme-dependent response of variable errors. The resulting weights therefore have a physical evaluation meaning, because they identify variables that are both difficult to simulate and influential for distinguishing the parameterization choices under evaluation.

765 ~~In multi-physics process simulations,~~ The multiplicative structure is central to this interpretation. It was not introduced simply to increase weight contrast, but to represent a non-compensatory joint constraint between the two diagnostic components. The MRE component identifies variables with large simulation difficulty, whereas the absolute-error CV component identifies variables whose errors respond strongly to the candidate schemes within the evaluated physical-process group. Under the proposed product rule, a variable receives a high final weight only when both conditions are satisfied. This design is consistent with the purpose of the framework: the integrated score should emphasize variables that are both difficult to simulate and informative for distinguishing parameterization choices, rather than variables that are high in only one component.

775 The additive-rule sensitivity test provides a useful contrast to this design. A weighted additive rule treats the MRE and CV components as partially compensatory, so a high value in one component can offset a lower value in the other. It is therefore a more permissive alternative than ~~the model's capacity to simulate various variables differs significantly, with the average relative error more indicative of its performance on specific variables than of discrepancies among the physical processes themselves. This implies that, while interactions between physical processes markedly influence the simulation outcomes, the disparities in~~ proposed multiplicative rule. The additive test produced the same selected configuration as the multiplicative rule in Southeast China and changed only the cumulus-stage choice in Northwest China. This pattern indicates ~~that the simulation capabilities of the current physical mechanisms remain relatively minor. Consequently, relative error serves as the primary criterion for determining weight distribution. As the model's physical mechanisms continue to advance, the simulation accuracy across different variables is expected to become more balanced (Pincus et al., 2008; Reichler and Kim, 2008). Therefore, distributing weights on the basis of the sensitivity of variables to physical processes will become increasingly~~ important in future simulations. main screening outcome was largely stable and was not an artifact of a single algebraic form. At the same time, the Northwest China difference shows that the product rule is not equivalent to a simple additive average and can impose a stronger joint-constraint criterion in boundary cases. In the independent 2010 Northwest China validation, the multiplicative-rule configuration also retained a slightly lower cMIEI than the additive-rule configuration. These results support the use of the multiplicative combination for the present evaluation objective, while not implying that a product rule would be universally superior for all model-evaluation contexts. The dependence analysis also clarifies the boundary of the weighting framework. GST and TEM are physically related thermal variables, and treating highly correlated variables as independent information can duplicate their influence in a multivariable score. However, their high correlation does not imply identical physical-process information. GST is more directly connected to the surface energy balance, land-surface exchange, and radiative heating or cooling at the ground surface, whereas TEM represents the near-surface air-temperature

795 response after surface forcing is coupled with surface-layer and boundary-layer mixing, radiative forcing, and transport. The
two variables may therefore show different error responses to different physical-process options. This distinction is one reason
for including the absolute-error CV component: it tests whether each variable's errors actually vary among the candidate
schemes within the evaluated physical-process group, rather than assuming that physically related variables carry identical
screening information. We did not apply formal decorrelation in the main evaluation because the variables are meteorologically
800 defined outputs with distinct diagnostic meanings, and orthogonalized components would be less directly interpretable for
WRF parameterization-scheme screening. Instead, we retained the physically defined variables and evaluated redundancy risk
explicitly through correlation diagnostics, the CRITIC benchmark, and the no-GST sensitivity test. The largely unchanged
stage-level selections indicate that the main screening outcome was not dominated by the GST-TEM dependence. The two
changes in Southeast China were confined to the PBL/surface-layer and land-surface stages, which is consistent with the close
805 connection of GST-related thermal information to near-surface turbulent exchange, land-atmosphere coupling, and surface
energy fluxes. The unchanged cumulus and radiation choices further indicate that removing GST did not overturn the core
precipitation/convection and radiation-related selection pathway in the humid coastal domain.

In multi-physics WRF simulations, variables differ substantially in simulation difficulty, as indicated by their mean relative
errors. The present results show that this component is a major driver of the final weights because precipitation and near-surface
810 wind remain difficult to simulate across regions. As physical parameterizations improve and variable-level errors become more
balanced, the coefficient-of-variation component may become increasingly important because it identifies variables whose
errors respond strongly to alternative schemes within each physical-process group.

The weights derived from the coefficient of variation of absolute errors did not exhibit ~~significant strong~~ regional differences,
indicating that the ~~sensitivity-weighting-of-variables-is-primarily-influenced-by-scheme-dependent~~ response of variable errors is
815 closely related to the physical mechanisms ~~underlying-the-represented-by-the-candidate~~ parameterization schemes. For instance,
the pronounced ~~sensitivity-of-precipitation-to-response-of-precipitation-errors-within-the~~ microphysics and cumulus ~~processes~~
~~groups~~ is consistent with ~~findings-from-previous-studies~~ previous studies showing that these processes strongly influence
precipitation simulation (Tian et al., 2017; Liu et al., 2018). Similarly, the ~~strong-correlation-between-surface-temperature~~
stronger response of surface temperature in the land surface group supports the value of the method in capturing physically
820 meaningful links between parameterization choices and variable-level model performance (Liu et al., 2023).

4.2 Physical interpretation and practical meteorological relevance

The regional differences in the selected configurations provide a basis for interpreting how the weighting method responds to
the dominant physical constraints in each climate setting. The weighting framework itself does not directly diagnose process
budgets or alter WRF physical parameterizations. Because the method gives greater influence to variables with larger relative
825 errors and stronger scheme-dependent responses within the evaluated physical-process group, the final scheme combinations
are not determined only by the lowest aggregate score; they also reflect which variables and processes most strongly limit
the multivariable simulation in each region. The selected schemes should therefore be interpreted as statistically preferred

configurations whose physical characteristics are consistent with the present regional climate backgrounds, rather than as universally optimal schemes or as proof of a single causal mechanism.

830 In the arid region of Northwest China, limited water-vapor supply, complex terrain, strong land-atmosphere coupling, and large diurnal temperature variations make precipitation, near-surface wind, and temperature particularly sensitive to cloud microphysics, boundary-layer mixing, radiation, and surface energy-water exchanges. The selection of the P3 microphysics scheme is physically plausible because P3 predicts bulk ice particle properties and explicitly represents the mass and volume of rimed ice, allowing a more flexible treatment of mixed-phase hydrometeors than schemes with fixed ice categories (Morrison and Milbrandt, 2015). This is relevant for precipitation simulation over arid and topographically complex regions, where precipitation events are intermittent and strongly affected by cloud microphysical uncertainty. The selection of the YSU PBL scheme is also consistent with the importance of near-surface wind and temperature in this region, because YSU uses a non-local K-profile approach with an explicit entrainment layer to represent turbulent exchange in the unstable mixed layer (Hong et al., 2006). The Tiedtke cumulus scheme, a mass-flux scheme with shallow convection and momentum transport, 840 provides a physically meaningful representation of sub-grid convective transport under conditions where convection is not fully resolved (Tiedtke, 1989; Zhang et al., 2011). Together with the GFDL radiation scheme, which accounts for radiative transfer with carbon dioxide, ozone, and cloud microphysical effects (Fels and Schwarzkopf, 1981), and the Noah LSM, which represents soil temperature, soil moisture, snow, and surface fluxes in the land-atmosphere system (Chen and Dudhia, 2001), this combination is consistent with the dominant controls on wind, temperature, and intermittent precipitation in the 845 arid Northwest domain. This interpretation is also supported by previous WRF studies showing that land surface choices can strongly affect summer climate simulations in arid Central Asia and that PBL schemes in China differ substantially in their representation of heat and momentum fields (Lu et al., 2021; Jia et al., 2023).

In the humid coastal region of Southeast China, the dominant simulation challenges are more closely related to monsoon moisture transport, moist convection, cloud-precipitation processes, and the coastal boundary layer. The selection of WDM6 850 is physically interpretable because this scheme extends WSM6 by including double-moment treatment of rain and cloud water as well as prognostic cloud condensation nuclei for warm-rain processes, which is relevant for warm and moist precipitation environments (Lim and Hong, 2010). The selected Shin-Hong PBL scheme includes scale dependency for vertical transport in the convective boundary layer while retaining YSU-type treatment for stable boundary-layer and ~~land-surface processes~~ further supports the validity of this method in effectively capturing the sensitivity relationships between physical processes and 855 ~~meteorological variables (Liu et al., 2023).~~ free-atmospheric mixing (Shin and Hong, 2015). This feature is consistent with the need to represent vertical exchange of heat, moisture, and momentum in coastal regions where sea-land thermal contrast and moist boundary-layer processes affect near-surface wind and humidity. The Grell 3 cumulus scheme is an improved Grell-Devenyi type mass-flux approach and can represent sub-grid convective effects through ensemble-based convective assumptions (Grell, 1993; Grell and Devenyi, 2002). Its selection in the Southeast domain is therefore consistent with the higher 860 weight assigned to precipitation in the cumulus evaluation and with previous studies showing that convection and microphysics parameterizations strongly influence precipitation and cloud properties over Asia and East Asian summer monsoon rainfall (Liu et al., 2018; Yang et al., 2015). The common selection of GFDL radiation and Noah LSM in both regions further suggests that

a balanced treatment of radiative heating and land-surface fluxes is important for the multivariable evaluation, although their specific roles differ between the arid inland and humid coastal climate backgrounds.

865 These physical interpretations should be treated as mechanism-informed explanations of the statistical selection results, not as direct process-attribution evidence. The present study did not conduct water-vapor budget analysis, hydrometeor diagnostics, turbulent kinetic energy diagnostics, PBL-height evaluation, or surface energy-balance decomposition. Therefore, the results support the conclusion that the selected configurations are physically consistent with the dominant regional processes, but they do not prove that a single parameterization mechanism caused the evaluated performance differences. Future applications
870 should therefore combine the performance-based weighting framework with process-level diagnostics and multi-year validation to further test whether the same scheme choices remain robust across different circulation patterns and types of extreme events.

The practical meteorological implication of the evaluated differences becomes clearer when the integrated scores are linked to the variables and physical processes that drive the scheme-selection pathway. Differences between competing
875 configurations are not only numerical changes in the evaluation metric; they indicate which parameterization choices better reproduce meteorological variables tied to the atmospheric processes of interest. For example, the proposed $\text{MRE} \times \text{CV}$ configuration reduced RMSE for temperature-related variables in Northwest China (TEM by 0.98 °C and GST by 2.47 °C) and for precipitation in Southeast China (PRE by 1.38 mm d⁻¹). These variable-level improvements translate into practical meteorological meaning because the affected variables control different parts of the regional climate system. Lower
880 temperature-related errors imply a more reliable representation of near-surface thermal conditions and land-atmosphere heat exchange, which is relevant for regional climate simulation and heat-related extreme-event assessment in arid Northwest China. Lower precipitation errors improve the representation of water input and rainfall-forming processes, which is important for hydroclimate simulation and heavy-precipitation evaluation in humid Southeast China. Near-surface wind is also a key constraint on boundary-layer mixing and moisture and heat transport. The proposed weighting framework therefore has
885 practical value for selecting physical-process parameterizations that better represent target meteorological processes and their application-relevant variables, while process-budget diagnostics would still be needed for formal attribution of the underlying mechanisms.

4.3 Robustness and uncertainty boundaries of the screening framework

The ~~WRF~~ representative-year screening and single independent extreme-year validation design used in this study was intended
890 to balance statistical representativeness, computational feasibility, and the need for an out-of-sample test. The screening years were not chosen subjectively or only because their annual mean values were close to the climatological means. Instead, all candidate years from 1991 to 2020 were evaluated against the 30-year climatological reference using centered multivariable metrics. The years with the lowest cMIEI were selected for the two regions, and their variable-level metrics did not show pronounced anomalous deviations among the seven variables evaluated in the WRF assessment (Tables S2-S3 and Figs. S1-S2).
895 Therefore, the selection was based on both the integrated cMIEI ranking and the absence of strong variable-level outliers, which

reduces the risk that the parameterization screening is driven by an anomalous year. The 2010 experiment further provides a single independent extreme-year test of the selected schemes outside the screening period.

The representative-year screening and independent 2010 validation therefore provide two complementary tests: one under multivariable climatological representativeness and one under an extreme climate background outside the screening year. Broader multi-year optimization, leave-one-year-out cross-validation, or validation across additional climate-background years would further quantify the range of this robustness under different circulation regimes. In the present WRF physics-ensemble framework, such extensions would require rerunning the full parameterization screening across multiple years and regions. The present design therefore provides a reproducible and computationally tractable evaluation of the proposed weighting framework, while leaving broader multi-year generalization as a clear direction for future applications. The stability analysis specifically addresses uncertainty caused by station selection and intra-seasonal temporal sampling. The similar dominant weight structure obtained for the 2007 Northwest China and 2009 Southeast China cases provides supporting consistency across two distinct region-year settings, but region and year vary simultaneously and their effects cannot be separated. These comparisons should therefore not be interpreted as a controlled same-region cross-year weight-stability test.

The full-sample ranking first identifies the best-performing configuration for the evaluated station-time sample. The bootstrap analysis then examines how consistently that ranking is retained when the finite station and time samples are resampled.

The scheme-ranking analysis complements the weight-stability results by evaluating whether the selected stage-level schemes remain competitive when the station and time samples are perturbed. Across the 20 region-stage-resampling comparisons, the selected schemes had a median top-three retention rate of 0.959. This result supports the use of the proposed framework to identify robust top-performing parameterization configurations in the evaluated station-time sample.

The WRF model offers many parameterization schemes that can be freely combined. However, this high degree of flexibility necessitates substantial computational resources to support the model's operation (Li et al., 2014). The ~~piecewise simulation method employed stepwise simulation method used~~ in this study, ~~which is based on the sensitivity of individual physical processes, effectively simplifies the complex multiplicative combinations of physical process parameterization schemes into additive combinations, thereby reducing the computational burden. However, in~~ reduces the computational burden by evaluating physical-process options sequentially, while the interactions among WRF physical processes remain nonlinear and cannot be converted into truly independent additive effects. In multivariate evaluations, the intricate interactions between physical processes and variables ~~introduce challenges related to~~ therefore continue to introduce uncertainty (Zeng et al., 2016; Jia et al., 2023). To address ~~this, the dynamic weighting method dynamically~~ the multivariable evaluation component of this problem, the proposed weighting framework adjusts variable weights during each stage of ~~physical-process simulation~~ physical-process evaluation, ensuring that each process emphasizes the ~~simulation of key elements most influential to specific variables. This approach helps to mitigate the uncertainty stemming from inter-process interactions caused by changes in parameterization schemes~~ variables most affected by simulation error and scheme-dependent response.

In existing studies, the common method of sequentially selecting the optimal parameterization scheme involves bringing the optimal parameterization scheme from each physical process into the simulation of the next physical process. The theoretical implication of this design is that the search target changes from an exhaustive global optimization over all feasible WRF

physics combinations to a sequence of conditional decisions. The scheme selected for an earlier process can modify the model state, the simulated error structure, and the performance landscape under which later processes are evaluated. For instance, as illustrated in Fig. 3(a), the selection of the YSU planetary boundary layer scheme ~~leads to improved wind-speed simulation~~ is associated with lower evaluated wind-speed errors in subsequent processes, ~~suggesting that the sequence in which physical processes are simulated can also introduce uncertainty. Throughout the evaluation process, such uncertainty is subject to continuous propagation and accumulation. Consequently, the resulting set of parameterization schemes is not one that is globally optimal, but rather one that is preferentially optimized for the initial scheme selection. However, the current literature lacks a robust theoretical or experimental basis for the prescribed simulation sequence. Therefore, a necessary and significant direction for future research is to quantify and mitigate the uncertainties arising from both the simulation sequence and the initial choice of parameterization schemes, indicating that earlier choices can propagate their influence into later stages. The resulting configuration should therefore be interpreted as the best-performing combination under the prescribed conditional screening framework, rather than as a mathematically guaranteed global optimum over all possible WRF physics combinations.~~

Notably, the dynamic weighting method proposed in this study is not only applicable to parameterization scheme evaluation in the WRF model but also has broad applicability, especially in complex climate simulations and ~~The prescribed order, from microphysics to planetary boundary layer, cumulus, radiation, and land surface processes, was adopted as a practical and pre-defined screening sequence based on previous WRF sensitivity and physics-ensemble evaluation studies (Stergiou et al., 2017; Dai et al., 2021). In this sense, the order has both a procedural precedent and an empirical rationale: it evaluates cloud and precipitation microphysical processes, boundary-layer turbulent exchange, and convective processes before the radiation and land-surface choices are finalized. These earlier processes commonly exert strong direct or indirect controls on precipitation, near-surface wind, temperature, and humidity, and the present results likewise show substantial multivariable differences associated with microphysics, cumulus, and planetary boundary layer choices. Nevertheless, the order is not theoretically unique. The proposed weighting framework helps reduce evaluation bias within each step by emphasizing variables with larger errors or stronger scheme-dependent responses, but it does not eliminate the path dependence of the stepwise search itself. Future applications could further quantify this source of uncertainty by comparing alternative process orders, applying multi-start stepwise screening, or using global optimization and surrogate-model approaches when computational resources allow.~~

The uncertainty addressed in this study should therefore be interpreted as uncertainty associated with WRF physical parameterization-scheme selection under a fixed model configuration. In the present experiments, all candidate simulations shared the same WRF dynamical core, horizontal resolution, domain configuration, vertical setup, initial and boundary conditions, land-use dataset, spin-up design, evaluation variables, and observational reference. This controlled design allows the proposed framework to diagnose how alternative physical parameterization schemes and variable-weighting choices affect the evaluated multivariable performance. It also keeps the comparison focused on the parameterization-screening problem that the method is designed to solve. Other sources of WRF uncertainty, including horizontal and vertical resolution, domain extent and nesting strategy, terrain and land-use representation, initial and boundary forcing, and spin-up length, can also influence

model performance. These factors were not independently perturbed or attributed in the present study. The proposed $MRE \times CV$ weighting framework should therefore be viewed as a reproducible evaluation tool for parameterization-scheme screening, rather than as a complete uncertainty-decomposition framework for WRF simulations. Future applications could combine this weighting framework with multi-resolution, multi-domain, land-use, forcing, or spin-up sensitivity experiments to assess how parameterization-scheme uncertainty interacts with these additional uncertainty sources.

4.4 Potential extension of the performance-based weighting framework to variable-level evaluation in multi-model ensembles

Beyond WRF parameterization-scheme evaluation, the performance-based weighting framework also suggests a possible extension for variable-level assessment in multi-model assessments. In comprehensive evaluations of complex climate models ensembles. The transferable component is not a direct attribution of structural uncertainty, but the use of observation-constrained error statistics to determine which variables should receive greater attention in a multivariable score. In the present WRF physics ensemble, the members share the same dynamical core, model configuration, domain setting, boundary conditions, and evaluation variables; therefore, the coefficient of variation of absolute errors can be interpreted mainly as the scheme-dependent response of each variable to alternative physical parameterization choices. In multi-model ensembles, such as multi-model ensembles (e.g., CMIP6), the dynamic adjustment of each variable's weight via two indicators on the basis of all model data structures—the average relative error and the CMIP-type ensembles, the same statistic would instead summarize variable-level inter-model spread, because differences among models integrate the effects of model structures, numerical schemes, spatial resolutions, physical process representations, tuning strategies, and model genealogy. This reinterpretation allows the performance-based weighting framework to be considered as a variable-level evaluation module for multi-model applications, while preserving the conceptual distinction between parameter perturbation within a single modelling framework and structural differences among distinct models.

Nevertheless, the proposed weighting idea can still provide value as a variable-level diagnostic component in future multi-model evaluation. Under this adapted interpretation, the mean relative error would identify variables with large systematic simulation errors across the ensemble, while the coefficient of variation of absolute error—effectively reduces errors caused by differences in model structure and parameters (Knutti et al., 2010). This characteristic enables the dynamic weighting method to provide a more precise and objective framework for model performance evaluation errors would be interpreted as variable-level inter-model spread rather than within-process scheme-dependent response. Combining these two components would highlight variables that are both difficult to simulate and associated with large inter-model disagreement. Such variables, for example precipitation or near-surface wind in many regional climate applications, may otherwise be masked in an equal-weighted multivariable score by variables that are simulated more consistently. In this sense, the method could help preserve the visibility of high-error and high-spread variables during multi-variable model evaluation, while the final ensemble weighting would still require separate model-level treatment.

This distinction also defines the boundary of the method. The proposed variable weighting framework does not by itself attribute structural uncertainty to specific model components, nor does it solve model dependence, shared model genealogy,

1000 or redundancy among related model families. If applied to multi-model ensembles, it should be embedded in a broader hierarchical evaluation framework in which model outputs are first harmonized to common variables, spatial grids, temporal scales, and observational references, and then combined with model-level performance weights, model-independence weights, model-family grouping, or uncertainty decomposition approaches. Future work should therefore test this variable-level weighting module in multi-model ~~assessments~~ensembles and examine how it interacts with model-level weighting and structural-uncertainty attribution.

Conclusion

4 Conclusions

This study proposes ~~an optimization method for WRF model parameterization schemes based on dynamic weight evaluation, which improves the accuracy of multivariable climate simulations by dynamically adjusting the weights of each variable.~~ Compared to traditional equal-weighting methods, the dynamic weighting approach offers a more accurate representation of overall model performance by accounting for simulation errors across different output variables and the sensitivity of these variables to various physical processes. Validation in both the arid region of Northwest and the coastal region of Southeast confirms the effectiveness of the proposed method a performance-based multivariable weighting framework for WRF parameterization-scheme evaluation. The method combines mean relative error and the coefficient of variation of absolute errors to give greater influence to variables that are both difficult to simulate and responsive to alternative schemes within the evaluated physical-process group. Compared with equal weighting, entropy weighting, coefficient-of-variation weighting, and CRITIC weighting, the proposed $MRE \times CV$ method produced the lowest integrated cMIEI in both representative screening years and in the independent 2010 extreme-year validation.

Bootstrap analysis further showed that the selected stage-level schemes generally remained within the leading group under station and time-block resampling. Across the 20 region-stage-resampling comparisons, the median top-three retention rate was 0.959. These results indicate that the proposed weighting framework provides a transparent and reproducible basis for selecting robust top-performing WRF parameterization configurations.

In the arid region of Northwest, the optimal parameterization scheme combination derived using the ~~dynamic~~proposed $MRE \times CV$ weighting method includes P3, YSU, Tiedtke, GFDL, and Noah LSM. This configuration ~~significantly enhances the simulation accuracy of air temperature and wind speed compared to that achieved with the equal-weighting method~~achieved lower integrated cMIEI than the configurations selected by the benchmark weighting methods under the present evaluation framework. Similarly, in the coastal region of Southeast ~~, the dynamic weighting method demonstrates its superiority, with the optimal combination comprising China, the optimal combination comprised~~ WDM6, Shin-Hong-MM5, Grell 3, GFDL-GFDL, and Noah LSM. ~~This configuration yields more accurate temperature and wind speed, and it also achieved the lowest integrated cMIEI among the five weighting strategies.~~ Compared with the configuration selected by equal weighting, the ~~dynamic weighting scheme provides more accurate results, improving the model's simulations, reflected in improved correlation coefficients and reduced RMSE values. Compared to the equal-weighting method, it more effectively captures the trends~~

and magnitudes of meteorological variability. Nonetheless, despite notable improvements in the simulation of near-surface meteorological variables, certain biases persist—particularly in the simulation of configurations selected by the proposed method showed stronger evaluated agreement with observed meteorological variability in several metrics. Nevertheless, remaining biases persisted, particularly for precipitation and wind speed. This suggests that, while the dynamic weighting method substantially enhances simulation performance, These remaining biases indicate that the weighting method improves the evaluation and selection of parameterization schemes, whereas further refinement of the model's physical mechanisms is necessary, especially for accurately WRF physical parameterizations remains necessary for representing complex weather systems and extreme events.

As the parameterization schemes for different physical processes in climate models parameterization schemes continue to evolve and with the increasing frequency of extreme climate events, the need for rapid and accurate simulations and predictions of climate change becomes even more critical. The dynamic weight method offers a flexible and precise tool that can optimize the evaluation process on the basis of the performance of different variables and models, thereby better addressing the uncertainties and complexities of climate change. The widespread application of this method not only optimizes existing climate models but also provides more reliable scientific foundations for climate change response strategies and policy-making. , multivariable evaluation methods need to account for both variable-level simulation difficulty and scheme-dependent response within each physical-process evaluation stage. The proposed weighting framework provides a reproducible way to incorporate these two aspects into WRF parameterization-scheme screening. Its broader value therefore lies in improving the transparency and diagnostic relevance of multivariable model evaluation, rather than replacing process-level model development or long-term validation.

Code and data availability. The Weather Research and Forecasting (WRF) model version 4.3.3 used in this study is freely available online and can be downloaded from https://www2.mmm.ucar.edu/wrf/users/download/get_source.html (Skamarock et al., 2019). The code used in this study to calculate the proposed $MRE \times CV$ weights is available at <https://doi.org/10.5281/zenodo.17414002> (Gou et al., 2025). The Zenodo repository also provides the WRF model simulation results and the evaluation process. Any future updates or additional scripts will be hosted there.

Author contributions. TG and SK conceptualized the study. TG and YD designed the methodology. TG developed the model code, performed the simulations and drafted the manuscript. JN and SK supervised the work and contributed to the writing and editing of the paper.

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