

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

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Abstract. The selection of physical parameterization schemes is a major source of uncertainty in WRF simulations. A comprehensive evaluation of model performance requires the simultaneous consideration of multiple output variables, 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 a performance-based multivariable weighting framework for WRF parameterization-scheme evaluation. The framework combines two components: mean relative error, which represents variable-level simulation difficulty quantified by relative simulation error, and the coefficient of variation of absolute errors, which represents the scheme-dependent response of each variable within the evaluated physical-process group. The approach was applied and evaluated in assessing WRF parameterization schemes across two climatically distinct environments: the arid Northwest and the humid coastal Southeast of China. The results show that the method assigns greater weights to variables that are difficult to simulate, such as precipitation and wind speed, thereby helping identify physically interpretable and well-performing parameterization-scheme combinations under the prescribed evaluation framework. Compared with equal weighting and established statistical weighting methods, the proposed $\text{MRE} \times \text{CV}$ weighting helped identify parameterization-scheme combinations that achieved the lowest integrated cMIEI in both representative screening years and in the independent 2010 extreme-year 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

Earth system models (ESMs) support climate-change detection and attribution, future climate projection, and adaptation research (Reichler and Kim, 2008; Knutti et al., 2010). Their reliability depends on systematic evaluation against observations, especially as model representations of physical processes become broader and more interconnected (Reichstein et al., 2019; Eyering et al., 2019; Hausfather et al., 2020). Model evaluation commonly uses performance metrics to quantify how well simulations reproduce climate characteristics or processes (Baker and Taylor, 2016). For single variables, correlation, root mean square error, and variance ratio are widely used, and the Taylor diagram combines these statistics into a compact graphical summary (Lambert and Boer, 2001; Taylor, 2001). However, single-variable or scalar summaries are insufficient when model

performance must be assessed across multiple coupled variables (Pincus et al., 2008). Multivariable metrics such as the Model
25 Climate Performance Index (MCPI) and multivariate integrated evaluation (MVIE) therefore provide useful bases for integrated
model assessment (Gleckler et al., 2008; Xu et al., 2017).

The Weather Research and Forecasting (WRF) model is a regional climate model used within the Coordinated Regional
Downscaling Experiment (CORDEX) under the World Climate Research Programme (WCRP). It includes multiple parameter-
ization schemes for microphysics, land surface, planetary boundary layer, cumulus, and radiation processes (Skamarock et
30 al., 2019). Different schemes and combinations can produce large differences in simulated meteorological variables (Yu et al.,
2022b). Because physical processes interact and individual schemes are region- and variable-dependent, no universally optimal
WRF configuration can be assumed (Fernández et al., 2007; Borge et al., 2008). This range of selectable schemes is a major
source of WRF simulation uncertainty (Mooney et al., 2013), making region-specific parameterization-scheme evaluation an
important prerequisite for WRF applications (Chen et al., 2014; Ferreira et al., 2014). The size of the configuration space also
35 creates a practical constraint. In WRF version 4.3, the available schemes yield a theoretical upper bound of more than 14.5 mil-
lion possible combinations 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).

A remaining difficulty is how to evaluate WRF configurations when several meteorological variables are considered to-
40 gether. WRF produces multiple output variables, but evaluations often emphasize key or difficult-to-simulate variables such
as precipitation. Such univariate evaluation can bias model assessment by overlooking other variables that are important for
regional climate dynamics (Lv et al., 2020). Multivariable evaluation has therefore been increasingly used to assess simula-
tion performance more comprehensively and to represent parameterization-related uncertainty more transparently (Righi et al.,
2020; Dai et al., 2021; Lu et al., 2021). Yet many multivariable approaches still assign equal weights to all variables or rely
45 on subjective expert 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 schemes typically affect precipitation more strongly than
some other near-surface variables. Thus, WRF parameterization-scheme screening requires a weighting rule that can incorpo-
rate both variable-level simulation difficulty and scheme-dependent response.

50 To address this need, this study proposes a performance-based multivariable weighting framework for WRF
parameterization-scheme evaluation. The proposed $\text{MRE} \times \text{CV}$ 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 distin-
55 guishing 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 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, 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.

The remainder of this paper is organized as follows. Sect. 2 describes the study areas, model configuration, datasets, and implementation of the proposed weighting framework. Sect. 3 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, applicability, and generalizability of the framework. Sect. 5 summarizes the main conclusions.

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—
 90 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.

95 **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
 100 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,
 105 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

110 In this study, the Advanced Research WRF model version 4.3.3 was used for numerical simulations. Different model config-
 urations 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
 115 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
Evaluation period	June 1st–Aug 31st, 2007	June 1st–Aug 31st, 2009
Spin-up period	May 1st–May 31st	May 1st–May 31st
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 the proposed MRE × CV weighting and equal weighting methods. 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 the physical parameterization scheme combinations. The selection of simulation years for the two study regions was based on long-term meteorological station observations from 1991 to 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 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 showed that 2007 and 2009 had the lowest cMIEI values in their respective regions and did not show pronounced outlying deviations among the seven variables evaluated in 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 S2–S3 and Figs. S1–S2 in Supporting Information).

As a single independent extreme-year validation, the year 2010, which was characterized by extreme climate events common to both study regions, was selected to examine whether the schemes obtained from the screening period retained their evaluated performance under a different climate 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 experienced drought and the coastal region of Southeast

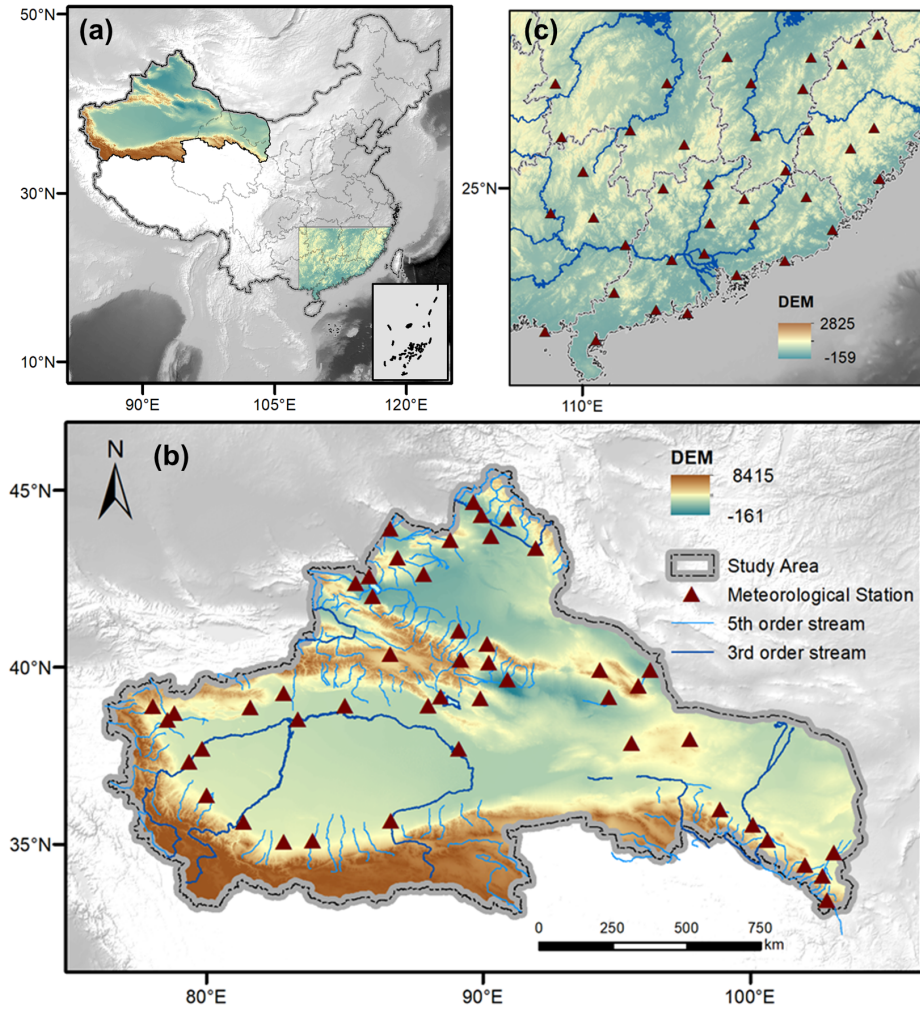


Figure 1. (a) Geographical location of the study area. (b) Overview of the arid region of Northwest China. (c) Overview of the coastal region of Southeast China.

135 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 significant flooding in the coastal region of Southeast, with substantial loss of life and property. Therefore, the 2010 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.

140 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 mi-

145 crophysics, planetary boundary layer, cumulus, radiation, and land surface processes, and 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, ra-
 150 diation, 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 pre-
 cipitation, wind speed, temperature, and humidity, which are key variables in the present multivariable evaluation. Therefore,
 155 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 (proposed
 MRE $\times$ CV weighting method) /43 (equal weighting method) combinations for the arid domain in Northwest China and 54
 (proposed MRE $\times$ CV weighting method) /53 (equal weighting method) combinations for the coastal domain in Southeast
 China (see Tables S4-S5 and S6-S7 in Supporting Information).

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-l>
160 evels ; <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>.

165 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 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

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 the combined results of multiple variables.

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

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

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

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

In the equation, m represents the output variable, and n represents the model's parameterization scheme. In the WRF
 190 parameterization-scheme evaluation, t denotes the valid daily station-level sample after pooling the station and day dimen-
 sions. 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 clima-
 tological averages. f_{mnt} represents the simulated value of the m variable at the t -th valid station-day sample for the model's
 195 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 indica-
 tors, they are limited in their ability to fully quantify model superiority in complex evaluation scenarios. While it is widely
 200 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 param-
 eterization 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
 205 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
 210 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
 215 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 Performance-based multivariable weighting framework

The performance-based multivariable weighting framework proposed in this study is used to calculate the variable weight ω_m in the evaluation metrics 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 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.

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

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

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) 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 component weights of variable m derived from 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 each variable to quantify variable-level simulation difficulty and the scheme-dependent response of variable errors within the evaluated physical-process group.

Step 3: Use the Softmax function to convert the two statistical indicators (mean relative error and coefficient of variation) into two 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 , 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 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 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 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 information that is less redundant with other variables.

The proposed $\text{MRE} \times \text{CV}$ 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 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.

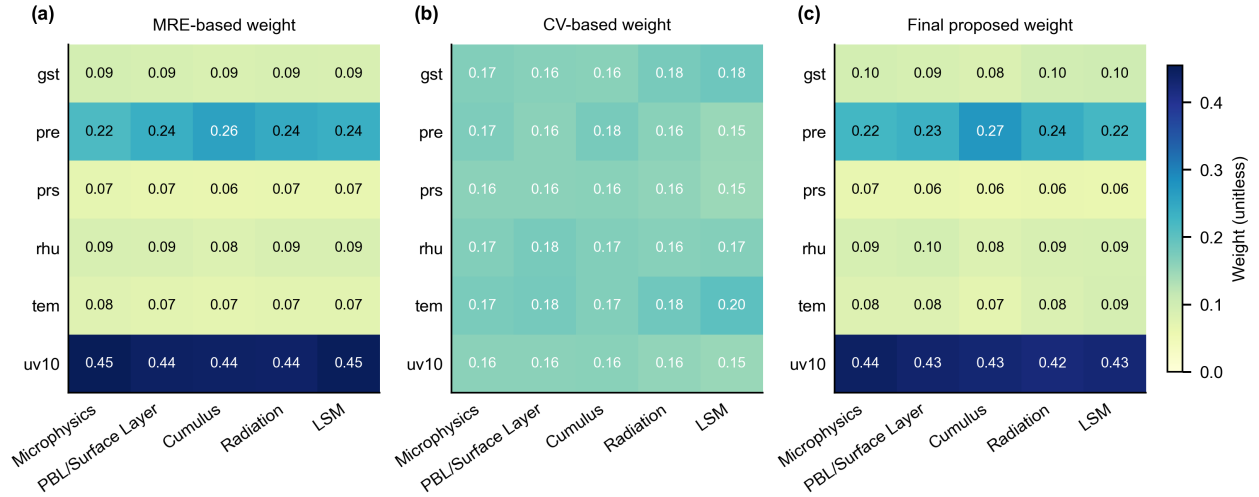


Figure 2. Weight distributions of the variables associated with the different physical processes of the WRF simulation in the arid region of Northwest. (a) MRE-based weight, (b) CV-based weight, and (c) final proposed weight. Weights are unitless.

3 Result

3.1 Optimal parameterization scheme combination for the arid region of Northwest

Figure 2 shows the weights assigned to variables in the WRF simulations of different physical processes for the arid region of Northwest using the proposed $\text{MRE} \times \text{CV}$ weighting method. Figure 2(a) shows the weights ω_{m1} assigned based on the mean relative error ($\overline{\text{MRE}_m}$), 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 ($\text{CV}_{|\text{ME}|_m}$) of the absolute error, where the weights for different variables showed considerable variation during the simulation process, reflecting differences in the 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 a strong response to alternative schemes in these two physical-process groups. In contrast, temperature 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.

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.

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, 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 stronger evaluated performance for wind speed and temperature 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 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

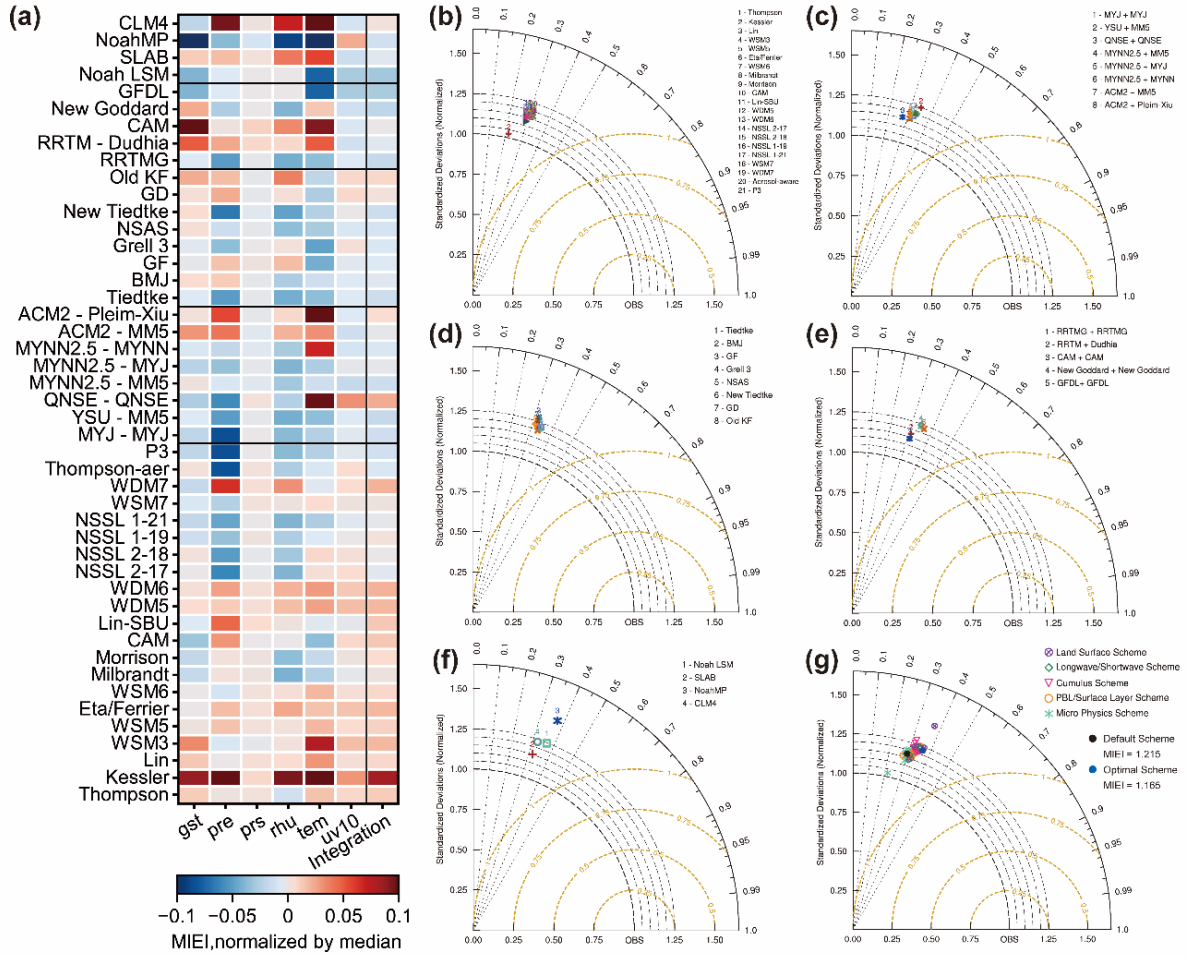


Figure 3. Evaluation results of parameterization schemes in the arid region of Northwest. (a) Normalized MIEI, with MIEI values normalized by the median MIEI value of the corresponding ensemble, and (b-f) Taylor diagrams of different physical processes. (b) Microphysics, (c) Planetary boundary layer, (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.

385 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
 390 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, 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), showing better evaluated agreement with the observed meteorological variables in 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 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 proposed $MRE \times CV$ weighting and equal weighting methods in the arid region of Northwest

In addition to employing the 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 proposed $MRE \times CV$ weighting and equal-weighting methods, providing a visual comparison of their respective performances. The optimal scheme identified through 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 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 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 high fitting degrees and simulated the changing trend of air pressure relatively accurately. For the simulation results of surface temperature and relative humidity, the 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 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 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 configuration selected by the proposed weighting scheme

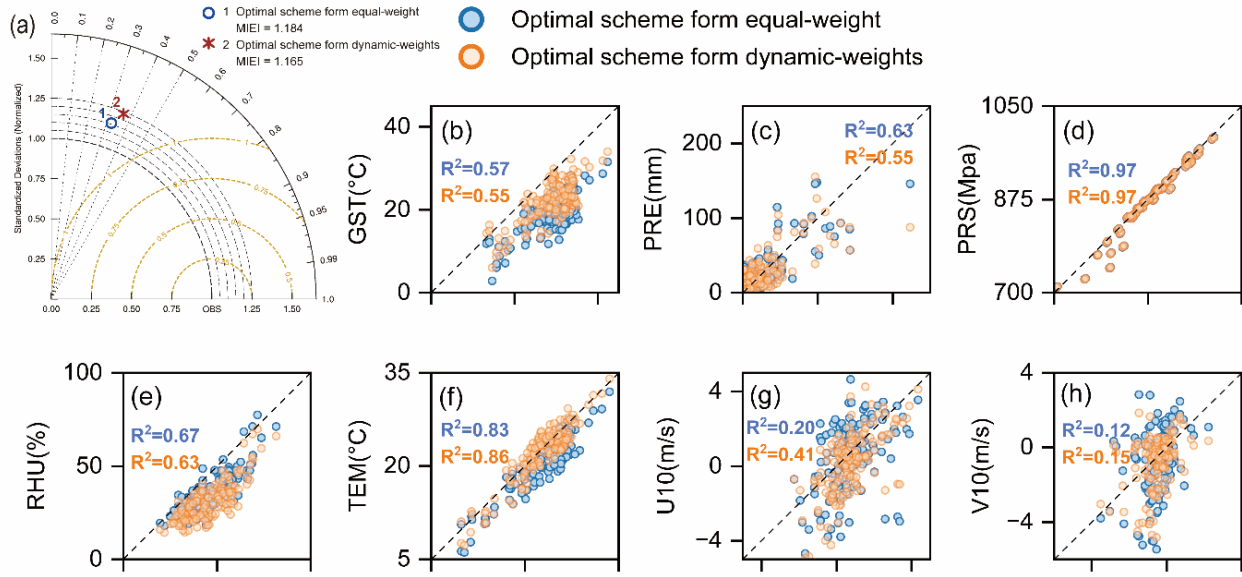


Figure 4. Comparison of simulation results obtained from the optimal parameterization schemes using the proposed $MRE \times CV$ weighting and equal weight methods. (a) Taylor plots of the optimal parameterization schemes obtained by different methods. (b-h) Scatter plots of the optimal parameterization 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.

reached 0.41 and 0.15, which were significantly higher than those of the equal weight scheme (0.20 and 0.12), indicating better evaluated agreement for wind speed. Although the simulation performances of some variables have slightly decreased, on the whole, the parameterization combination selected by the proposed $MRE \times CV$ weights showed better overall agreement with observed meteorological variability in the arid region of Northwest China 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 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

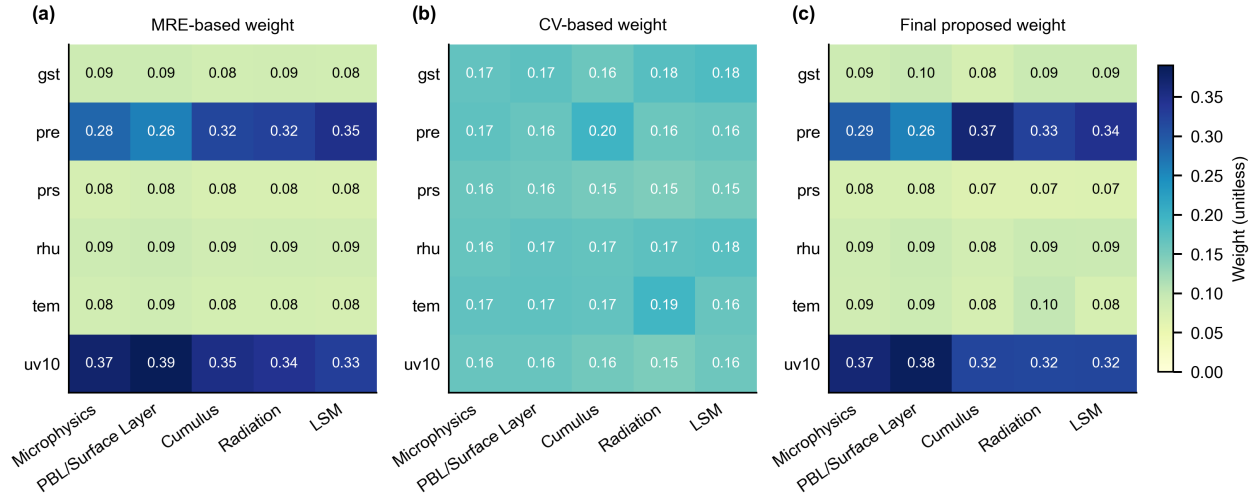


Figure 5. Weight distributions of the variables in the WRF simulations of the different physical processes in the coastal region of Southeast. (a) MRE-based weight, (b) CV-based weight, and (c) final proposed weight. Weights are unitless.

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.

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 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 that precipitation errors responded strongly to alternative cumulus schemes. In contrast, air temperature and surface temperature 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 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 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
455 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 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),
460 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
470 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
475 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
480 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, 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), showing better eval-
485 uated agreement with the observed meteorological variables in 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 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.

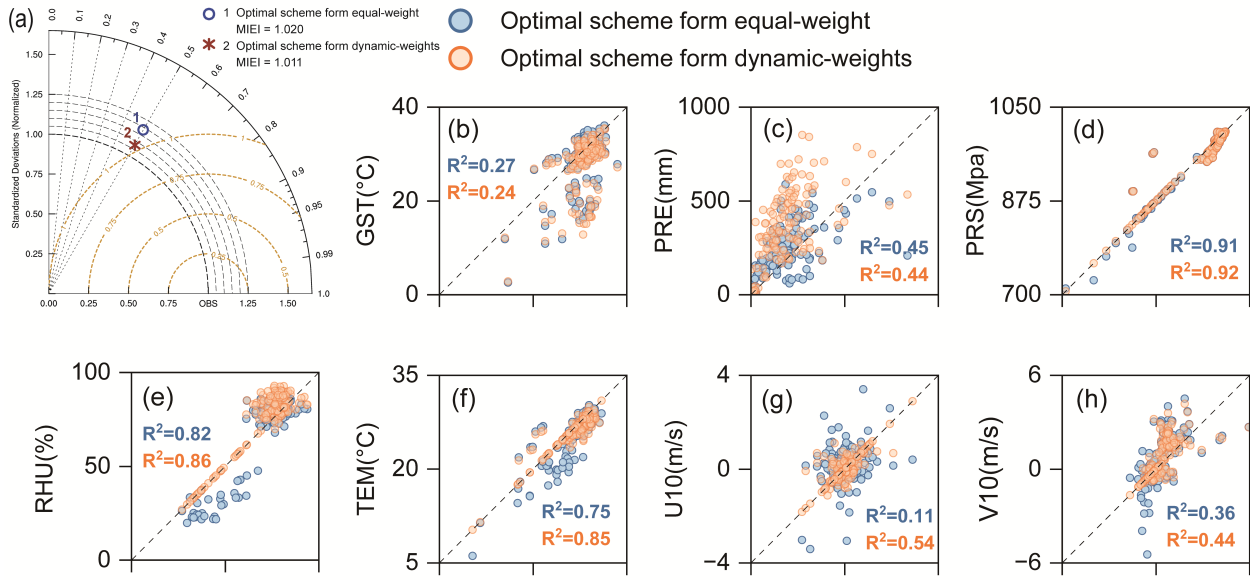


Figure 7. Comparison of simulation results obtained from the optimal parameterization schemes using the proposed $MRE \times CV$ weighting and equal weight methods. (a) Taylor plots of the optimal parameterization schemes obtained by different methods. (b-h) Scatter plots of the optimal parameterization 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.

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 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 configuration selected by the proposed weighting scheme yielded an R_s 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 configuration selected by the proposed weighting scheme achieved an R_s value of 0.92, effectively capturing the variability in air pressure. In the case of relative humidity, the configuration selected by the proposed weighting scheme outperformed the equal-weighting approach, with R_s values of 0.86 and 0.82, respectively.

The simulation of air temperature further highlighted the advantage of the configuration selected by the proposed weighting

approach, which yielded a substantially higher correlation and an R^2 of 0.85. For wind variables, the 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 wind. Overall, the parameterization combination selected by the proposed MRE $\times$ CV weighting method showed better overall agreement with observed meteorological variability in the coastal region of Southeast than the combination selected by the equal-weighting approach.

To further clarify how the proposed MRE $\times$ 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 pairwise MIEI difference between the MRE $\times$ CV-weight winner and the equal-weight winner changed sign, from positive under equal weighting to negative under MRE $\times$ CV weighting ($D_{eq} = 0.0047, 0.0074, \text{ and } 0.0013$; $D_{dyn} = -0.0056, -0.0119, \text{ and } -0.0059$ 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 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 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 coefficient-of-variation weighting, while assigning low weights to PRS and UV10. In Southeast China, both methods gave relatively high weights to GST,

540 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.

545 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,

550 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

555 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-

560 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.

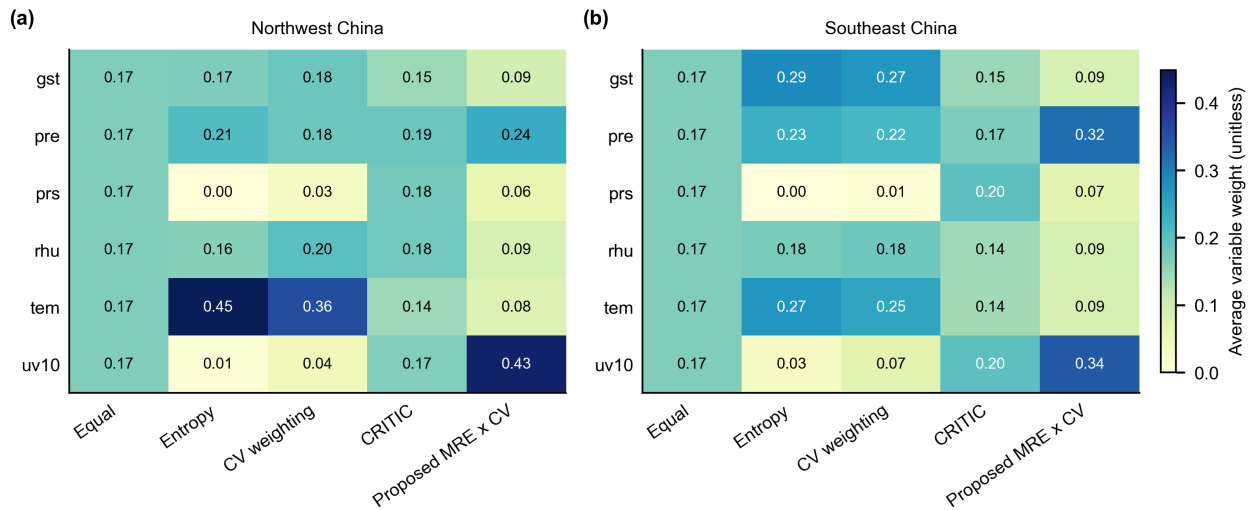


Figure 8. Comparison of average variable weights derived from equal weighting, entropy weighting, coefficient-of-variation weighting, CRITIC weighting, and the proposed MRE $\times$ CV weighting. Values represent averages across the five physical-process evaluation stages. (a) Arid region of Northwest 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: Performance comparison of the configurations selected by five weighting methods in the screening years. The selected configuration is identified by the weighting method used in the 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

Southeast China	2009	CV weighting	1.207	0.355	1.443	5
		CRITIC weighting	1.186	0.321	1.167	2
		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

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 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 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
		CRITIC weighting	1.017	0.504	1.065	3

4 Discussion

4.1 Evaluation meaning and weight-allocation mechanism

The performance-based multivariable weighting framework proposed in this study introduces a two-component mechanism for assigning 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 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 precipitation 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 proposed framework addresses this issue by ensuring that critical variables with large simulation errors or strong scheme-dependent responses consistently receive appropriate weighting, thereby maintaining their influence and visibility throughout the model evaluation.

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 $\text{MRE} \times \text{CV}$ weighting is designed to address a specific scientific problem in WRF parameterization screening: key variables with large simulation errors may be diluted in a multi-variable 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.

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.

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 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 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 response after surface forcing is

coupled with surface-layer and boundary-layer mixing, radiative forcing, and transport. The two variables may therefore show
640 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 defined outputs with distinct diagnostic
meanings, and orthogonalized components would be less directly interpretable for WRF parameterization-scheme screening.
645 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 connection of GST-related thermal information to
near-surface turbulent exchange, land-atmosphere coupling, and surface energy fluxes. The unchanged cumulus and radiation
650 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
wind remain difficult to simulate across regions. As physical parameterizations improve and variable-level errors become more
655 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 strong regional differences, indicating
that the scheme-dependent response of variable errors is closely related to the physical mechanisms represented by the can-
didate parameterization schemes. For instance, the pronounced response of precipitation errors within the microphysics and
660 cumulus groups is consistent with previous studies showing that these processes strongly influence precipitation simulation
(Tian et al., 2017; Liu et al., 2018). Similarly, the stronger response of surface temperature in the land surface group supports
the value of the method in capturing physically meaningful links between parameterization choices and variable-level model
performance (Liu et al., 2023).

4.2 Physical interpretation and practical meteorological relevance

665 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
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
670 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.

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 (Morrisson 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, 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 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 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 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 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.

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 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 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 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 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 representative-year screening and single independent extreme-year validation design used in this study was intended 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). 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 stepwise simulation method used in this study 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 therefore continue to introduce uncertainty (Zeng et al., 2016; Jia et al., 2023). To address the multivariable evaluation component of this problem, the proposed weighting framework adjusts variable weights during each stage of physical-process evaluation, ensuring that each process emphasizes the variables most affected by simulation error and scheme-dependent response.

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 is associated with lower evaluated wind-speed errors in subsequent processes, 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.

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 $\text{MRE} \times \text{CV}$ 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 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 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.

810 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 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, 815 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 820 attribute structural uncertainty to specific model components, nor does it solve model dependence, shared model genealogy, 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 825 multi-model ensembles and examine how it interacts with model-level weighting and structural-uncertainty attribution.

5 Conclusions

This study proposes 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 830 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 835 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 proposed $MRE \times CV$ weighting method includes P3, YSU, Tiedtke, GFDL, and Noah LSM. This configuration achieved lower integrated cMIEI than the configurations selected by the benchmark weighting methods under the present evaluation framework. Similarly, in 840 the coastal region of Southeast China, the optimal combination comprised WDM6, Shin-Hong-MM5, Grell 3, GFDL-GFDL, and Noah LSM, and it also achieved the lowest integrated cMIEI among the five weighting strategies. Compared with the configuration selected by equal weighting, the 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. These remaining biases indicate that the weighting method improves the evaluation and selection of parameterization schemes, whereas further refinement of WRF physical parameterizations remains necessary for representing complex weather systems and extreme events.

As parameterization schemes continue to evolve, 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 $\text{MRE} \times \text{CV}$ 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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