

Article

Evaluation of NEX-GDDP-CMIP6 and CMIP6 for Extreme High Temperature Frequency and Intensity in the Sichuan–Chongqing Region with Future Projections

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Abstract

Based on CN05.1 observational data, this study systematically evaluates the performance of the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) and the original Coupled Model Intercomparison Project Phase 6 (CMIP6) in simulating extreme high-temperature (EHT) events over the Sichuan–Chongqing region during 1981–2014. Furthermore, it projects changes in EHT indices under different emission scenarios for the mid- and late-21st century using the NEX-GDDP-CMIP6 dataset. The results indicate that NEX-GDDP-CMIP6 exhibits higher spatial correlation (>0.90) and lower root-mean-square error (RMSE) than CMIP6 in depicting the spatial distribution of maximum temperature ($T_{\max}$), with mean biases reduced from approximately $-2\text{ }^{\circ}\text{C}$ to within $1\text{ }^{\circ}\text{C}$. This dataset also captures the spatial patterns of EHT frequency (EHTF) and intensity (EHTI), although it exhibits a systematic underestimation of their magnitudes due to the inherent smoothing effect of the Bias Correction and Spatial Disaggregation (BCSD) method. The comprehensive TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranking shows that NEX-GDDP-CMIP6 generally ranks higher than the original CMIP6 in simulating EHT indices across all three weighting schemes and exhibits higher inter-model consistency, which further validates its overall applicability in the Sichuan–Chongqing region. Under the Shared Socioeconomic Pathway (SSP) scenarios SSP2-4.5 and SSP5-8.5, all 22 models project positive changes in $T_{\max}$, EHTF, and EHTI for both the mid- and late-21st century. The ensemble median increases reach approximately $5.5\text{ }^{\circ}\text{C}$ for $T_{\max}$, 28 days per year for EHTF, and $1.8\text{ }^{\circ}\text{C}$ for EHTI, which are 2–3 times the mid-century values and roughly double the corresponding increments under SSP2-4.5. The extreme heat hotspots are primarily located along the Sichuan–Chongqing border, with greater intensification and broader spatial coverage under SSP5-8.5 than under SSP2-4.5, indicating a progressive worsening of heatwave conditions across the study region.

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Keywords: model intercomparison; BCSD; TOPSIS; climate projection

1. Introduction

Since the early 21st century, global warming has driven an unprecedented rise in the frequency and intensity of record-breaking high temperatures worldwide [1,2]. Located in the transitional zone between the eastern Tibetan Plateau and the Sichuan Basin, the Sichuan–Chongqing (SC) region is influenced by the synergistic effects of complex topography and basin-related thermal forcing, making it one of the major hotspots for extreme high-temperature events across China [3,4]. Given its dense population and concentrated economic activity, the SC region is highly susceptible to EHT events, thereby severely straining public livelihoods, energy security, and industrial and agricultural production [5,6]. Therefore, skillful simulation and reliable projection of summer EHT events over this region are of critical importance for local disaster risk reduction and climate adaptation policymaking.

Global climate models serve as the primary tools for reproducing historical climates and projecting future scenarios. CMIP6 represents a notable advance over its predecessor, with improved physical parameterizations and enhanced grid resolutions that have led to better overall performance [7–9]. However, most CMIP6 models still operate at relatively coarse resolutions (approximately 0.5° to 3°), with considerable inter-model spread. Beyond resolution limitations, climate projections are also influenced by differences in model structure and climate sensitivity, along with internal climate variability. Furthermore, CMIP6 models are not fully independent, as some share common components or developmental lineages, which can introduce redundancy when models are simply averaged. Recent studies have therefore advocated for accounting for model independence, applying performance-based weighting, and exercising careful ensemble selection to better constrain projection uncertainties [10]. In topographically complex regions like the SC region with steep climatic gradients, these coarse-grid models often fail to sufficiently capture local topographic forcing. This limitation consequently introduces systematic biases and uncertainties into their output [11–13]. Hence, the incorporation of high-resolution, bias-corrected datasets has become indispensable for refining regional extreme-event simulations.

In response to these deficiencies, NASA has developed the NEX-GDDP-CMIP6 dataset, which applies the BCSD method to generate daily climate projections at a fine $0.25^\circ \times 0.25^\circ$ resolution for both historical and future periods [14]. By statistically correcting systematic biases and enhancing spatial detail, this product has been shown to substantially improve climate simulations over regions with complex terrain [15–18]. These improvements, however, vary across variables, regions, and climatic conditions. For instance, Dioha et al. [15] reported improvements in precipitation climatology across diverse climatic regions of Africa, while Yang et al. [17] showed enhanced representation of extreme high-temperature spatial patterns across China. Zhao et al. [19] found that bias correction improves some aspects of heatwave simulations but has limited effectiveness in correcting temporal autocorrelation and related heatwave characteristics. He et al. [20] demonstrated that the dataset effectively improves the representation of annual cycles, bimodal seasonal patterns and spatial precipitation structures, but struggles to capture long-term trends and interannual variability over South China. Although previous studies have compared these two datasets over many regions, a systematic intercomparison specifically for summer EHT events over the SC region has not yet been conducted. Zhang et al. [21] recently evaluated NEX-GDDP-CMIP6 performance over southwestern China, which encompasses the SC region, but their analysis focused solely on the downscaled product without benchmarking it against the original CMIP6 GCMs.

To fill this knowledge gap, this study examines the hypothesis that the NEX-GDDP-CMIP6 downscaled product outperforms the raw CMIP6 GCMs in representing summer EHT characteristics over the SC region. Specifically, we evaluate the performance of the

NEX-GDDP-CMIP6 data against its original CMIP6 counterparts and rank them using the TOPSIS multi-criteria decision framework for comprehensive skill assessment. This diagnostic comparison not only tests the hypothesis but also establishes a basis for assessing the credibility of future EHT projections derived from the NEX-GDDP-CMIP6 dataset. Building on this evaluation, we further examine projected changes in EHT events under the SSP2-4.5 and SSP5-8.5 scenarios for the mid- and late-21st century, using the heatwave hotspot index to identify sub-regions of pronounced change. By achieving these goals, this study seeks to clarify the applicability and limitations of the NEX-GDDP-CMIP6 dataset for EHT research over the SC region, providing a scientific foundation for regional heat risk prevention and energy security planning.

2. Data and Methodology

The overall workflow of this study is illustrated in Figure 1.

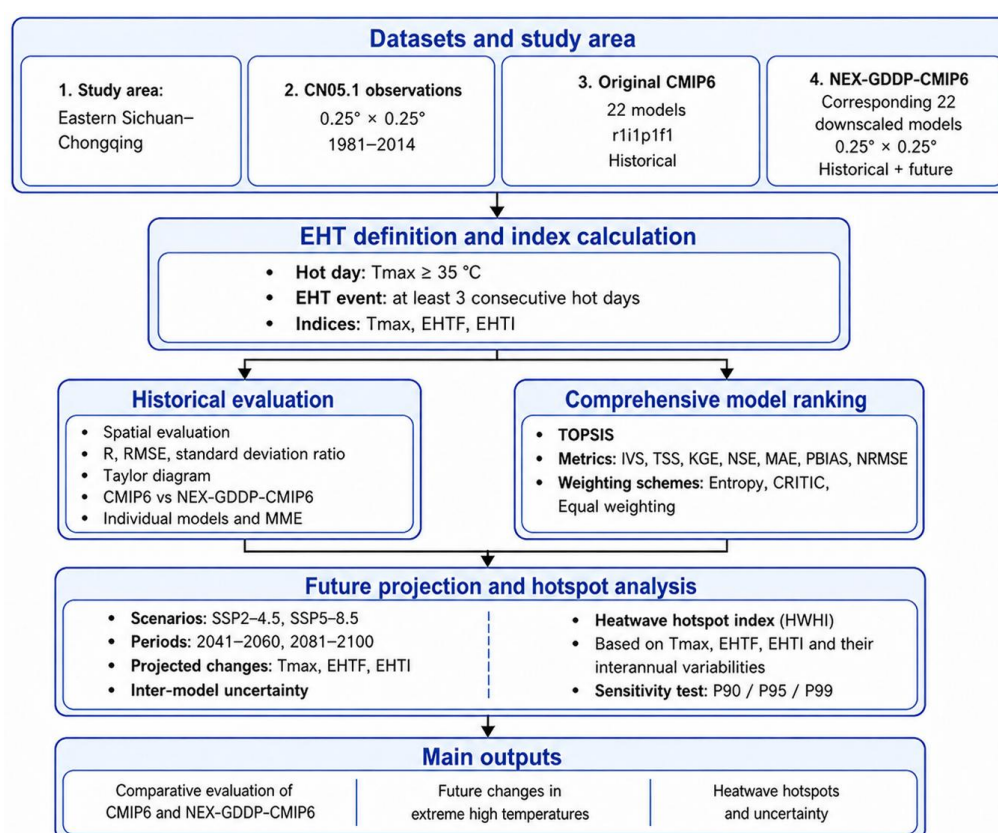


Figure 1. Schematic workflow of this study.

2.1. Study Area

The Sichuan–Chongqing (SC) region, comprising Sichuan Province and Chongqing Municipality in southwestern China, covers approximately 5.68×10^5 km² between 26–34° N and 97–110° E. The region exhibits a pronounced west–high, east–low elevational gradient (Figure 2a), which gives rise to a marked east–west thermal contrast during summer (July–August): mean daily Tmax exceeds 30 °C over the eastern basin but falls below 20 °C in the high-altitude western mountains (Figure 2b). Given the considerably cooler summer conditions and the rarity of EHT events in high-elevation western Sichuan, this study focuses on the eastern Sichuan–Chongqing basin, where EHT events occur with sufficient frequency for robust statistical evaluation. This domain is defined a priori, without reference to any model output, and all performance comparisons are conducted over this same fixed spatial domain. It should be noted that the results do not extend to the complex

climate-transition zones of western Sichuan, where contrasting topographic and thermal regimes may alter downscaling behavior.

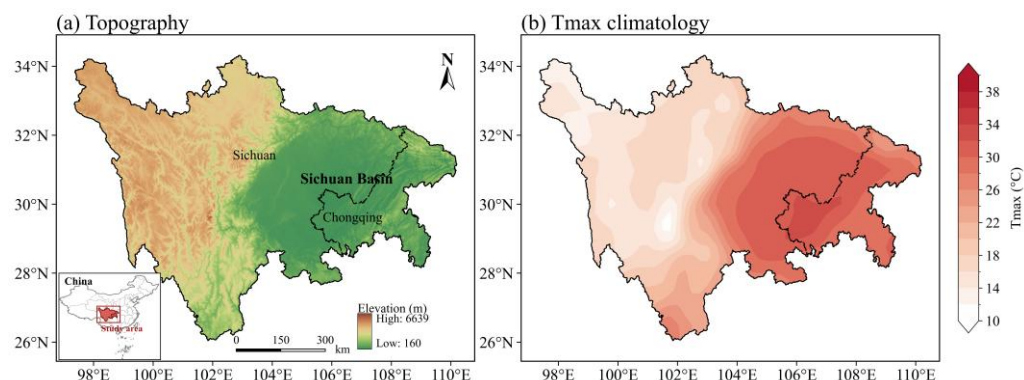


Figure 2. Geographic location and topography of the Sichuan–Chongqing region ((a); units: m) and climatological mean of Tmax for the period 1981–2014 ((b); units: °C).

2.2. Observational and Model Datasets

To evaluate the performance of both CMIP6 and NEX-GDDP-CMIP6 in simulating historical EHT events, we adopt the CN05.1 gridded dataset [22] as the observational reference. Spanning 1961–2022 at a $0.25^\circ \times 0.25^\circ$ resolution, CN05.1 is widely recognized for its ability to accurately capture regional climate features across China and has been extensively applied in model evaluation, regional climate diagnostics, and impact assessment studies.

For the model simulations, we utilize daily Tmax data from 22 CMIP6 models (Table 1). We use only the first realization (r1i1p1f1) to ensure consistency and focus on the multi-model ensemble (MME) mean response, while the associated uncertainty from internal variability is further assessed in the Section 4. Since the native CMIP6 outputs are provided at relatively coarse resolutions, they are interpolated to a $0.25^\circ \times 0.25^\circ$ grid via bi-linear interpolation to align with both CN05.1 and NEX-GDDP-CMIP6. This regridding is performed solely for inter-dataset comparability and does not enhance the effective resolution of the raw CMIP6 models. For the NEX-GDDP-CMIP6 dataset [14], which is derived from CMIP6 model simulations using the BCSD method, we employ the versions corresponding to the same 22 models and realization (r1i1p1f1) to ensure a strict one-to-one correspondence between the original and downscaled outputs. These models are chosen primarily based on data availability for daily Tmax in both datasets. Although this subset does not cover the full CMIP6 ensemble, the selected models originate from major independent modeling centers and span a broad range of climate sensitivities represented within the CMIP6 ensemble. In this study, we analyze the historical period 1981–2014 and two future periods: 2041–2060 and 2081–2100.

Table 1. Basic information of the 22 CMIP6 models used in this study.

No.	Model	Institution/Country	Resolution (Lon × Lat)
1	ACCESS-CM2	ACCESS/Australia	$1.9^\circ \times 1.3^\circ$
2	ACCESS-ESM1-5	ACCESS/Australia	$1.9^\circ \times 1.3^\circ$
3	BCC-CSM2-MR	CMA/China	$1.1^\circ \times 1.1^\circ$
4	CanESM5	CCCMA/Canada	$2.8^\circ \times 2.8^\circ$
5	CMCC-ESM2	CMCC/Italy	$1.3^\circ \times 1.9^\circ$
6	EC-Earth3	EC-Earth-Consortium	$0.7^\circ \times 0.7^\circ$
7	EC-Earth3-Veg-LR	EC-Earth-Consortium	$0.7^\circ \times 0.7^\circ$
8	GFDL-CM4	GFDL/USA	$1.3^\circ \times 1.0^\circ$
9	GFDL-ESM4	GFDL/USA	$1.3^\circ \times 1.0^\circ$
10	INM-CM4-8	INM/Russia	$2.0^\circ \times 1.5^\circ$
11	INM-CM5-0	INM/Russia	$2.0^\circ \times 1.5^\circ$

12	IPSL-CM6A-LR	IPSL/France	2.5° × 1.3°
13	KACE-1-0-G	NIMS-KMA/Republic of Korea	1.9° × 1.3°
14	KIOST-ESM	NIMS-KMA/Republic of Korea	1.9° × 1.3°
15	MIROC6	MIROC/Japan	1.4° × 1.4°
16	MPI-ESM1-2-HR	MPI/Germany	0.9° × 0.9°
17	MPI-ESM1-2-LR	MPI/Germany	1.9° × 1.9°
18	MRI-ESM2-0	MRI/Japan	1.1° × 1.1°
19	NESM3	NUIST/China	1.9° × 1.9°
20	NorESM2-LM	NCC/Norway	2.5° × 1.9°
21	NorESM2-MM	NCC/Norway	1.3° × 0.9°
22	TaiESM1	AS-RCEC/Taiwan, China	1.3° × 0.9°

2.3. Methods

2.3.1. Definition of EHT Events and Indices

Since relative thresholds may be affected by model-specific climatological biases, this study employs an absolute threshold to identify EHT events. According to the criteria of the China Meteorological Administration (CMA), a hot day is defined as $T_{\max} \geq 35^\circ\text{C}$ [23,24], and an EHT event comprises at least three consecutive hot days. Two indices are adopted to quantify EHT characteristics: (1) EHTF, the total number of hot days during July–August each year, and (2) EHTI, the mean $T_{\max}$ exceedance above 35°C during all EHT events.

2.3.2. Evaluation Metrics

The spatial agreement between model outputs and observations is evaluated using three statistical metrics: the spatial correlation coefficient (R), the root-mean-square error (RMSE), and the ratio of spatial standard deviations. These metrics are comprehensively visualized via Taylor diagrams [25], with CN05.1 as the reference field. In the Taylor diagram, the azimuthal angle of each model point indicates the spatial correlation with the reference, the radial distance from the origin represents the normalized spatial standard deviation, and the distance between the model point and the reference point is proportional to the centered RMSE.

2.3.3. Model Ranking by TOPSIS

We employ the TOPSIS method to systematically evaluate and compare the performance of NEX-GDDP-CMIP6 and the original CMIP6 models in simulating EHT events over the eastern SC region. As a widely used multi-criteria decision analysis method, TOPSIS ranks alternatives by their relative closeness to an ideal solution, providing a balanced and objective framework for model assessment [26]. We construct the evaluation system using seven indicators: Index of Variability Skill Score (IVS), Taylor skill score (TSS), Kling–Gupta Efficiency (KGE), Nash–Sutcliffe Efficiency (NSE), Mean Absolute Error (MAE), Percentage Bias (PBIAS), and Normalized Root Mean Square Error (NRMSE) (Table 2). These indicators assess model performance across multiple aspects, including spatial pattern consistency, interannual variability, goodness-of-fit, error magnitude, and systematic biases. To reduce the sensitivity of TOPSIS rankings to weighting choices, we compare three weighting schemes: the entropy weight method (C1), the Criteria Importance Through Intercriteria Correlation (CRITIC) method (C2), and equal weighting (C3). Consistency across these objectively and subjectively derived schemes would indicate the robustness of the evaluation, allowing us to focus on common patterns rather than interpreting any single weighting method in isolation. Further details of the TOPSIS procedure are described in He et al. [20].

Table 2. Model performance indicators.

	Evaluation Metric	Equation	Range	Ideal Value
1	IVS	$IVS = \left(\frac{\sigma_m}{\sigma_o} - \frac{\sigma_o}{\sigma_m}\right)^2$	0 to ∞	0
2	TSS	$TSS = \frac{4(1 + R_m)^2}{\left(\frac{\sigma_m}{\sigma_o} + \frac{\sigma_o}{\sigma_m}\right)^2 (1 + R)^2}$	0 to 1	1
3	KGE	$KGE = 1 - \sqrt{(R - 1)^2 + \left(\frac{\sigma_m}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_m}{\mu_o} - 1\right)^2}$	$-\infty$ to 1	1
4	NSE	$NSE = 1 - \frac{\sum_{i=1}^n (X_{i,o} - X_{i,m})^2}{\sum_{i=1}^n (X_{i,o} - \bar{X}_o)^2}$	$-\infty$ to 1	1
5	MAE	$MAE = \frac{1}{n} \sum_{i=1}^n X_{i,m} - X_{i,o} $	0 to ∞	0
6	PBIAS	$PBIAS = \frac{\sum_{i=1}^n X_{i,m} - X_{i,o} }{\sum_{i=1}^n X_{i,o}} \times 100\%$	$-\infty$ to ∞	0
7	NRMSE	$NRMSE = \frac{RMSE}{\bar{X}_o}$	0 to ∞	0

In Table 2, for the observations and model simulations, σ_o and σ_m denote the standard deviations, μ_o and μ_m the means, and $X_{i,o}$ and $X_{i,m}$ the values at the index i . $\bar{X}_o$ is the overall mean of the observations. Additionally, R represents the spatial correlation coefficient between the observations and simulations, and R_m is the maximum achievable correlation, which is set to 1 in this study. To facilitate the assessment of model accuracy, standard performance ratings were adopted based on previous studies. Specifically, IVS and MAE indicate better performance as their values approach 0. TSS approaches 1 for optimal skill, with values exceeding 0.8 generally representing strong model agreement [25]. KGE values above 0.75 indicate good performance, whereas values below 0.50 are deemed poor [27]. NSE values greater than 0.75 are considered good, and below 0.50 are considered unsatisfactory [28]. For PBIAS, absolute values within $\pm 10\%$, $\pm 10\text{--}15\%$, and $\pm 15\text{--}25\%$ are regarded as excellent, good, and satisfactory, respectively [28]. NRMSE below 10% indicates excellent performance, and above 30% indicate poor performance.

2.3.4. Heatwave Hotspot Index

Describing heatwaves using a single indicator, such as frequency, duration, or intensity, may fail to capture their inherently multidimensional and holistic nature [29–31]. To overcome this limitation, recent studies have adopted composite heatwave indices that integrate multiple characteristics, thereby providing a more comprehensive representation of EHT event evolution [31–34]. Following Sheng et al. [33], this study introduces the Standard Euclidean Distance (SED) approach to construct a heatwave hotspot index (HWHI) using six metrics: Tmax, EHTF, EHTI, and their respective interannual variabilities. The index is calculated as follows:

$$HWHI = \sqrt{\sum_t SED_t} \quad (1)$$

$$SED_t = \left(\frac{|\Delta t|}{P_{95}|\Delta t_{ij}|}\right)^2 \quad (2)$$

Here, t denotes one of the six metrics; $|\Delta t|$ is the absolute change in metric t at each grid point between the future periods and the reference period; and $P_{95}|\Delta t_{ij}|$ is the fixed normalization value for metric t . For each metric, $P_{95}|\Delta t_{ij}|$ is calculated as the 95th percentile of the pooled absolute changes across all valid grid cells, all 22 models, and all four

scenario–period combinations (SSP2-4.5 and SSP5-8.5 for 2041–2060 and 2081–2100). The 95th percentile is selected to balance sensitivity to extreme changes with robustness against outliers. A sensitivity analysis using the 90th and 99th percentiles confirms that the spatial patterns of HWHI are largely insensitive to this threshold choice. A larger HWHI value indicates a higher heatwave risk.

2.3.5. GenAI Tool

The authors used DeepSeekV4 (an AI language model) solely for language editing. No AI tools were used for data analysis, experimental design, or generation of research findings. The authors carefully reviewed all AI-generated suggestions and take full responsibility for the final content.

3. Results

3.1. Comparison of Model Simulation Performance

A comparative evaluation of the original CMIP6 models and the NEX-GDDP-CMIP6 downscaled products is conducted to assess their performance in simulating EHT events over the eastern SC region. We first examine the spatial patterns of summer daily Tmax during the period 1981–2014. Figures 3 and 4 present the spatial climatology simulated by the CMIP6 and NEX-GDDP-CMIP6 models, respectively, alongside the CN05.1 observational reference. The spatial correlation coefficient (R) between each model simulation and the observations is also indicated in the figures.

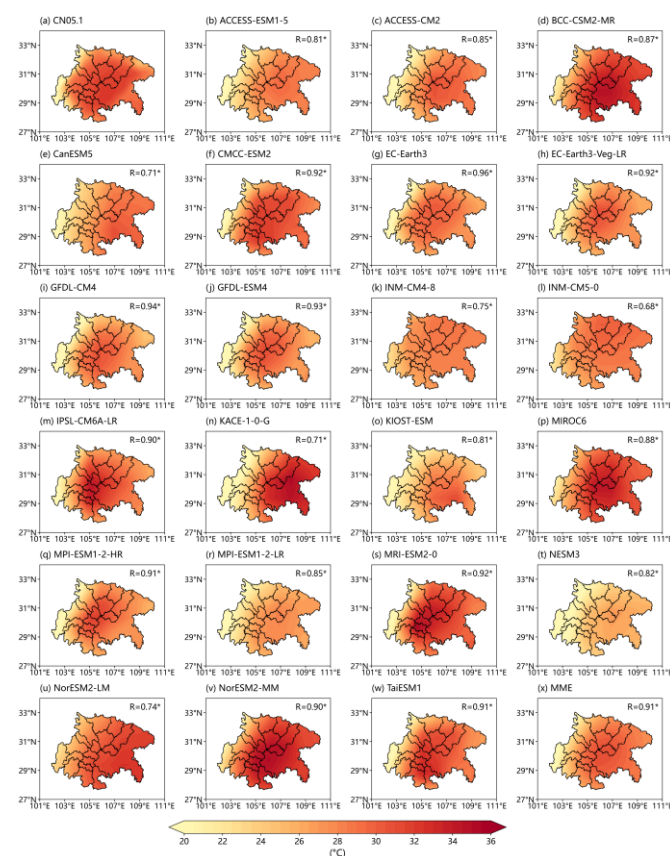


Figure 3. Climatological spatial distribution of daily Tmax during 1981–2014 from the original CMIP6 models and observations: (a) CN05.1; (b) ACCESS-ESM1-5; (c) ACCESS-CM2; (d) BCC-CSM2-MR; (e) CanESM5; (f) CMCC-ESM2; (g) EC-Earth3; (h) EC-Earth3-Veg-LR; (i) GFDL-CM4; (j) GFDL-ESM4; (k) INM-CM4-8; (l) INM-CM5-0; (m) IPSL-CM6A-LR; (n) KACE-1-0-G; (o) KIOST-ESM; (p) MIROC6; (q) MPI-ESM1-2-HR; (r) MPI-ESM1-2-LR; (s) MRI-ESM2-0; (t) NESM3; (u)

NorESM2-LM; (v) NorESM2-MM; (w) TaiESM1; and (x) MME. R denotes the spatial correlation coefficient relative to CN05.1, and * indicates significance at the 95% confidence level ($p < 0.05$).

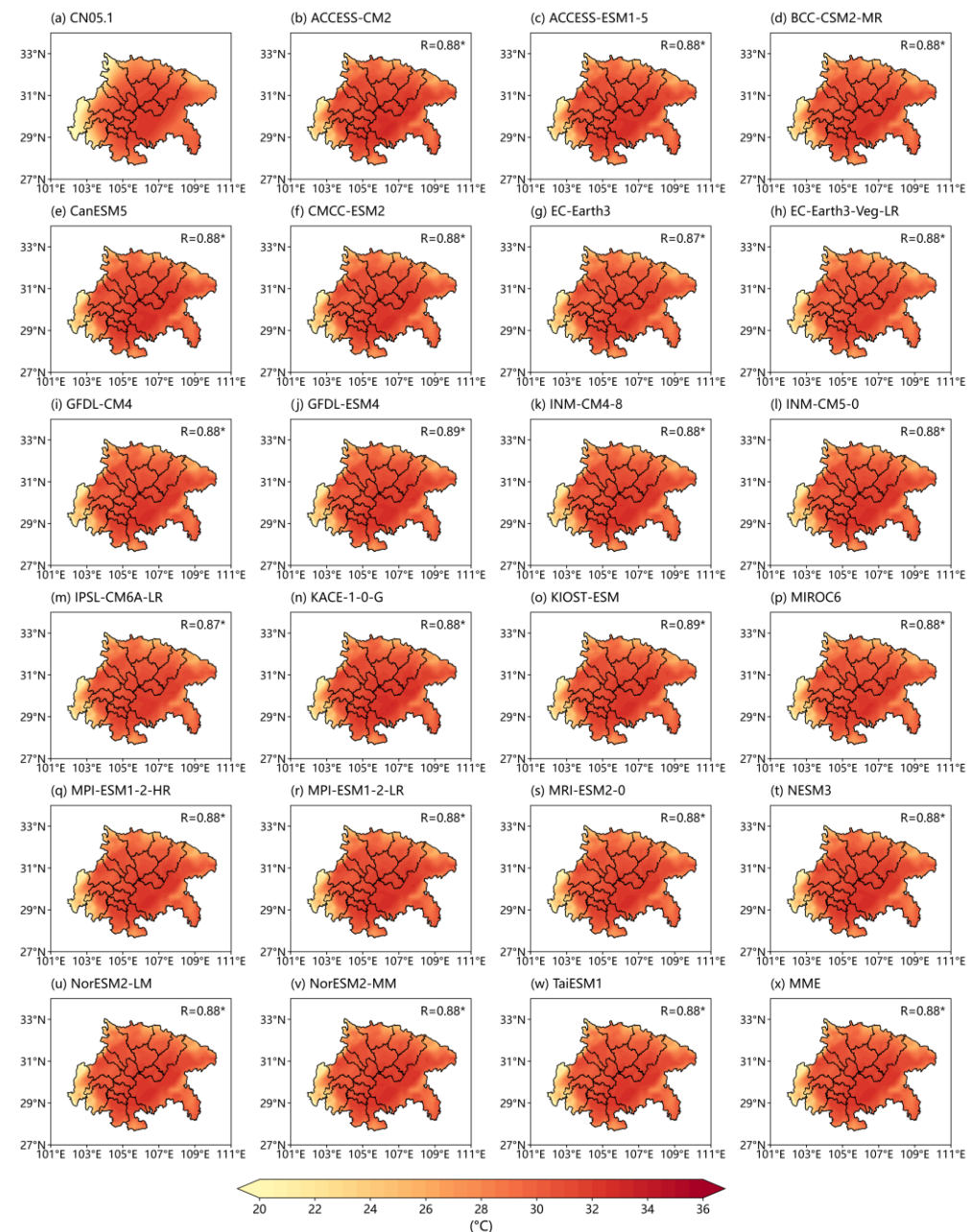


Figure 4. Same as Figure 3, but for the NEX-GDDP-CMIP6 models.

As shown in Figure 3, the raw CMIP6 models exhibit considerable variability in reproducing the observed summer Tmax distribution, with correlation coefficients ranging from 0.68 to 0.96. Despite these generally high spatial correlations, the models tend to systematically underestimate Tmax, with many biases exceeding $-2\text{ }^{\circ}\text{C}$ (Figures 3 and 5a). A notable example is EC-Earth3, which achieves the highest correlation ($R = 0.96$) yet retains a significant bias of $-1.8\text{ }^{\circ}\text{C}$. This discrepancy underscores that spatial correlation alone is an insufficient metric for performance assessment, as a high spatial correlation does not guarantee accuracy in magnitude.

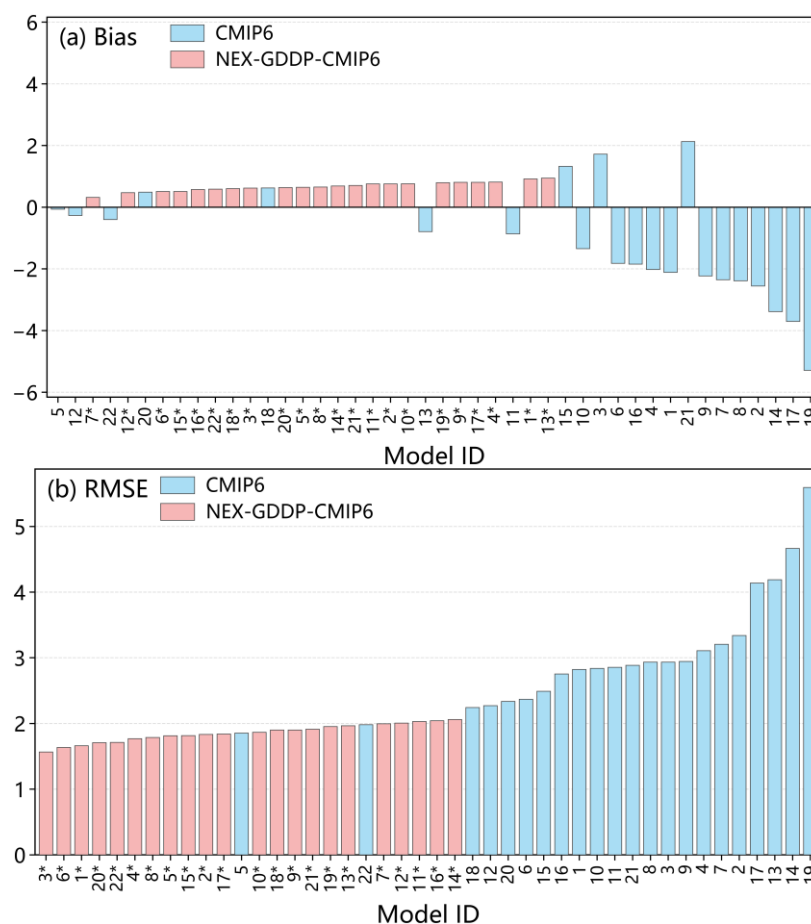


Figure 5. Performance evaluation of original CMIP6 models (blue) and NEX-GDDP-CMIP6 models (pink) for Tmax in eastern Sichuan–Chongqing region. (a) Bias; (b) RMSE. Numbers represent model identifiers as follows: 1: ACCESS-CM2; 2: ACCESS-ESM1-5; 3: BCC-CSM2-MR; 4: CanESM5; 5: CMCC-ESM2; 6: EC-Earth3; 7: EC-Earth3-Veg-LR; 8: GFDL-CM4; 9: GFDL-ESM4; 10: INM-CM4-8; 11: INM-CM5-0; 12: IPSL-CM6A-LR; 13: KACE-1-0-G; 14: KIOST-ESM; 15: MIROC6; 16: MPI-ESM1-2-HR; 17: MPI-ESM1-2-LR; 18: MRI-ESM2-0; 19: NESM3; 20: NorESM2-LM; 21: NorESM2-MM; 22: TaiESM1. Asterisks (*) denote the corresponding NEX-GDDP-CMIP6 models for each model ID.

In contrast, the NEX-GDDP-CMIP6 downscaled datasets demonstrate a distinct advantage over the raw CMIP6 outputs in terms of mean bias, which is generally reduced to within 1 °C (Figures 4 and 5a). Meanwhile, the RMSEs of NEX-GDDP-CMIP6 are significantly lower than those of the raw CMIP6 (Figure 5b). This improvement is consistent with the capability of the BCSD method in reducing systematic biases [14]. Furthermore, the NEX-GDDP-CMIP6 products maintain robust spatial correlation coefficients ($R = 0.87\text{--}0.89$) with small inter-model spread. Overall, these results indicate that the NEX-GDDP-CMIP6 products provide a more accurate depiction of the Tmax spatial distribution compared to the original CMIP6 models.

We next evaluate EHTF and EHTI to assess whether the NEX-GDDP-CMIP6 dataset can better reproduce the spatial distribution of EHT events over the eastern SC region relative to the raw CMIP6 outputs. An absolute threshold of 35 °C is adopted to define high-temperature days. CN05.1 observations reveal that summer EHTF and EHTI generally exhibit a spatial pattern decreasing from the center toward the edges (Figure 6a,d). The maximum centers for both indices are located in western Chongqing, specifically in its main urban area, where EHTF exceeds 10 days/yr and EHTI exceeds 1.2 °C. The NEX-GDDP-CMIP6 multi-model ensemble mean (MME) reproduces this spatial gradient well,

with high-value centers aligning closely with the observed locations and spatial correlation coefficients reaching 0.92 and 0.87 for EHTF and EHTI, respectively (Figure 6c,f). In contrast, the CMIP6 MME shifts the maximum centers westward from western Chongqing to the Sichuan–Chongqing border (Figure 6b,e). Thus, the NEX-GDDP-CMIP6 MME shows improved skill over the CMIP6 MME in simulating the spatial structure of EHT events, indicating that the downscaling process enhances the physical realism of regional spatial patterns. However, it should be noted that both MMEs underestimate the frequency and intensity of EHT events, with a more pronounced underestimation in the NEX-GDDP-CMIP6 MME.

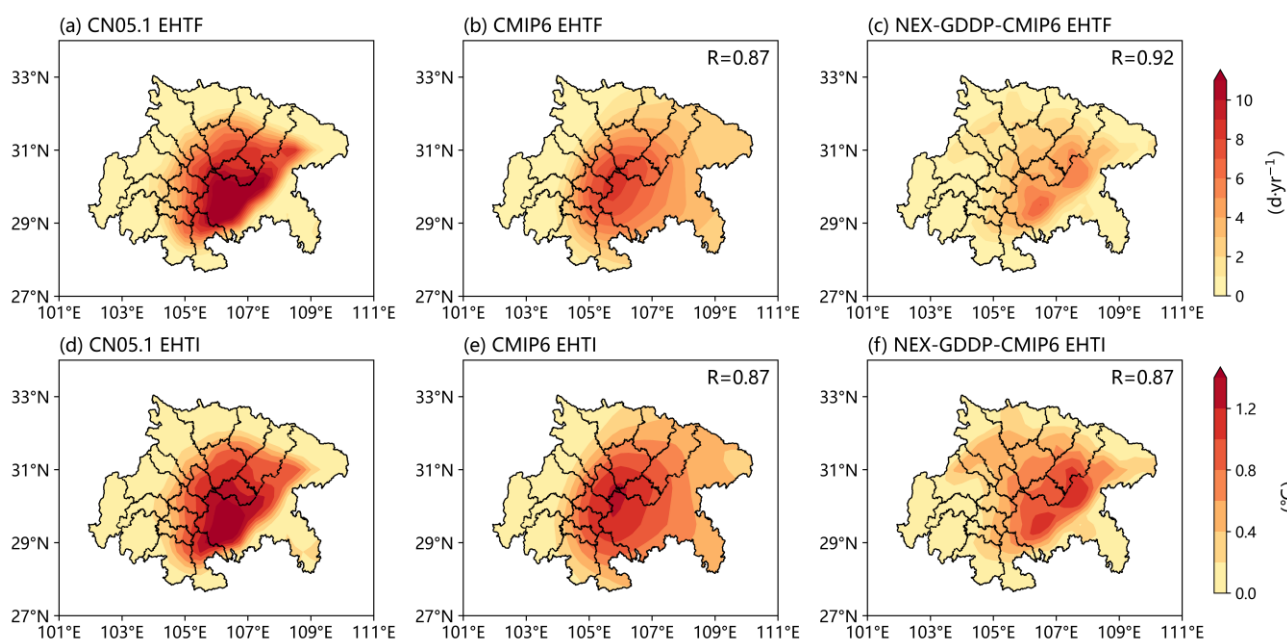


Figure 6. Climatological spatial distributions of EHTF (a–c) and EHTI (d–f) over the eastern SC region during 1981–2014, derived from CN05.1 observations (a,d), CMIP6 MME (b,e), and NEX-GDDP-CMIP6 MME (c,f).

Figure 7 presents the Taylor diagrams of the simulated EHT indices during 1981–2014. In terms of spatial correlation, the NEX-GDDP-CMIP6 MME (red diamond) achieves coefficients exceeding 0.90 for both EHTF and EHTI, compared with approximately 0.85 and 0.82 from the raw CMIP6 MME (blue diamond). Regarding standard deviation (SD), however, a distinct trade-off is observed. While the raw CMIP6 MME exhibits an SD closer to the reference observations, the downscaled NEX-GDDP-CMIP6 MME shows a substantially lower value, indicating that the BCSD downscaling method systematically suppresses spatial gradients and also reduces the inter-model spread. In addition, the downscaled models cluster more tightly around their MME than their raw CMIP6 counterparts in the Taylor diagram, a pattern quantitatively corroborated by the consistently smaller inter-model standard deviations of the three statistics for NEX-GDDP-CMIP6 relative to CMIP6 across both EHTF and EHTI (Table S1 in Supplementary Material). This narrowing reflects the reduced inter-model variability introduced by the common bias-correction procedure. These findings suggest that the NEX-GDDP-CMIP6 dataset substantially improves spatial pattern fidelity, but users should be aware that its representation of magnitude and spatial variability is constrained by the inherent smoothing effect of the BCSD method.

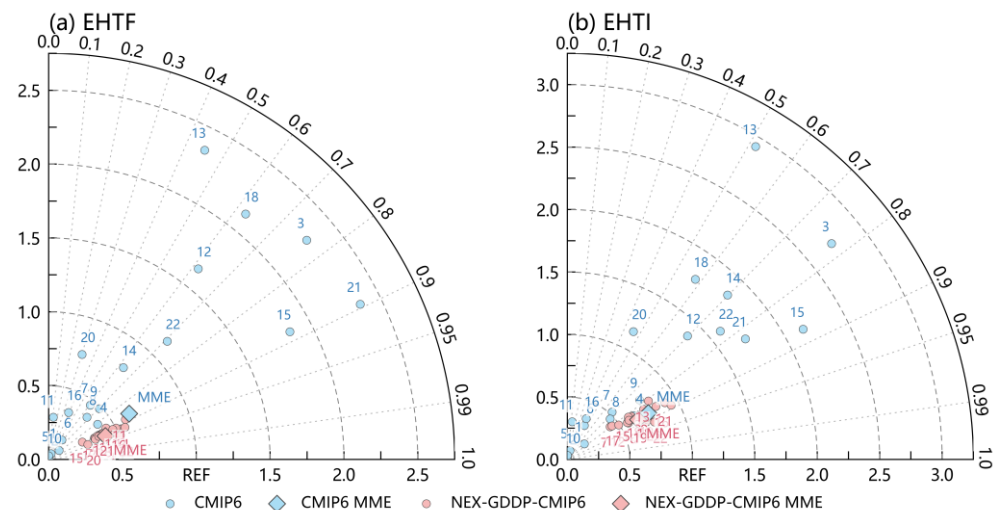


Figure 7. Taylor diagrams for (a) EHTF and (b) EHTI over the eastern SC region, comparing NEX-GDDP-CMIP6 (pink) and original CMIP6 (blue) simulations. Numbers represent model identifiers as follows: 1: ACCESS-CM2; 2: ACCESS-ESM1-5; 3: BCC-CSM2-MR; 4: CanESM5; 5: CMCC-ESM2; 6: EC-Earth3; 7: EC-Earth3-Veg-LR; 8: GFDL-CM4; 9: GFDL-ESM4; 10: INM-CM4-8; 11: INM-CM5-0; 12: IPSL-CM6A-LR; 13: KACE-1-0-G; 14: KIOST-ESM; 15: MIROC6; 16: MPI-ESM1-2-HR; 17: MPI-ESM1-2-LR; 18: MRI-ESM2-0; 19: NESM3; 20: NorESM2-LM; 21: NorESM2-MM; 22: TaiESM1.

To quantify the overall performance of the models, we further apply the TOPSIS method to rank them based on multiple evaluation metrics. Three weighting schemes are employed to minimize the dependence on any single approach. Figure 8 compares the composite scores of the 22 models. For Tmax (Figure 8a–c), most NEX-GDDP-CMIP6 models achieve higher scores than their original CMIP6 counterparts. Notable exceptions are found for six models, including CMCC-ESM2, EC-Earth3, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, and TaiESM1. For EHTF (Figure 8d–f), all NEX-GDDP-CMIP6 models except TaiESM1 rank higher than their CMIP6 counterparts. For EHTI (Figure 8g–i), NEX-GDDP-CMIP6 products consistently outrank their CMIP6 counterparts. Although the exact scores vary slightly across weighting methods, the overall pattern remains consistent: the NEX-GDDP-CMIP6 models rank consistently higher than the CMIP6 models in simulating EHT events over the eastern SC region. More detailed ranking information is provided in Tables S2–S7 of the Supplementary Material. These results suggest that, for most models and variables, bias correction and downscaling yield performance improvements, though exceptions exist.

To understand why downscaling degraded Tmax performance specifically for these exceptions, we further investigate this issue. As shown in Figure 9, these models exhibit a distinct drop in IVS scores after downscaling compared to their raw CMIP6 counterparts, suggesting that their original simulations already captured the Tmax interannual variability reasonably well. The BCSD method employed in NEX-GDDP-CMIP6 relies on quantile mapping, which, while effective for correcting mean biases, can inadvertently smooth out high-frequency variations. For these particular models, this smoothing effect appears to overcorrect the Tmax variability, leading to poorer IVS scores. This degradation is less pronounced for EHTF and EHTI because these compound indices depend more on the accurate representation of spatial patterns and threshold exceedances, both of which benefit from downscaling, rather than on the preservation of raw interannual variance.

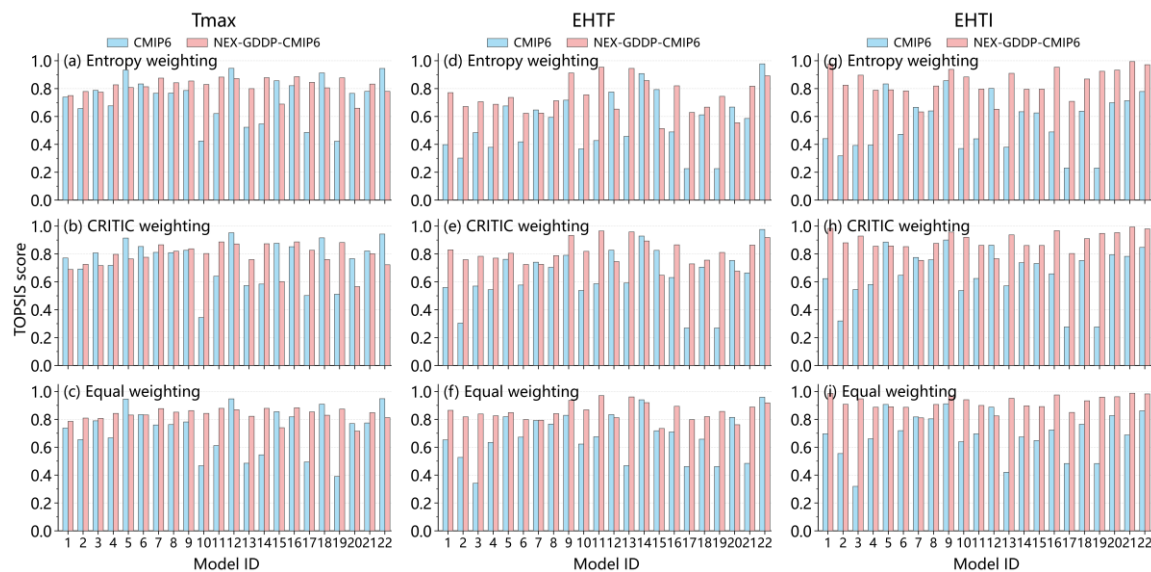


Figure 8. Model rankings based on the TOPSIS method for Tmax (a–c), EHTF (d–f), and EHTI (g–i) under three weighting schemes: (a,d,g) entropy, (b,e,h) CRITIC and (c,f,i) equal weighting. Pink bars denote NEX-GDDP-CMIP6 models and blue bars denote CMIP6 models. Model identifiers are as in Figure 5.

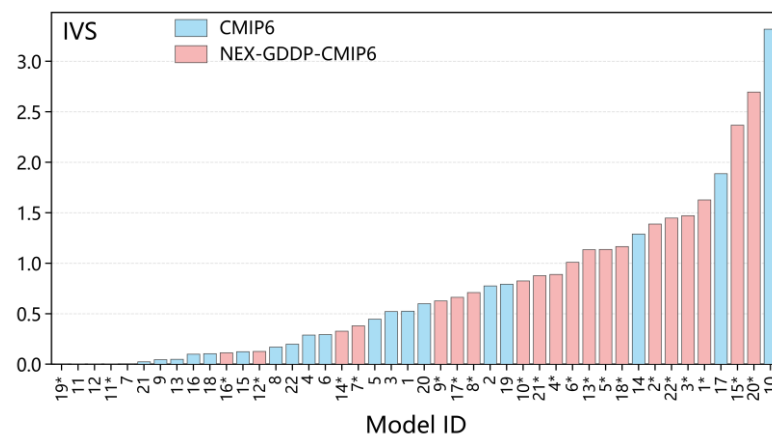


Figure 9. Comparison of performance IVS for Tmax between the original CMIP6 (blue) and NEX-GDDP-CMIP6 (pink) models in eastern Sichuan–Chongqing region. Numbers represent model identifiers as follows: 1: ACCESS-CM2; 2: ACCESS-ESM1-5; 3: BCC-CSM2-MR; 4: CanESM5; 5: CMCC-ESM2; 6: EC-Earth3; 7: EC-Earth3-Veg-LR; 8: GFDL-CM4; 9: GFDL-ESM4; 10: INM-CM4-8; 11: INM-CM5-0; 12: IPSL-CM6A-LR; 13: KACE-1-0-G; 14: KIOST-ESM; 15: MIROC6; 16: MPI-ESM1-2-HR; 17: MPI-ESM1-2-LR; 18: MRI-ESM2-0; 19: NESM3; 20: NorESM2-LM; 21: NorESM2-MM; 22: TaiESM1. Asterisks (*) denote the corresponding NEX-GDDP-CMIP6 models for each model ID.

3.2. Projection of Future Changes in EHT

The analysis in the previous section shows that, compared with the original CMIP6 data, the NEX-GDDP-CMIP6 dataset significantly improves the spatial representation and reduces the biases in simulating EHT events over the eastern SC region. Therefore, this section uses the NEX-GDDP-CMIP6 MME to project the future evolution of extreme high temperatures. Figures 10 and 11 present the spatial patterns of changes in Tmax, EHTF, and EHTI relative to the baseline period (1981–2014) for the mid- (2041–2060) and late- (2081–2100) 21st century under the SSP2-4.5 and SSP5-8.5 scenarios, respectively.

In the mid-term period, the increases in Tmax under SSP2-4.5 and SSP5-8.5 are 1.5–2.5 °C (Figure 10a) and 2–3 °C (Figure 10d), respectively. For EHTF, the adjacent areas of

Chongqing and Sichuan serve as centers of increase, with increases of 10–20 days (Figure 10b) and 15–25 days (Figure 10e) under the two scenarios, while the increases in the remaining regions generally range from 0 to 5 days. Spatially, the increase in EHTI under SSP2-4.5 is relatively uniform, ranging from 0.5 to 1.0 °C (Figure 10c). Under SSP5-8.5, northern Sichuan shows a larger increase than other regions, reaching 1.0–1.5 °C (Figure 10f).

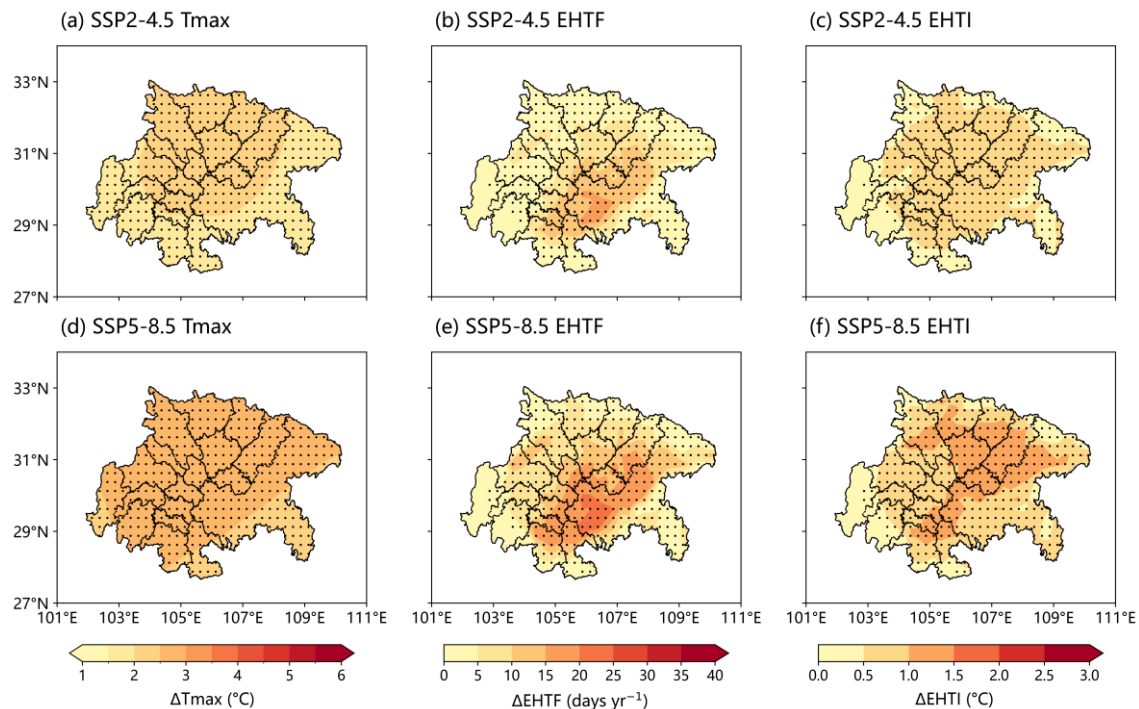


Figure 10. Spatial distribution of NEX-GDDP-CMIP6 MME extreme high temperature index anomalies for 2041–2060 relative to the historical reference period (1981–2014) under the SSP2-4.5 (a–c) and SSP5-8.5 (d–f) scenario: (a,d) Tmax; (b,e) EHTF; (c,f) EHTI. Stippling indicates grid cells where the projected changes are statistically significant at the 95% confidence level.

By the end of the 21st century, the spatial patterns of all indices are generally consistent with those in the mid-term period, but the magnitudes of increase are substantially larger, particularly under the SSP5-8.5 scenario (Figures 10 and 11). Under SSP2-4.5, the increases in Tmax, EHTF, and EHTI reach 2.5–3.5 °C (Figure 11a), 5–25 days (Figure 11b), and 1.0–1.5 °C (Figure 11c), respectively. Under SSP5-8.5, the increases in certain parts of the study region can exceed 4.5 °C for Tmax (Figure 11d), 30 days for EHTF (Figure 11e), and 2 °C for EHTI (Figure 11f). These magnitudes are also consistent with previous regional assessments [21], though quantitative estimates should be interpreted with caution due to extrapolation uncertainties inherent to the statistical downscaling.

Figure 12 further illustrates that all 22 NEX-GDDP-CMIP6 models project positive changes in regional mean Tmax, EHTF, and EHTI under both SSP2-4.5 and SSP5-8.5 for the mid- (2041–2060) and late-21st century (2081–2100). Crucially, the lower whiskers of the boxplots remain above zero across all scenarios and periods, indicating that even the least sensitive models predict a robust increase. This provides high confidence in the projected warming trends despite inter-model uncertainties. Under SSP2-4.5, the ensemble median increases by the mid-century are approximately 2.0 °C for Tmax, 5 days/yr for EHTF, and 0.6 °C for EHTI. By the late century, these values rise to approximately 3.0 °C, 10 days/yr, and 1.0 °C, respectively. Under SSP5-8.5, the corresponding mid-century median increases are ~2.5 °C for Tmax, ~8 days/yr for EHTF, and ~0.7 °C for EHTI. By the late century, the median increases reach approximately 5.5 °C for Tmax, 28 days/yr for EHTF,

and 1.8 °C for EHTI. Notably, the late-century distributions under SSP5-8.5 and SSP2-4.5 show minimal overlap for all three indicators, indicating robust scenario separation despite the greater inter-model spread under higher forcing.

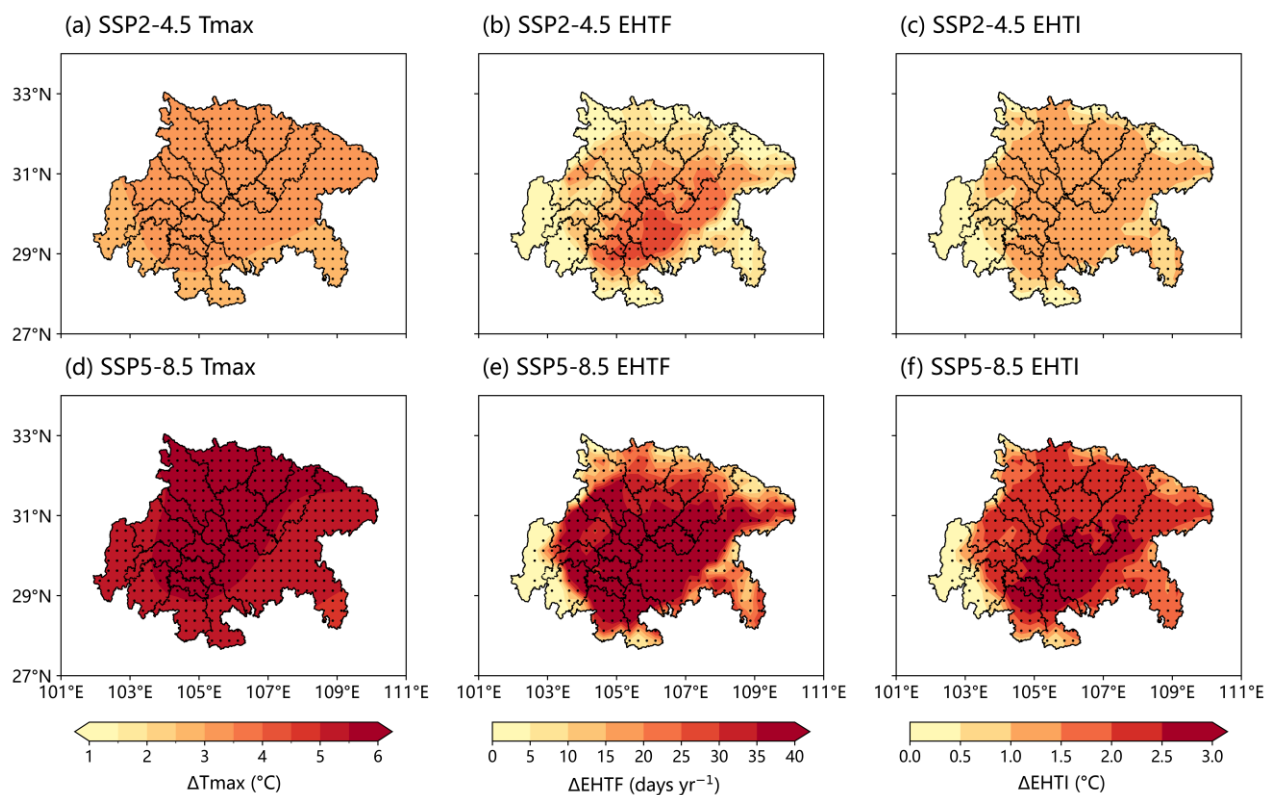


Figure 11. Same as Figure 10, but for 2081–2100.

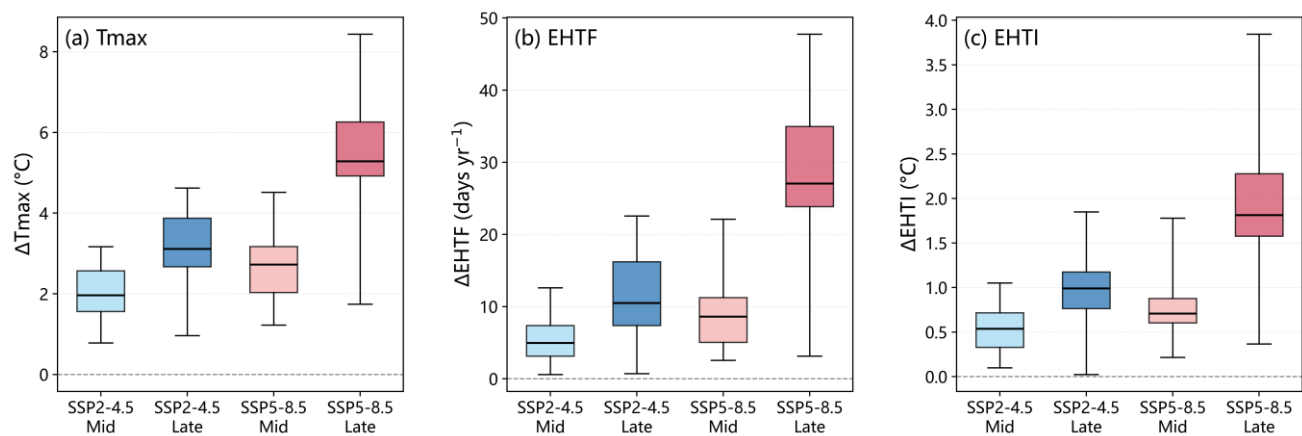


Figure 12. Inter-model uncertainty in future changes in (a) Tmax, (b) EHTF, and (c) EHTI over the Sichuan–Chongqing region during the mid- and late 21st century based on 22 NEX-GDDP-CMIP6 models.

In terms of the heatwave hotspot index, under the SSP2-4.5 scenario, the hotspot areas are mainly located along the Sichuan–Chongqing border during the mid-21st century (Figure 13a,e,i). By the end of the 21st century, the HWHI values increase significantly across the entire study area (Figure 13c,g,k). In contrast, the HWHI values under the SSP5-8.5 scenario (Figure 13b,d,f,h,j,l) are consistently larger than those under the SSP2-4.5 scenario during the same periods, and are notably higher for 2081–2100 than for 2041–2060.

A sensitivity analysis using the 90th and 99th percentiles confirms that the spatial patterns of HWHI are robust to the choice of normalization percentile.

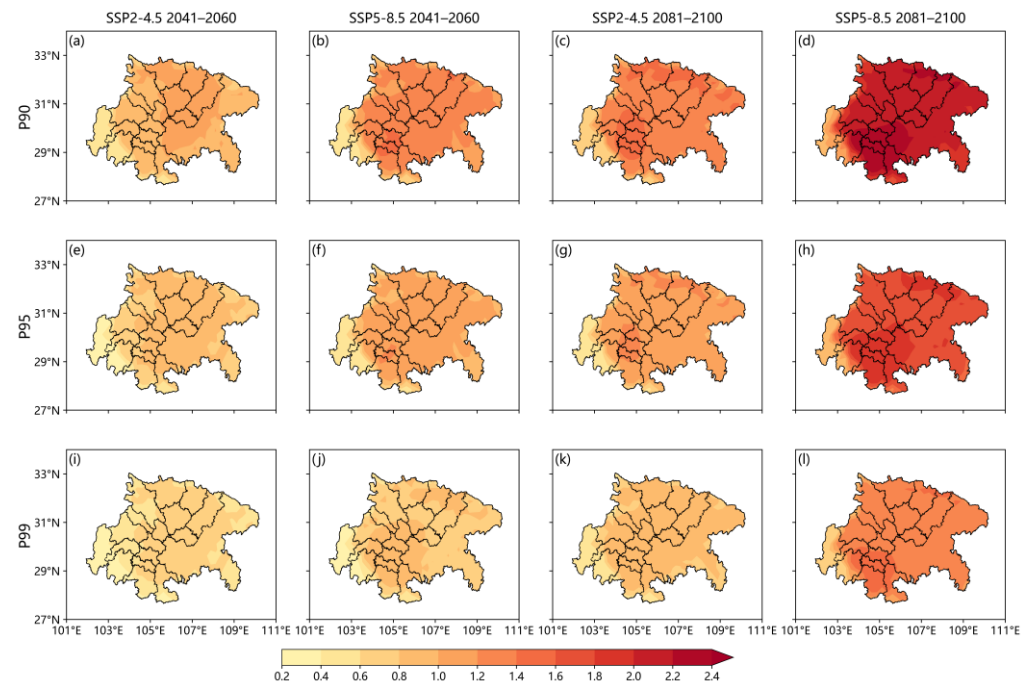


Figure 13. Spatial distribution of heatwave hotspot index (HWHI) under the SSP2-4.5 and SSP5-8.5 scenarios for 2041–2060 and 2080–2100 using P90 (a–d), P95 (e–h) and P99 (i–l) as the normalization denominator.

Figure 14 further illustrates the inter-model uncertainty in HWHI under the three normalization schemes (P90, P95, and P99). Crucially, the absolute magnitude of HWHI naturally decreases from P90 to P99 due to the increasing normalization scale, but the relative differences among scenarios and periods remain highly consistent. Specifically, HWHI consistently increases toward the late 21st century and is significantly higher under SSP5-8.5 than under SSP2-4.5 across all thresholds. Furthermore, the boxplots reveal that the inter-model spread widens in the late century, particularly under SSP5-8.5, highlighting greater uncertainty in the magnitude of future hotspot intensification under high-emission scenarios. These results confirm that our main conclusions regarding the spatio-temporal evolution of heatwave hotspots are robust to the choice of normalization percentile.

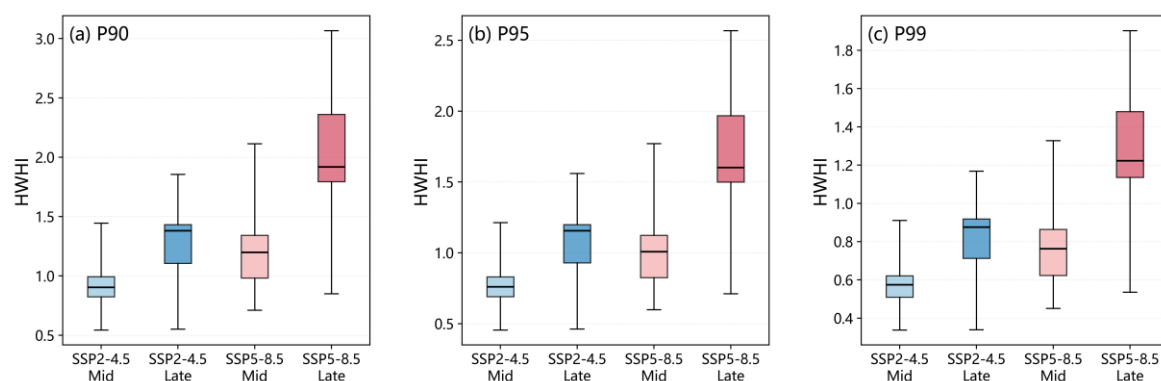


Figure 14. Inter-model uncertainty in regional mean heatwave hotspot index (HWHI) using (a) P90, (b) P95, and (c) P99 normalization under SSP2-4.5 and SSP5-8.5 during the mid- and late 21st century, based on 22 NEX-GDDP-CMIP6 models.

In summary, under both SSP2-4.5 and SSP5-8.5 scenarios, the T_{max} , EHTF, EHTI, and HWHI indices are projected to rise markedly during both mid- and late-21st century. These increases become more evident with time and higher radiative forcing levels, suggesting that EHT events in the SC region will become more frequent and severe, escalating heatwave risk continuously.

4. Discussions

Despite the improved spatial correlation and inter-model consistency achieved by the NEX-GDDP-CMIP6 MME relative to the original CMIP6 outputs, it still notably underestimates EHTF and EHTI magnitudes, likely due to its limited skill in reproducing T_{max} interannual variability (Figure 8). First, the BCSD method adjusts statistical distributions but inevitably smooths interannual and low-frequency climate signals [20,35]. Second, because BCSD applies univariate bias correction independently to each variable, it may alter the physical consistency among variables (e.g., temperature and humidity) that is inherently maintained in the original GCMs [36]. Third, the downscaled outputs inherit biases from the parent GCMs [35]. In addition, while the CN05.1 reference data, derived from station interpolation, may introduce additional uncertainties across the complex terrain of the Sichuan–Chongqing region, the statistical relationships assumed in BCSD itself may also be less valid in such topographically complex areas, potentially limiting the reliability of the downscaled results [37,38]. Furthermore, because the BCSD method's quantile mapping relies on statistical relationships derived from the historical reference period (1960–2014), future projections extending beyond the historical training range are subject to extrapolation uncertainties—a known limitation of the NEX-GDDP-CMIP6 dataset. We partially mitigate these uncertainties by using the multi-model ensemble mean, which reduces the influence of internal variability and individual model biases. However, total projection uncertainty can be decomposed into three dominant sources: internal climate variability, model response uncertainty, and scenario uncertainty [19,39,40]. Under the high-emission SSP5-8.5 pathway, scenario uncertainty becomes progressively dominant toward the end of the century, whereas internal variability remains non-negligible at regional scales [39]. Consequently, quantitative estimates for the late-century SSP5-8.5 scenario should be interpreted with caution. It should also be noted that we apply equal weighting to all 22 models without explicitly filtering for model independence. While this preserves the one-to-one comparison between each downscaled product and its parent GCM, it may introduce ensemble redundancy due to shared model components among some CMIP6 models. Future work could adopt independence-based model selection or performance-weighted averaging to refine ensemble uncertainty estimates.

A threshold of 35 °C is used in this study to define hot days, consistent with the operational definition of the China Meteorological Administration. Given the systematic T_{max} biases in CMIP6 and NEX-GDDP-CMIP6 simulations over the Sichuan–Chongqing region, a model-specific percentile threshold would yield inconsistent baselines that complicate cross-model and cross-dataset comparisons. The uniform 35 °C threshold therefore ensures a consistent, physically interpretable benchmark. We acknowledge that a fixed threshold does not account for shifting climatic baselines or physiological acclimatization, and we suggest that future studies examine the sensitivity of the results to relative thresholds.

A further limitation is that this study focuses primarily on EHTF and EHTI, without considering other widely used heatwave metrics such as heatwave duration (HWD), heatwave magnitude index (HWMi), warm spell duration index (WSDI), and excess heat factor (EHF). These indices provide complementary information on different dimensions of heatwave characteristics, and have been increasingly adopted in recent heatwave assessments [41–43]. The exclusion of these metrics means that our evaluation does not capture

the full multi-dimensional nature of heatwave events. Future work should extend the assessment to include a broader suite of extreme temperature indices to provide a more comprehensive evaluation.

It is important to note that this study focuses on climate projection and statistical downscaling evaluation, rather than event attribution. Previous studies suggest that changes in extreme heat may be associated with large-scale circulation anomalies, soil moisture–temperature feedbacks, and urban heat island effects [6,44,45]. These processes are not directly examined here because this study focuses on model evaluation and future changes in extreme heat. Future work should therefore consider atmospheric circulation, soil moisture, surface energy balance, and urbanization to better understand the underlying mechanisms. Nevertheless, recent attribution studies have demonstrated that the intensification of heatwaves over East Asia is increasingly linked to anthropogenic greenhouse gas forcing [46,47]. Consistent with this attribution, our projections show that late-century increases under SSP5-8.5 are approximately double those under SSP2-4.5, reflecting stronger radiative forcing. This divergence highlights the efficacy of mitigation in reducing future EHT risks. However, the wider inter-model spread under SSP5-8.5 indicates greater uncertainty at higher forcing levels, suggesting caution when interpreting the magnitude of changes under the most extreme scenario.

Building on these scenario differences, an important dimension not explicitly quantified in this study is the time of emergence (ToE) of anthropogenic heat-stress signals. Recent studies indicate that the forced response of temperature extremes may emerge from the noise of internal variability at different times across sub-regions, depending on local land–atmosphere feedbacks and topographic modulation [48,49]. While our analysis emphasizes end-of-century changes under SSP5-8.5, the ToE for EHTF and EHTI over the Sichuan–Chongqing region warrants future investigation to better inform near-term adaptation planning. Furthermore, this study does not assess probability distributions, extreme quantiles, or return periods of EHTF and EHTI, which would require a dedicated extreme-value statistical framework and are therefore left for future work.

5. Conclusions

This study systematically evaluates the simulation performance of the NEX-GDDP-CMIP6 dataset and the original CMIP6 models in reproducing extreme high-temperature events over the Sichuan–Chongqing region during 1981–2014, using CN05.1 observational data as the benchmark. The TOPSIS multi-criteria decision method is applied to rank the model performance comprehensively. Finally, future changes in extreme high-temperature events are projected based on the NEX-GDDP-CMIP6 MME. The main conclusions are as follows:

- (1) Although both the original CMIP6 and NEX-GDDP-CMIP6 models show high spatial correlation coefficients for T_{max} against observations, the NEX-GDDP-CMIP6 MME achieves coefficients exceeding 0.90, notably surpassing those of the original CMIP6 MME (approximately 0.85). The original CMIP6 models generally underestimate T_{max} , with mean biases often exceeding $-2\text{ }^{\circ}\text{C}$, and exhibit large inter-model spread. In contrast, the NEX-GDDP-CMIP6 ensemble shows smaller inter-model differences and substantially lower biases (reduced to within $1\text{ }^{\circ}\text{C}$) and lower RMSE in T_{max} , indicating that the BCSD method effectively reduces systematic biases. However, this method also systematically suppresses spatial gradients and reduces inter-model spread, and for six models whose raw simulations already captured T_{max} interannual variability well, the smoothing effect overcorrects variability and thereby degrades IVS performance.
- (2) Both the original CMIP6 and NEX-GDDP-CMIP6 MME are able to capture the large-scale spatial patterns of EHTF and EHTI, with correlation coefficients exceeding 0.85.

The NEX-GDDP-CMIP6 MME exhibits higher spatial fidelity, particularly in accurately delineating the maximum center of these indices over western Chongqing, although it still underestimates their magnitudes. The comprehensive TOPSIS ranking shows that, under all three weighting schemes, NEX-GDDP-CMIP6 ranks consistently higher than the original CMIP6 in simulating EHTF and EHTI, indicating improved overall performance in representing extreme high-temperature events over the Sichuan–Chongqing region.

- (3) The NEX-GDDP-CMIP6 MME projects that Tmax, EHTF, EHTI, and the hotspot index HWHI over the Sichuan–Chongqing region will increase markedly over time and with rising radiative forcing, with late-century increases under SSP5-8.5 reaching approximately 5.5 °C for Tmax, 28 days/yr for EHTF, and 1.8 °C for EHTI, which are roughly 2–3-fold those in the mid-century and approximately double those under SSP2-4.5. All 22 models project positive changes, providing high confidence in the projected warming trends despite inter-model uncertainties. These results indicate more frequent and intense heatwaves and growing high-temperature risks in the future. Furthermore, the projected changes in HWHI are robust across the P90, P95, and P99 normalization schemes, confirming that the main conclusions regarding the spatiotemporal evolution of heatwave hotspots are insensitive to the choice of normalization percentile.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/atmos17090886/s1>. Table S1: Inter-model standard deviations of the Taylor-diagram statistics for EHTF and EHTI from the CMIP6 and NEX-GDDP-CMIP6 models; Table S2: Evaluation metrics and TOPSIS scores and rankings of the 22 NEX-GDDP-CMIP6 models for summer daily maximum temperature (Tmax); Table S3: Evaluation metrics and TOPSIS scores and rankings of the 22 original CMIP6 models for summer daily maximum temperature (Tmax); Table S4: Evaluation metrics and TOPSIS scores and rankings of the 22 NEX-GDDP-CMIP6 models for extreme high-temperature frequency (EHTF); Table S5: Evaluation metrics and TOPSIS scores and rankings of the 22 original CMIP6 models for extreme high-temperature frequency (EHTF); Table S6: Evaluation metrics and TOPSIS scores and rankings of the 22 NEX-GDDP-CMIP6 models for extreme high-temperature intensity (EHTI); Table S7: Evaluation metrics and TOPSIS scores and rankings of the 22 original CMIP6 models for extreme high-temperature intensity (EHTI).

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Institutional Review Board Statement: Not applicable.

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Data Availability Statement: The CMIP6 model outputs used in this study are publicly available through the Earth System Grid Federation (ESGF) at <https://esgf-node.llnl.gov/projects/cmip6/> (accessed on 10 July 2026). The NEX-GDDP-CMIP6 dataset is publicly available through the NASA Center for Climate Simulation at <https://www.nccs.nasa.gov/data-collections/nex-gddp-cmip6/> (accessed on 11 July 2026). The CN05.1 gridded observational dataset is available from the Climate Change Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, at

<https://nzc.iap.ac.cn/content?cid=24&aid=999> (accessed on 1 July 2026). The processed data generated and analyzed during this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CMIP6	Coupled Model Intercomparison Project Phase 6
NEX-GDDP-CMIP6	NASA Earth Exchange Global Daily Downscaled Projections–Coupled Model Intercomparison Project Phase 6
SSP	Shared Socioeconomic Pathways
EHT	Extreme High Temperature
EHTF	Extreme High-Temperature Frequency
EHTI	Extreme High-Temperature Intensity
HWHI	Heatwave Hotspot Index
SC	Sichuan–Chongqing
BCSD	Bias Correction and Spatial Disaggregation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
ToE	Time of Emergence

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