

Article

Statistical Downscaling of Precipitation in the South and Southeast of Mexico

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Abstract: The advancements in global climate modeling achieved within the CMIP6 framework have led to notable enhancements in model performance, particularly with regard to spatial resolution. However, the persistent requirement for refined techniques, such as dynamically or statistically downscaled methods, remains evident, particularly in the context of precipitation variability. This study centered on the systematic application of a bias-correction technique (quantile mapping) to four designated CMIP6 models: CNRM-ESM2-6A, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0. The selection of these models was informed by a methodical approach grounded in previous research conducted within the southern–southeastern region of Mexico. Diverse performance evaluation metrics were employed, including root-mean-square difference (*rmsd*), normalized standard deviation (*NSD*), bias, and Pearson’s correlation (illustrated by Taylor diagrams). The study area was divided into two distinct domains: southern Mexico and the southeast region covering Tabasco and Chiapas, and the Yucatan Peninsula. The findings underscored the substantial improvement in model performance achieved through bias correction across the entire study area. The outcomes of *rmsd* and *NSD* not only exhibited variations among different climate models but also manifested sensitivity to the specific geographical region under examination. In the southern region, CNRM-ESM2-1 emerged as the most adept model following bias correction. In the southeastern domain, including only Tabasco and Chiapas, the optimal model was again CNRM-ESM2-1 after bias-correction. However, for the Yucatan Peninsula, the IPSL-CM6A-LR model yielded the most favorable results. This study emphasizes the significance of tailored bias-correction techniques in refining the performance of climate models and highlights the spatially nuanced responses of different models within the study area’s distinct geographical regions.

Keywords: climate change; southern–southeastern Mexico; CMIP6; precipitation; bias correction



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1. Introduction

Climate change is a phenomenon that affects the planet, manifesting itself mainly through changes such as extreme events [1,2]. The latest assessment report of the Intergovernmental Panel on Climate Change (IPCC-AR6), as usual, displays data on projected climate changes globally [1]. This information is based on the use of the new Coupled Model Intercomparison Project Phase 6 (CMIP6) scenarios [3]. CMIP6 comprises nearly 40 modeler groups with over 70 general circulation models (GCMs) [4]. These GCMs have improved in their complexity to simulate the climate system and increase the spatial and temporal resolution of climate information, as well as to update their input information [4–7].

The fact that different general circulation models (GCMs) utilize varied parameterizations and internal physics is commonly acknowledged. This leads to unique simulations of climatic conditions in particular regions, resulting in variations in effectiveness based on

the specific study area [8]. Recently, the CMIP6 initiative has produced valuable outcomes for multiple geographical regions [9–11], one of them being the Americas [12,13].

Downscaling techniques play a crucial role in enhancing the spatial resolution of climate information derived from GCMs, which typically operate at resolutions as coarse as $100\text{ km} \times 100\text{ km}$ [14]. The need for downscaling arises from the requirement of GCM information on smaller scales to address more localized and finer-grained climate phenomena. These methods have been divided into statistical and dynamical categories, with the latter often characterized by the employment of regional climate models (RCMs) with boundary conditions determined by GCM variables [15].

On the other hand, there are several types of statistical downscaling techniques that are commonly used in climate science. Some of the most well-known techniques include [1] (i) regression-based methods (bias-correction being one of them) [16–23]; (ii) weather typing approaches [24–27]; (iii) empirical statistical downscaling [28–31]; (iv) weather generator techniques [24,27,32,33]; and (v) neural network methods [33–38]. Note that there are different variations and combinations of these techniques, and as research in statistical downscaling progresses, new approaches may arise.

The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) developed a bias-correction method to adjust climate model data for systematic departures of the simulated historical data from observations at a global level [39]. This technique maintains the warming signal, absolute changes in monthly temperature, relative changes in monthly precipitation data, and other ISI-MIP-required variables. Later on, ref. [40] introduced a joint bias-correction (JBC) methodology for correcting the joint distribution of temperature (T) and precipitation (Pr) fields from climate model simulations. The JBC method corrects the individual distributions of T and Pr as well as their joint distribution, thereby improving the assessment of climate change impacts. On the other hand, the JBC method represents an important step in impact-based research as it explicitly accounts for inter-variable relationships as part of the bias-correction procedure.

Another type of technique, quantile mapping, can be used to address bias in the precipitation variable [41–44]. This method allows the adjustment of a model's precipitation to match the actual observed precipitation [45] by applying cumulative distribution functions to a specific quantile to calculate the probability of observation. The necessary correction is then determined using the inverse cumulative distribution function. Some of the available approaches include [46] (a) Normal Distribution Mapping; (b) Empirical Quantile Mapping; (c) Empirical Robust Quantile Mapping; (d) Quantile Mapping with Linear Transform Function; and (e) Quantile Delta Mapping.

Ref. [41] investigated the extent to which quantile mapping algorithms modify GCM trends in mean precipitation and precipitation extremes indices. The study presented a bias-correction algorithm, Quantile Delta Mapping (QDM), which explicitly preserves relative changes in precipitation quantiles and compares it with detrended quantile mapping (DQM) and standard quantile mapping (QM) on synthetic data.

Limited research has been devoted to implementing bias-correction techniques in the realm of climate studies within Mexico. Among these is the study of [47], which implemented the Palmer drought severity index to measure the severity of droughts in continental USA and Mexico. A total of 19 climate models were used to examine the ability of the models to reproduce observed statistics of drought over North America. The study found that there were substantial biases in the models' surface air temperature and precipitation fields, which needed correction. Even after bias correction, there were significant differences in the models' ability to reproduce observations. Nonetheless, the study found that all the models projected increases in future drought frequency and severity.

Another study evaluated six bias-correction techniques for monthly precipitation forecasts due to climate change over Costa Rica [48]. The findings demonstrated that bias adjustment should be taken into account when applying GCM–RCM precipitation estimates directly across topographically complicated areas like Costa Rica or Mexico.

The aim of the present study is to statistically downscale precipitation data from ERA5 [49] and four CMIP6 models in the south and southeast of Mexico by applying a quantile mapping bias-correction technique. The method, results, discussion, and conclusions are described below.

2. Materials and Methods

2.1. Study Zone

The southern–southeastern region of Mexico (Figure 1) comprises a wide range of climates, from tropical climates to subtropical marine climates, according to a modified version of the Köppen classification [50,51]. It is an area affected by tropical cyclones; in the southern part, these phenomena originate in the Pacific Ocean [52], while in the southeast, it is affected by events in both the Pacific and Atlantic Oceans [53]. Both areas are influenced by cold fronts, but the southeastern zone tends to be more exposed to these phenomena towards the end of the season [54].

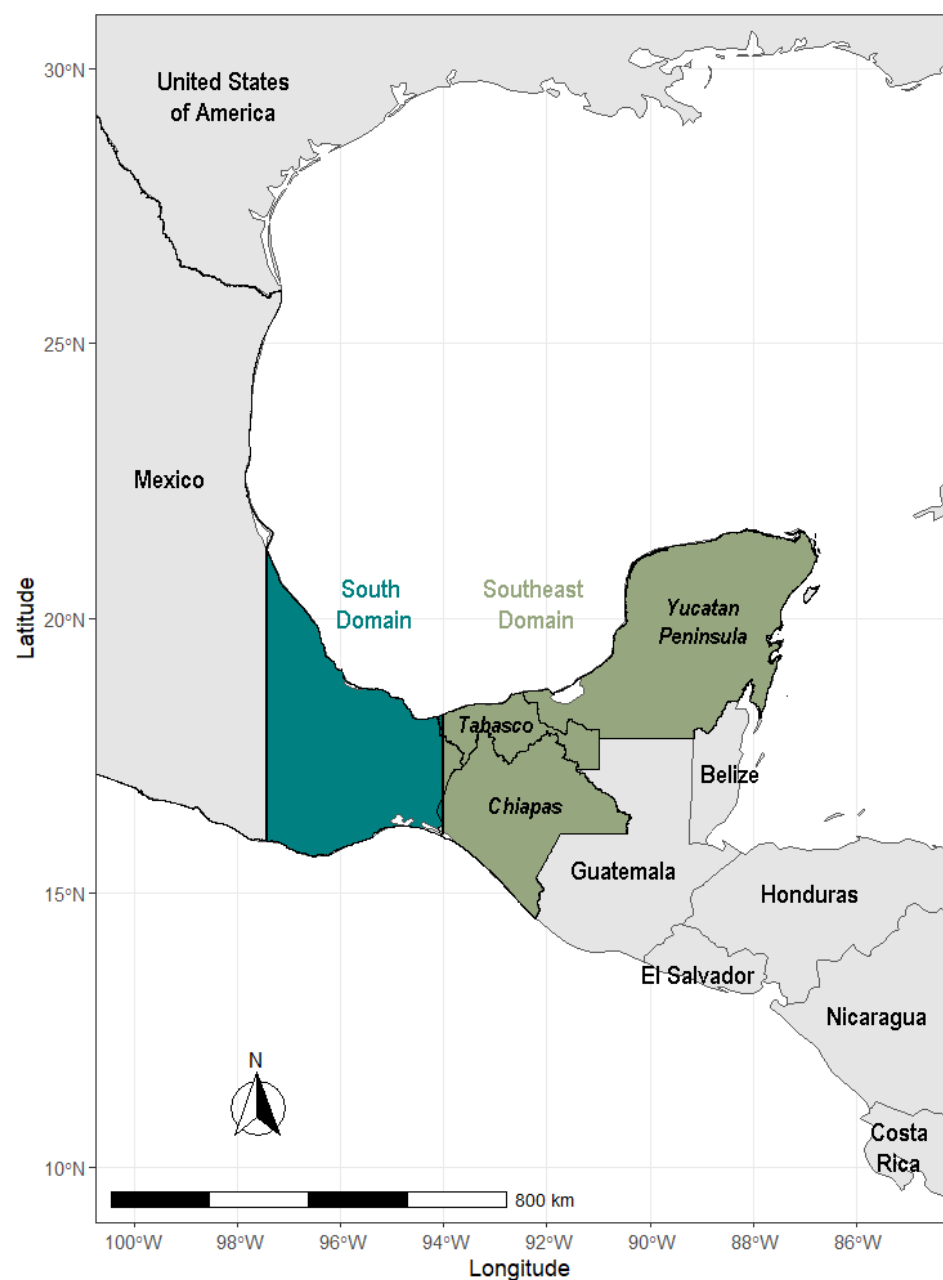


Figure 1. Study area for the southern and southeastern domains of Mexico.

The southeastern region is influenced by various meteorological phenomena, notably the Intertropical Convergence Zone (ITCZ) and, indirectly, the Caribbean Low-Level Jet (CLLJ) [55]. Notably, precipitation patterns exhibit distinctive behavior between May and November, marked by the mid-summer drought (MSD), a phenomenon explored by [56].

Regarding annual precipitation levels, the southeast region, encompassing the Grijalva–Usumacinta basin, received an average of 2500 to 2880 mm of rainfall for the period spanning 1960 to 2016 [57]. In contrast, the southern region experienced lower annual precipitation, averaging approximately 1000 to 1300 mm from 1950 to 2010 [51]. This distinction underscores the southeast region’s relatively higher moisture content compared to the southern region [58].

Furthermore, the research of ref. [23] delved into temperature trends in both regions, revealing remarkable similarities. Any deviations in these trends may be attributed to the greater altitude gradient present in the southern region compared to the southeast, further elucidating the complexity of climatic influences in these areas.

The southern–southeastern zone is affected by El Niño–Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO), and the Pacific Decadal Oscillation (PDO), according to refs. [58,59]. Environmentally, the zone contains significant ecological reserves [60]. Its approach to natural resource management and indigenous traditions allows for sustainable development. However, it is being impacted by major government projects, such as the Tren Maya and the Isthmus of Tehuantepec Interoceanic Corridor [61].

Socially, the area faces significant disparities and inequalities [62]. Hence, these projects aim to promote regional development in the southern–southeastern region [63,64]. The socioeconomic conditions in this area match the characteristics of the SSP4-6 scenario [65]. The authors of that paper conducted a study using the average temperature variable to determine the CMIP6 scenario. They also conducted a similar exercise using CMIP5.

The southern region of the study area holds significance in the CORDEX-FPS pilot project titled “North America: Dynamical Downscaling Experiments and Hydrological Modeling for Canada and Mexico.” This project aims to conduct thorough investigations and hydrological modeling in Canada and Mexico (For more details, refer to: <https://cordex.org/experiment-guidelines/flagship-pilot-studies/endorsed-cordex-flagship-pilot-studies/north-america-dynamical-downscaling-experiments-and-hydrological-modelling-for-canada-and-mexico/>, accessed on 21 August 2023).

2.2. Statistical Downscaling

There are different statistical downscaling techniques available, such as perfect prognosis and model output statistics, for example [66]. When dealing with the precipitation variable, quantile mapping methods are commonly employed [20,22,66,67]. For this study, we have chosen to perform bias correction using linear quantile mapping, following the approach of ref. [22]. The correction was applied using the equation proposed by [46]:

$$F(\tau)_{era5}^{-1} = a + b \times F(\tau)_{modh}^{-1} \quad (1)$$

where F^{-1} is the inverse cumulative distribution function (CDF), and τ denotes the percentile between 0 and 1. This method assumes a linear relationship between the quantile functionals of the ERA5 data (*era5*) and the models in the historical period (*modh*), where a and b are the coefficients of the linear fit by the regression of least squares. Subsequently, the bias correction is applied for a given time t with the following equation:

$$x(t)_{era5} = a + b \times x(t)_{modh} \text{ for } x > 0.1\text{mm/d} \quad x(t)_{era5} = 0 \text{ for } x \leq 0.1\text{mm/d}. \quad (2)$$

To measure the performance of the bias correction, we used the root-mean-square deviation (*rmsd*), the normalized standard deviation (*NSD*), the bias in percentage, and the Pearson correlation coefficient. The *rmsd* is defined here as

$$rmsd = \sqrt{\frac{\sum_{t=1}^n [Pr_{era5}(t) - Pr_{modh}(t)]^2}{n}} \quad (3)$$

where *Pr* is the precipitation variable, *era5* is ERA5 observations, and *mod* is the model historical data. The *NSD* is

$$NSD = \sigma_{modh} / \sigma_{era5} \quad (4)$$

where σ is the standard deviation for the historical model (*modh*) and ERA5 (*era5*). The bias in percentage is

$$Bias(\%) = 100 \bullet [(\overline{Pr_{modh}} - \overline{Pr_{era5}}) / \overline{Pr_{era5}}] \quad (5)$$

where $\overline{Pr_{modh}}$ is the mean precipitation of the model in the historical period, and $\overline{Pr_{era5}}$ is the mean precipitation of ERA5. Finally, the Pearson correlation coefficient is

$$\rho_{era5,mod} = cov(Pr_{era5}, Pr_{modh}) / (\sigma_{era5} \sigma_{modh}) \quad (6)$$

where *cov* is the covariance of both *Pr_{era5}* and *Pr_{modh}*, and σ is the standard deviation.

To represent the measurements, we used Taylor's diagram [68] (Taylor, 2001). These types of diagrams summarize statistical information for evaluating complex models, i.e., correlation, average square-root difference, and the *NSD*. In this case, we also represented bias. The simulation models that are well consistent with observations are near the point marked "REF"; these models have a high correlation and a low *rmsd*. Models that are close to the scoring line will have an *NSD* equal to 1, i.e., a standard deviation equal to or close to the observed [69].

2.3. Data

In this study, we used the ERA5 database to gather historical daily precipitation data and conducted a comprehensive comparison of four climate models: CNRM-ESM2-6A, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0. The chosen models were in accordance with the work of ref. [23], and their characteristics are summarized in Table 1.

Table 1. Data used for the precipitation (*Pr*) of ERA5 and the historical data of four GCMs in the period 1980–2014 (<https://creativecommons.org/licenses/by/4.0/>, accessed on 21 August 2023).

Number	Data	Resolution	Reference
1	ERA5	25 km × 25 km	[49]
2	CNRM-ESM2-1	250 km × 250 km	[70]
3	IPSL-CM6A-LR	250 km × 250 km	[71]
4	MIROC6	250 km × 250 km	[72]
5	MRI-ESM2-0	100 km × 100 km	[73]

To ensure consistency and facilitate analysis, we interpolated the data onto a $0.25^\circ \times 0.25^\circ$ grid (the same as ERA5). Subsequently, we applied the bias-correction methodology outlined in Section 2.2 to enhance the reliability of the results.

3. Results

3.1. Linear Adjustment

In our analysis, we conducted linear adjustments to the inverse CDFs for both the climate models and ERA5 dataset during the historical period 1980–2014. To facilitate transparency and reproducibility, we have provided the specific parameters (*a* and *b*) for the southern and the southeastern regions in Table 2. These adjustments are essential to

ensure consistency and comparability between the model outputs and the observational data from ERA5.

Table 2. Parameters a and b of the linear adjustment of quantile mapping [Equation (1)] for the two regions and four models analyzed in this study.

Number	Data	a (South)	b (South)	a (Southeast)	b (Southeast)
1	CNRM-ESM2-1	7.743	0.762	10.609	0.281
2	IPSL-CM6A-LR	6.365	0.427	10.896	−0.003
3	MIROC6	15.420	−0.114	9.061	0.236
4	MRI-ESM2-0	12.398	0.195	9.757	0.087

3.2. Bias-Correction Performance

To assess the effectiveness of the bias correction, we employed Equations (3) and (4) as performance metrics. The *rmsd* and the *NSD* values for the southern and southeastern regions are depicted in Figures 2–5.

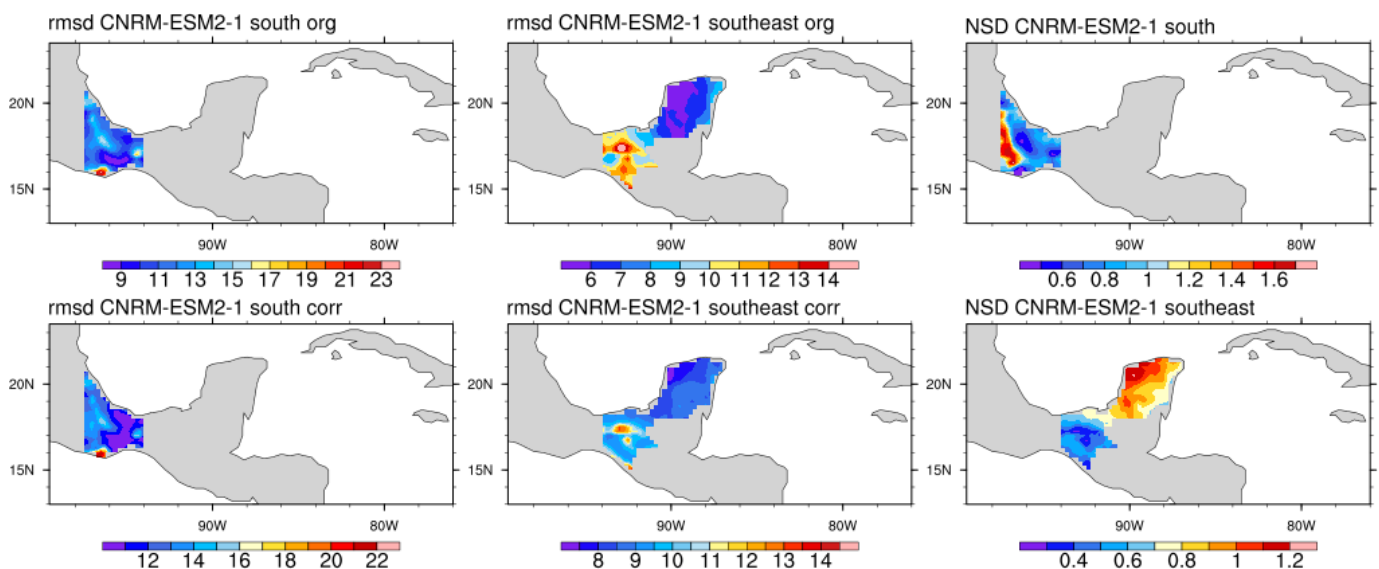


Figure 2. Original (org) and bias-corrected (corr) *rmsd* for southern (plots on the left) and southeastern (plots in the middle) Mexico of the CNRM_ESM2-1 model. In addition, the *NSD* for both southern (plot in the top right) and southeastern Mexico (plot in the bottom right) are shown for the same model.

First, we observed that the degree of improvement through bias correction varied depending on the model. For instance, with the CNRM-ESM2-1 model (Figure 2), the *rmsd* values for the southern region fluctuated between 0 and 23 mm/d, and for the southeastern region, they ranged from 0 to 14 mm/d. A dispersion of *rmsd* values was observed depending on the grid point (Figure 2). That is why the arial average *rmsd* was obtained (see Table 3). We will talk about this later. These results indicate a notable improvement in the performance of the CNRM-ESM2-1 model after applying bias correction for both regions.

Overall, the bias correction demonstrated significant improvements in the model's accuracy, especially for the CNRM-ESM2-1 model, in both the southern and southeastern regions.

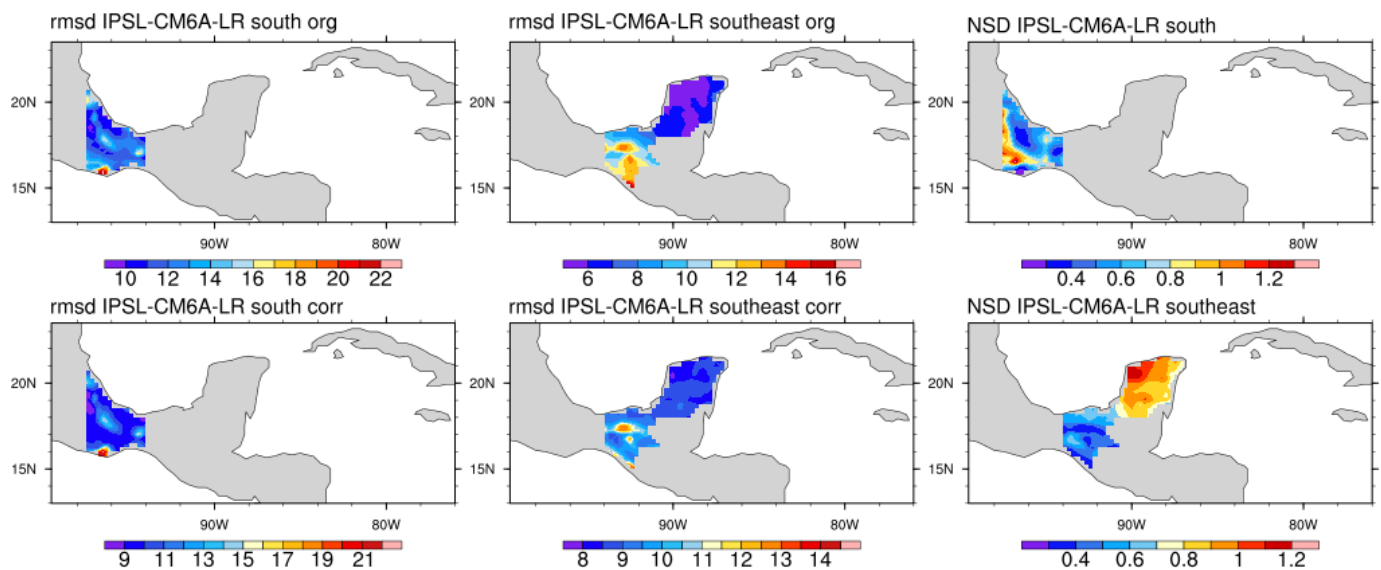


Figure 3. The same as in Figure 2 but for the IPSL-CM6A-LR model.

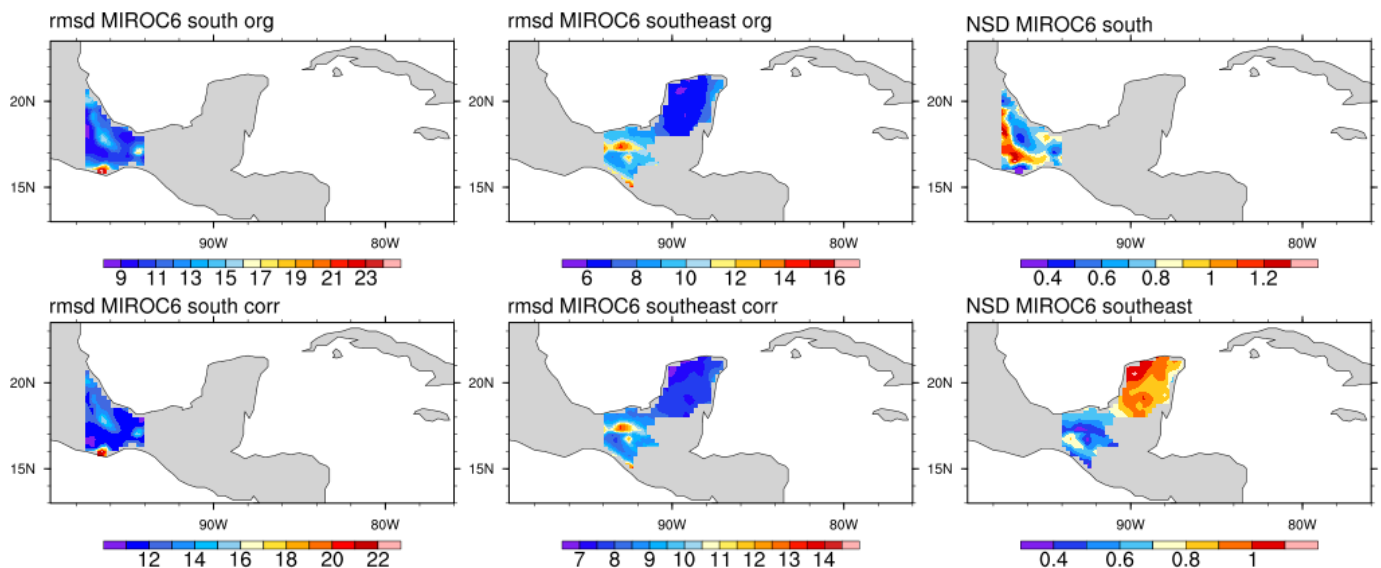


Figure 4. The same as in Figure 2 but for the MIROC6 model.

In the analysis of the *NSD*, interesting patterns emerged for different regions. For the southern region, we observed a smaller range of dispersion between values compared to the central and eastern parts, but the western part exhibited a much greater dispersion, with values exceeding 1. This significant dispersion in the western part can be attributed to its proximity to surrounding mountain ranges, which likely influenced the climate dynamics.

Focusing on the southeastern region, we found that the Yucatan peninsula showed a higher dispersion than expected (~ 1.2), indicating greater variability in its climate. Conversely, the state of Chiapas displayed a much lower dispersion in the model than what was observed (~ 0.7). It is worth noting that the state of Chiapas experiences notable orographic changes, contributing to its climate's substantial variability. In contrast, the relief of the Yucatan Peninsula and the state of Tabasco remained relatively stable, and thus, their dispersions are not as significant.

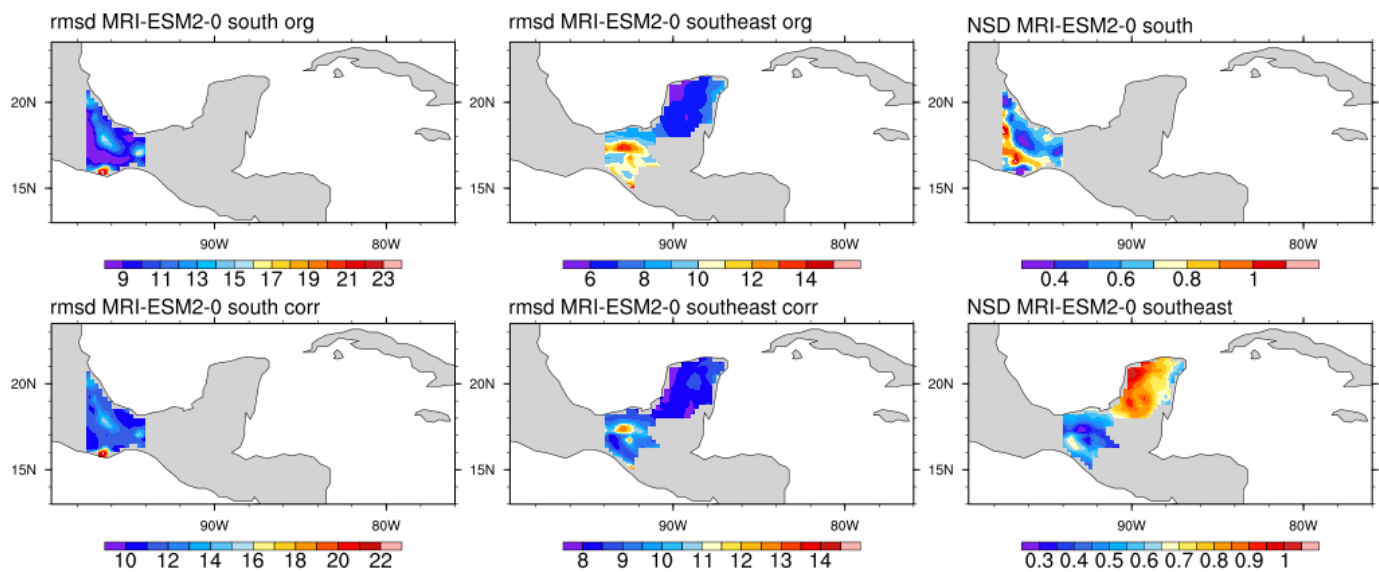


Figure 5. The same as in Figure 2 but for the MRI-ESM2-0 model.

Table 3. The *rmsd* and *NSD* values for the four models and the regions in the study area. Note that the southeast was divided into Southeast 1 (Tabasco, Chiapas) and Southeast 2 (Yucatan Peninsula).

Data	South <i>rmsd</i> Orig	South <i>rmsd</i> Corr	South <i>rmsd</i> Corr/Orig	Southeast 1 <i>rmsd</i> Orig	Southeast 1 <i>rmsd</i> Corr	Southeast 1 <i>rmsd</i> Corr/Orig	Southeast 2 <i>rmsd</i> Orig	Southeast 2 <i>rmsd</i> Corr	Southeast 2 <i>rmsd</i> Corr/Orig
CNRM-ESM2-1	12.155	6.756	0.556	12.928	9.735	0.753	9.870	8.535	0.865
IPSL-CM6A-LR	12.639	6.322	0.500	10.951	9.934	0.907	10.066	8.704	0.865
MIROC6	12.600	7.126	0.566	12.940	9.323	0.720	9.823	7.782	0.792
MRI-ESM2-0	11.260	6.998	0.621	12.620	9.389	0.744	9.649	8.411	0.872

Moreover, the influence of orographic factors on local precipitation becomes evident. The orographic component seems to play a role in shaping the patterns observed in the southern region, as indicated by the IPSL-CM6A-LR model (Figure 3). Similarly, the CNRM-ESM2-1 model showed a comparable signal of the orographic component for the southern region.

When examining the IPSL-CM6A-LR model, we found that its *rmsd* was also higher for the southern region, ranging from 0 to 22 mm/d, whereas the southeast region exhibited an *rmsd* range of 0 to 18 mm/d. Applying bias correction to the model data improved the *rmsd*, which highlights the importance of addressing biases in climate modeling.

For Tabasco and Chiapas, the dispersions of the model with respect to the observations were less than 1 (range 0.4 to 0.8), which suggests a reasonably good fit with the observed values, while for the Yucatan peninsula, values greater than 1 were observed (range from 0.8 to 1.3).

In the context of the MIROC6 model (Figure 4), the *rmsd* for the southern region exhibited a range of 0 to 24 mm/d, while for the southeast region, it ranged from 0 to 14 mm/d. We observed that applying bias correction to the model data resulted in a slight improvement in *rmsd*, but significant optimization was not evident.

Regarding the *NSD*, it is noteworthy that the dispersion of the model was considerably lower than that of the observations, as indicated by values of *NSD* well below 1. However, despite this difference, the orographic pattern was still evident in the representation of the model in the southern region.

While the southeast region appears distinct, there were variations in the *NSD* for different areas: for the Yucatan peninsula, the *NSD* ranged from 0.7 to 1.3, whereas for Tabasco and Chiapas, it ranged from 0.4 to 0.8.

Now, focusing on the MRI-ESM2-0 model (Figure 5), we found that the *rmsd* for the southeast region showed improvement, particularly in Tabasco and Chiapas, but not for the southern region. The behavior of the *NSD* in this model was similar to MIROC6, except for the Yucatan peninsula, where its values reached about 1.1.

We have observed that the values of *rmsd* and *NSD* not only vary between different climate models but also depend on the specific region under consideration. In order to provide a more comprehensive analysis, we divided the southeast region into two sub-regions: Southeast 1, comprising the states of Tabasco and Chiapas, and Southeast 2, which included the Yucatan Peninsula. To assess the model performance, we calculated the average values for both unbiased and bias-corrected data, as shown in Table 3.

Upon analyzing the results, it becomes evident that bias correction improves the overall signal of the data, particularly for the southern region, followed by the Southeast 1, and the Southeast 2 regions. For the southern region, IPSL-CM6A-LR emerged as the best-performing model with bias correction, followed by CNRM-ESM2-1 and MIROC6.

On the other hand, for the Southeast 1 region, the best bias-corrected model was MIROC6, followed by MRI-ESM2-0 and CNRM-ESM2-1, while for the Southeast 2 region, MIROC6 again was the best model with bias correction, followed by a tie in the performance between CNRM-ESM2-1 and IPSL-CM6A-LR with bias correction.

However, it is crucial to consider the *NSD* as well, as it indicates the similarity in dispersion with the observed data. When combining the *NSD* with the *rmsd*, we found that CNRM-ESM2-1 presented the best overall value for all three regions.

Figure 6 presents the Taylor diagrams for the four models, comparing their performance with and without bias correction. It is evident from all three diagrams that bias correction significantly enhances the performance of the models.

Upon analyzing the Pearson correlation coefficient, we found that the best correlation was observed in the Southeast 2 region, specifically for the Yucatan Peninsula. However, for the south and the Southeast 1 regions, encompassing Tabasco and Chiapas, the correlation was relatively low.

Another important observation is the improvement in the *NSD* for the south and the Southeast 2 region after bias correction. However, for the Southeast 1 region, although there are changes in the *NSD* values, the improvement is not as evident as in the other regions.

Regarding the bias itself, we note that after bias correction, all the models exhibited positive values, indicating that they tended to be wetter compared to the original uncorrected data.

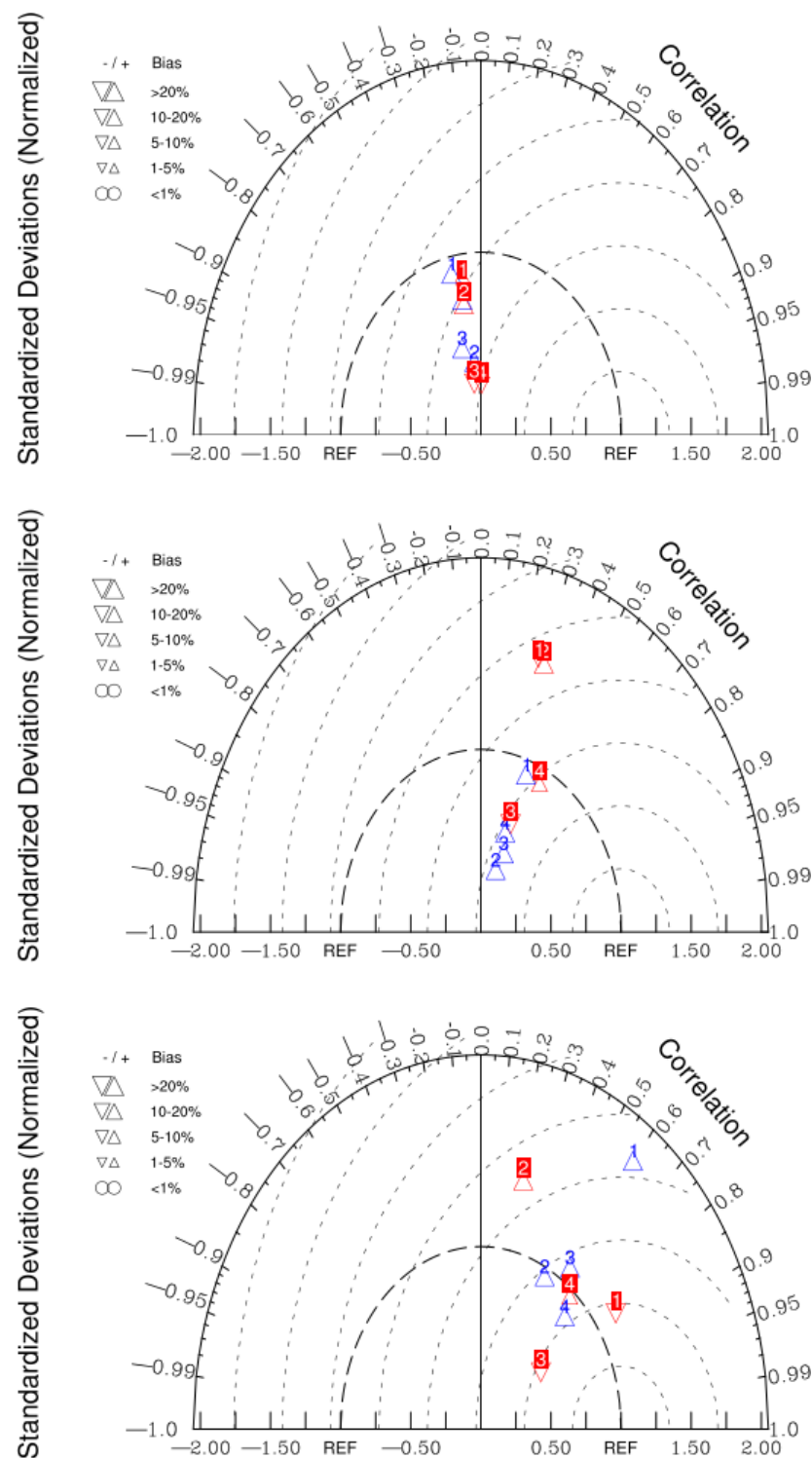


Figure 6. Taylor diagrams comparing the performance of the four models with and without bias correction. Each model is represented by a number: (1) CNRM-ESM2-6A, (2) IPSL-CM6A-LR, (3) MIROC6, and (4) MRI-ESM2-0. The diagrams are presented in blue for the case with bias correction and in red for the case without bias correction. The top diagram relates to the southern region, the middle one to the Southeast 1 region (Tabasco and Chiapas), and the bottom one to the Southeast 2 region (Yucatan Peninsula). The dotted semicircles represent the difference between the *rmsd* of the model and that of the observations.

4. Discussion and Conclusions

According to the results, bias correction significantly improved the model performance for the study area.

Ref. [70] reported, for the same study area, that the CNRM-ESM2-1 model exhibited a bias of 0.30 mm/day for winter precipitation and 0.28 mm/day for summer precipitation, with a corresponding root-mean-square error (*rmse*) of 1.47 and 1.56, respectively, for the period 1981–2010. In the study area, model errors ranged between 1 and −1 mm/day for winter and between −2 and −6 mm/day for summer when compared to observations. The application of bias correction resulted in a considerable improvement in *rmse*, reducing it by almost 50% for the south and approximately 15–25% for the southeast. It is worth noting that the regional error was greater than the worldwide average. CNRM-ESM2-1, being a second-generation model with increased code complexity, physical parameterization, and improved mesh resolution, was reported to exhibit a 10% increase in future processes according to Séférian et al. (2019).

For the IPSL-CM6A-LR model, ref. [71] noted an improvement in simulating precipitation climatology for the south–southeast region of Mexico compared to its CMIP5 version for the period 1980–2005. However, the model tends to globally overestimate precipitation by 0.3 mm/day, which corresponds to 10% of the observed value. In the study area, the NSD was 38% below observations for the south region, 45% below observations for the Southeast 1 region, and 15% below observations for the Southeast 2 region. IPSL-CM6A-LR exhibited improved equilibrium climatic sensitivity, and a better simulation of variables like wind, temperature, and precipitation. Nonetheless, some persisting issues remain, such as the double Intertropical Convergence Zone and the frequency of blocks in winter at medium altitudes.

Ref. [72] showed that the MIROC6 model continued to underestimate global precipitation in the tropical zone, although it was an improvement compared to MIROC5. In the study area, MIROC6 underestimated precipitation in winter for both the south and southeast, while for summer, underestimation was observed only for the south. The NSD values for the study area showed a 25% underestimation for the south, 37% for Southeast 1, and 13% for Southeast 2. MIROC6's improvements over its predecessor include a new parametrization for convection processes and the inclusion of the stratosphere.

Ref. [73] reported that MRI-ESM2-0 exhibited behavior similar to its predecessor but with an improved correlation of 0.84 compared to 0.79. Globally, MRI-ESM2-0 has a bias of 0.32 mm/day and an *rmse* of 1.28 mm/day. For the study area, the bias ranged between −1 and −2 mm/day. Like other models, the regional *rmse* was higher than the global average, exceeding 10 mm/day in the study area. However, applying bias correction reduced this error by up to 50% for the southern region and 15–25% for the southeast. Improvements in MRI-ESM2-0 include a spatial resolution of 100 km, a better redistribution of radiation, and improvements in the parameterization of nonorographic gravitational waves. Nevertheless, the model still presented an overestimation of the temperature during the cooling period from 1950 to 1960.

In summary, the four models showed improvements in the *rmsd*, of up to 50% for the southern region and between 15 and 25% for the southeast. However, in the case of the NSD and its correlation with ERA5, the best model was CNRM-ESM2-0 for the south and Southeast 1 region. In the Southeast 2 region, this model was last.

Analyzing the diagrams for the southern and the Southeast 1 regions, we observed that IPSL-CM6A-LR and MIROC6 exhibited a strong positive correlation with low *rmsd* compared to the observations. However, they displayed minimal variability in relation to the observed data. On the other hand, CNRM-ESM2-1 demonstrated a moderate correlation and *rmsd* difference, aligning closely with the observed variability. Therefore, CNRM-ESM2-1 emerges as the preferred model for these two regions in the southern sector.

Conversely, in the case of the Southeast 2 region, CNRM-ESM2-1 exhibited a notably higher *rmsd* difference and greater variability compared to the observed data. In contrast, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0 displayed a strong positive correlation, minimal

rmsd difference, and variability patterns that closely resembled the observations. Consequently, these three models emerge as the more suitable choices for modeling the Southeast 2 region.

These results allow us to discriminate between these four models in both the study regions for the future analysis of projections under climate change. This study offers updated information on the use of the MGC of the new generation of CMIP6 for the south-southeast area of Mexico. Finally, it provides a basis for the generation of climate change scenarios in the area for rainfall.

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