Agromet 39 (1): 33-39, 2025

PERHIMPI

Agromet

journal.ipb.ac.id/index.php/agromet

ISSN : 0126 - 3633

# Bias Correction of CMIP6 Models for Assessment of Wet and Dry Conditions Over Sumatra

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ARTICLE INFO

**Received**
27 February 2025

**Revised**
25 May 2025

**Accepted for Publication**
3 June 2025

**Published**
5 June 2025

doi: 10.29244/j.agromet.39.1.33-39

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ABSTRACT

The performance of CMIP6 models in capturing local and regional precipitation patterns often requires refinement due to inherent biases. This study evaluates eleven CMIP6 models for their applicability over Sumatra Island and applies two bias correction methods namely Linear Scaling (LS) and Quantile Delta Mapping (QDM). We used ERA5 precipitation datasets as a reference bias correction during 1981-2014. The performance was assessed using MAE, correlation, and PBIAS. Results reveals that raw model of CMIP6 generally underestimate precipitation, particularly during the DJF and SON seasons, with the largest errors over the mountainous western Sumatra. LS tends to overcorrect and shift precipitation estimates toward a wetter bias, while QDM significantly improves the accuracy and seasonal consistency of the simulations. The multi-model ensemble mean (CMIP6-avg) outperforms individual models, and its performance is further enhanced with QDM, yielding higher correlation and lower error metrics. Spatial and seasonal analyses demonstrate that QDM more effectively reduces both dry and wet biases, especially during peak rainfall seasons. These findings underscore the importance of robust bias correction techniques to improve climate projections for hydrological and climate impact studies in Sumatra and other tropical regions with complex terrain.

KEYWORDS
linear scaling, model evaluation, precipitation, topography, quantile delta mapping

## 1. INTRODUCTION

An accurate simulation of tropical precipitation remains a major challenge for global climate models (GCMs), such as those in phase 5 (CMIP5;Taylor et al., 2012) and the latest phase 6 (CMIP6; Eyring et al., 2016) of the Coupled Model Intercomparison Project. Despite advancements in model physics and forcings, substantial uncertainties persist, particularly in reproducing the spatial and temporal characteristics of precipitation. This limitation is largely attributed to the coarse spatial resolution of GCMs, typically ranging from 100 to 250 km, which is often insufficient to reliably capture local and regional precipitation processes (Guo et al., 2021; Teutschbein and Seibert, 2012).

The CMIP6 historical experiments form a critical foundation for assessing model performance by simulating the climate from 1850 to 2014 under observed external forcings (Meinshausen et al., 2017). These simulations help evaluate the ability of models to reproduce historical climate variability, assess sensitivity to different forcings, and provide a baseline for detection and attribution studies (Eyring et al., 2016; Stott et al., 2006). While CMIP6 models generally outperform their CMIP5 predecessors in capturing large-scale features such as global monsoon systems and interannual precipitation variability (Wang et al., 2021; Zamani et al., 2020), key issues remain. Persistent biases and considerable spread across models (Lun et al., 2021; Ortega et al., 2021; Seneviratne and Hauser,

2020) underscore the need for additional processing to refine climate signals at regional scales.

Given the limited spatial resolution and inherent biases in raw GCM outputs, it becomes critical to apply bias correction and downscaling techniques to produce climate projections suitable for finer-scale impact studies (Cannon et al., 2015; Piani et al., 2010; Pierce et al., 2015). This is especially important for regions like Southeast Asia, where climate processes are strongly influenced by local terrain and land–sea interactions. Evaluation of CMIP6 precipitation performance is thus most meaningful when conducted at the regional scale, where the model limitations are most evident and where actionable climate information is urgently needed.

The island of Sumatra, located in the Maritime Continent of Indonesia (MCI), exhibits unique precipitation patterns due to its direct border with the Indian Ocean and the presence of the Barisan Mountains. These mountains significantly influence the region's convection processes, blocking winds from the Indian Ocean and resulting in higher precipitation on the western side of Sumatra (As-syakur et al., 2019; Ogino et al., 2016; Yamanaka, 2016). In addition, the region's diurnal cycle, governed by land–sea heating contrasts and localized convection, dominates daily precipitation variability and contributes to the spatial complexity of rainfall patterns (Wang and Sobel, 2017; Yamanaka, 2016).

This interplay of global climate drivers, complex topography, and fine-scale atmospheric processes offers challenges for climate modeling, especially in regions vulnerable to drought and fires. Accurate rainfall representation is crucial for managing these risks. Therefore, evaluating model performance and the effectiveness of bias correction methods in such complex settings is essential.

In this study, we address two key research questions how well do CMIP6 models reproduce historical precipitation patterns over Sumatra? and to what extent do two widely used bias correction methods of Linear Scaling (LS) and Quantile Delta Mapping (QDM) will improve the representation of precipitation from CMIP6 models in this complex tropical environment?

## 2. MATERIAL AND METHODS

### 2.1 Study Area

Sumatra, located on the equator within the Maritime Continent, receives a high annual rainfall exceeding 2000 mm, with two distinct peaks in November–December and March–April, typical of an equatorial climate regime (Taufik et al., 2023). Seasonal rainfall distribution varies spatially, with higher precipitation in the southern region during the December–February (DJF) season, and increased rainfall in the northwest during June–August (JJA), while the eastern parts remain relatively dry (As-syakur et al., 2019).

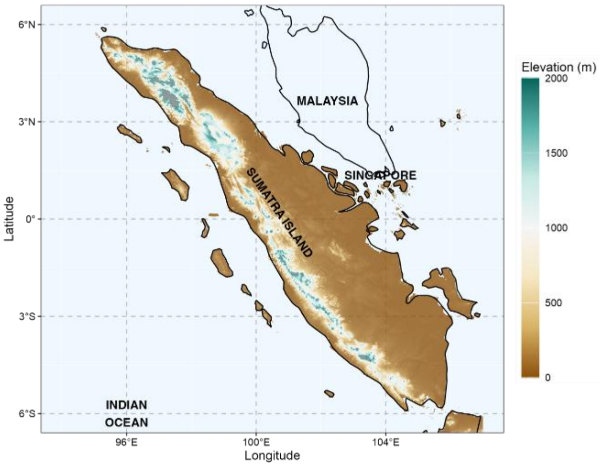


**Figure 1.** Distribution of elevation in Sumatra Island

### 2.2 Datasets

This study used monthly precipitation data from ERA5 and historical simulations from 11 CMIP6 models from 1981-2014. ERA5 is a global reanalysis dataset with a spatial resolution of 0.25° × 0.25°, provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) for operational climate monitoring (Hersbach et al., 2020). It offers a best estimate of the atmosphere–land–ocean system worldwide and has shown good agreement with observed precipitation station data (Hersbach et al., 2020; Lavers et al., 2022). For spatial analysis, the island of Sumatra (6°S–6°N) was divided into 590 grid points, covering distinct geographic and climatic regions. To ensure spatial consistency between datasets, all CMIP6 model outputs in Table 1 were regridded and downscaling to match the ERA5 resolution using bilinear interpolation (Navarro-Racines et al., 2020).

### 2.3 Model Evaluation

Bias correction is commonly applied in climate modeling to adjust selected statistics (e.g., mean, variance, or quantiles) of model outputs to better match observations during a reference period (Navarro-Racines et al., 2020; Teutschbein and Seibert, 2012). This study employed linear scaling (LS) and quantile delta mapping (QDM) to correct precipitation data from CMIP6 models.

In the first step, the LS method adjust precipitation at each grid point ($P_{i,j}$ (d)), using the ratio of climatological monthly means from observations $\bar{P}_{obs\,i,j}$ and models $\bar{P}_{model\,i,j}$ during 1981-2014. Next, the relative change (Eq.1) is calculated, followed by the

Table 1 List of CMIP6 Model (variant label r1i1p1f1)

| No | Model | Institution | Resolution | Country |
|---|---|---|---|---|
| 1 | ACCESS-CM2 | Commonwealth Scientific and Industrial Research Organization (CSIRO) | 1.25 x 1.875 | Australia |
| 2 | ACCESS-ESM1-5 | Commonwealth Scientific and Industrial Research Organization (CSIRO) | 1.25 x 1.875 | Australia |
| 3 | BCC-CSM2-MR | Beijing Climate Centre | 1.125x1.125 | China |
| 4 | CanESM5 | Canadian Centre for Climate Modelling and Analysis (CCCma) | 2.81 × 2.81 | Canada |
| 5 | CESM2 | National Center for Atmospheric Research (NCAR) | 1.25 × 0.94 | USA |
| 6 | FIO-ESM-2-0 | First Institute of Oceanography, Ministry of Natural Resource | 0.94 x 1.25 | China |
| 7 | FGOALS-f3-L | Chinese Academy of Sciences Flexible Global Ocean-Atmosphere–Land System model | 1 x 1,25 | China |
| 8 | HadGEM3-GC31-LL | Met Office Hadley Centre | 1.25×1.875 | UK |
| 9 | MIROC6 | Japan Agency for Marine-Earth Science and Technology (JAMSTEC) | 1.4 x 1.4 | Japan |
| 10 | MIROC-ES2L | Japan Agency for Marine-Earth Science and Technology (JAMSTEC) | 2.8 x 2.8 | Japan |
| 11 | MRI-ESM2-0 | Meteorological Research Institute | 1.125x1.125 | Japan |

corrected precipitation (Eq.2). To prevent negative values, the absolute value of the relative change is used.

$$\Delta P_{i,j}(d) = \frac{\bar{P}_{obs\,i,j} - \bar{P}_{model\,i,j}}{\bar{P}_{model\,i,j}} \quad (1)$$

$$P_{model\,i,j}(cor, d) = P_{model\,i,j} * (1 + \Delta P_{i,j}(d)) \quad (2)$$

Additionally, QDM was applied following Cannon et al., 2015 approaches to address residual biases in GCM simulations. Specifically, the fitting was performed separately for each month (e.g., January, February, etc.) using the corresponding values across years, rather than using the full time series. This month-wise approach allows the corrected data to retain important seasonal characteristics. Both LS and QDM were applied independently at each grid cell across Sumatra, preserving spatial coherence, interannual variability, and physically meaningful climate change signals.

We evaluated the performance of raw, LS, and QDM output simulations using Pearson correlation, mean absolute error (MAE), and percent bias (PBIAS) for both monthly and seasonal precipitation. All analysis were performed in R language (R Core Team, 2023) using the tidyverse and ggplot2 for data manipulation and visualization (Wickham et al., 2019), and metrics were computed using the hydroGOF package in R (Zambrano-Bigiarini, 2024).

## 3. RESULTS AND DISCUSSION

### 3.1 Model Evaluation

This section evaluates the performance of raw and bias-corrected CMIP6 models in simulating historical precipitation over Sumatra. When compared with the ERA5 reanalysis, the raw CMIP6 outputs exhibit substantial biases, reflected in high mean absolute errors (MAE > 80 mm) and low Pearson correlation coefficients (r < 0.40), limiting their reliability for regional and local-scale applications, particularly in topographically complex areas such as Sumatra (Figure 2a).

To address these limitations, two statistical bias correction techniques, Linear Scaling (LS) and Quantile Delta Mapping (QDM) were applied. While LS resulted in moderate improvements in correlation, it showed limited impact on reducing MAE. In contrast, QDM significantly enhanced model performance by reducing MAE by up to 35 mm and increasing correlation values to around 0.5 across most models (Figure 2a). The multi-model ensemble mean (CMIP6-avg) consistently outperformed individual models, with correlation to ERA5 increasing from 0.72 (RAW; p ≤0.05), to 0.73 (LS; p ≤0.05), and reaching 0.80 under QDM (p ≤0.05), emphasizing the advantage of ensemble approaches combined with advanced correction techniques.

Spatial analysis further highlights these improvements. Figure 2b shows that raw simulations exhibits

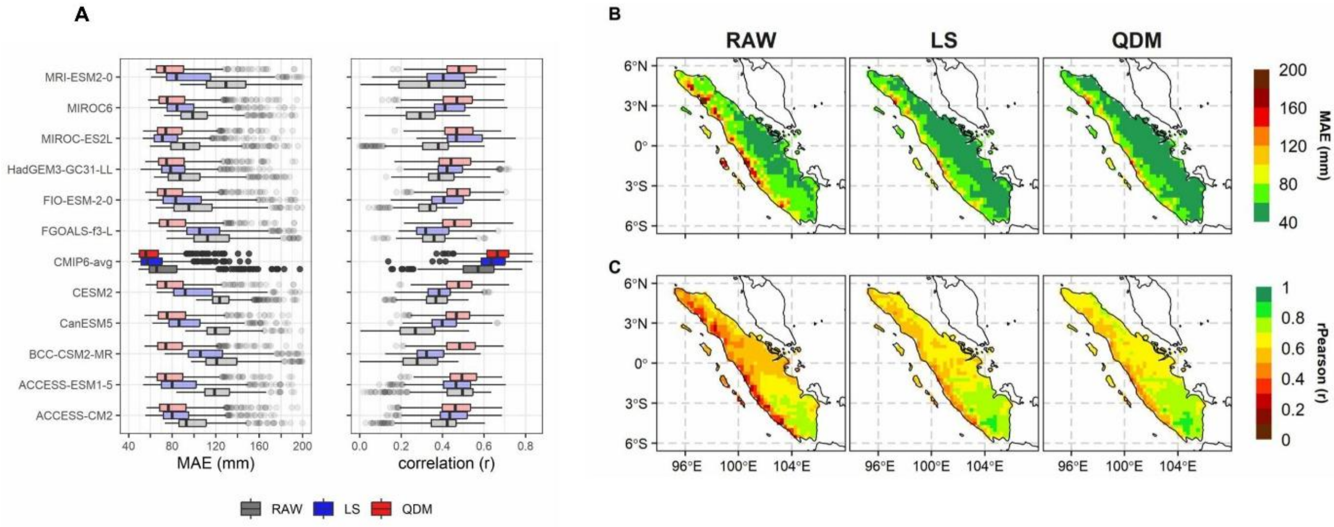


**Figure 2.** Performance of CMIP6 monthly precipitation over Sumatra: (a) Mean Absolute Error (MAE) and Pearson correlation of raw, linear scaling (LS), and quantile delta mapping (QDM) methods; (b) spatial distribution of MAE; and (c) correlation from the multi-model mean (CMIP6-avg). The Y-axis in (a) shows CMIP6 model names as listed in Table 1.

large MAE over western Sumatra, a region characterized by complex terrain and high precipitation variability. Post processed outputs, especially those corrected using QDM demonstrate a substantial reduction in spatial biases. Similarly, spatial correlation in Figure 2c reveal improved agreement with observations after applying QDM.

These findings underscore the difficulty of simulating precipitation in Sumatra, where orographic effects and oceanic dynamics dominate. The Barisan Mountains, stretching longitudinally along the island, enhance convective precipitation by blocking moist westerly winds from the Indian Ocean, causing distinct precipitation gradients between western and eastern Sumatra (Ogino et al., 2016). Such fine-scale geographic and climatic complexities are often poorly represented in coarse-resolution general circulation models (GCMs).

Similar challenges have been reported in regions with complex terrain and strong ocean-atmosphere interactions, such as Central America and Central Asia, where GCMs fail to capture sub-regional variability due to coarse resolution and simplified parameterizations (Guo et al., 2021; Mehran et al., 2014). Typical GCM spatial resolutions (100–250 km) are insufficient to resolve steep elevation gradients and localized climate processes (Chen et al., 2013; Christensen et al., 2008), leading to issues such as excessive wet days, misrepresented precipitation intensity, and unrealistic seasonal cycles (Sanusi et al., 2021; Wilcke et al., 2013).

Thus, applying bias correction and downscaling techniques is essential to improve the spatial and temporal accuracy of GCM outputs (Cannon et al., 2015; Piani et al., 2010; Pierce et al., 2015). This study demonstrates that QDM, especially when combined with multi-model ensembles, substantially enhances the realism and reliability of precipitation simulations over Sumatra, providing a more robust foundation for regional climate impact assessments.

### 3.2 Assessment Dry and Wet Biases

Building on the performance evaluation, this section examines seasonal biases in both raw and bias-corrected CMIP6 simulations. Raw model outputs consistently underestimate precipitation over western and northern Sumatra during SON and DJF seasons, which typically associated with peak monsoonal (Figure 3a). In these regions, PBIAS values exceed –40%, indicating that raw models considerably misrepresent precipitation intensity. Conversely, overestimation occurs in the eastern and southern regions during JJA, with PBIAS values up to +20%, resulting in unrealistic wet conditions during the dry season.

Figure 3b supports these findings by illustrating the monthly PBIAS distribution across models. Most raw simulations exhibit a negative median PBIAS, indicating a dry bias, although some models show positive biases exceeding +20%, reflecting significant inter-model variability. Figure 3c further illustrates seasonal PBIAS distributions, where raw simulations show broad bias ranges and multiple outliers, especially during SON and DJF, highlighting consistent underestimations across models.

Applying bias correction methods improved model performance. In particular, QDM provided greater reductions in both the magnitude and spread of biases, especially during extreme precipitation periods.

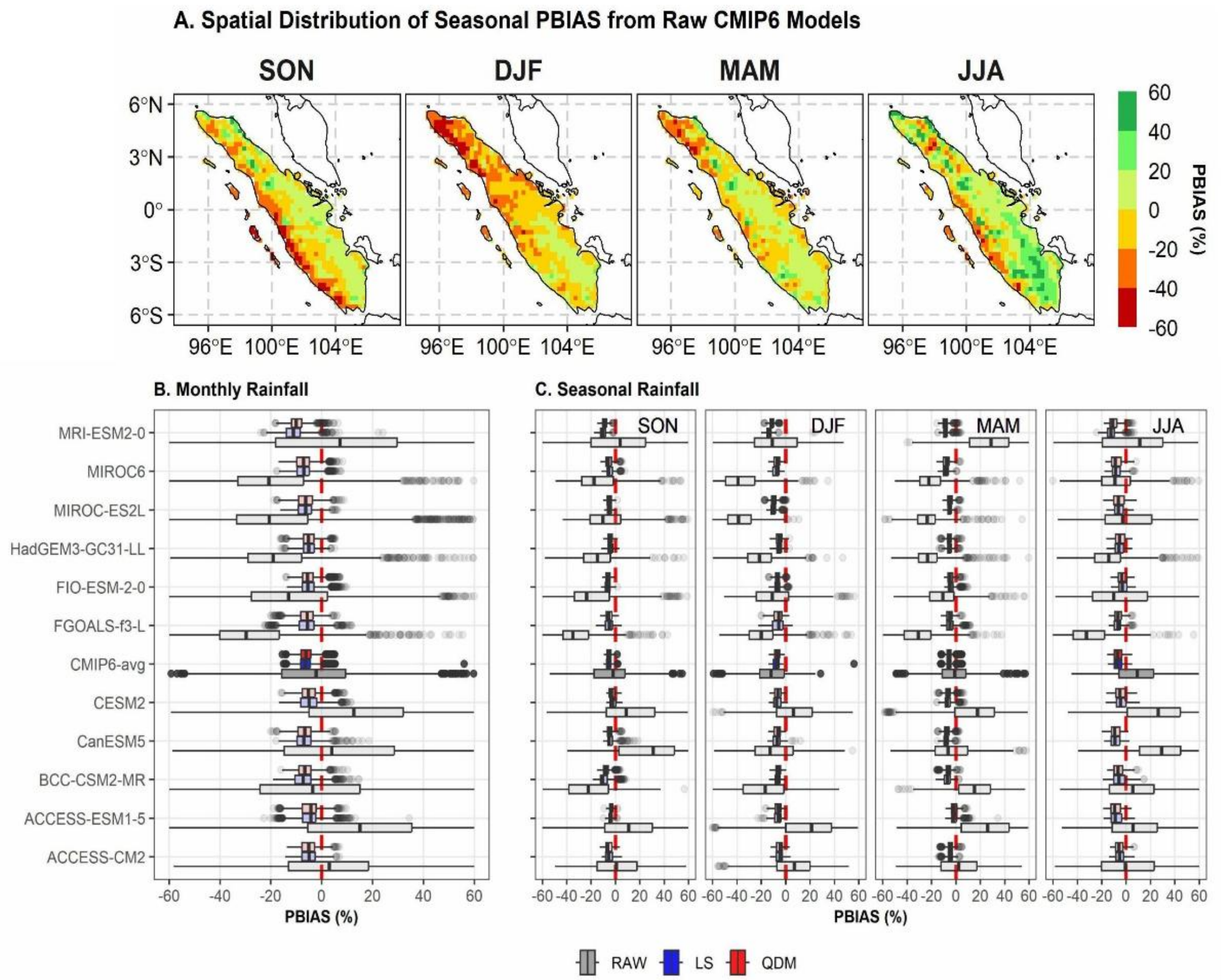


**Figure 3.** PBIAS of CMIP6 simulations relative to ERA5: (a) Spatial distribution of raw CMIP6-avg; (b) Monthly PBIAS; and (c) Seasonal PBIAS distributions for raw, LS, and QDM (1981–2014).

By adjusting the full precipitation distribution, QDM achieved better alignment with observed seasonal and monthly patterns, particularly during SON and DJF. In contrast, LS left larger residual biases and showed less consistency across models and seasons.

Both methods led to a noticeable reduction in the magnitude of seasonal precipitation anomalies across all models and seasons, resulting in more accurate seasonal precipitation patterns. However, some models still showed slight overestimations or underestimations in specific seasons, indicating that while bias correction improves accuracy, it may not fully eliminate all biases. These improvements are particularly valuable for hydrological modeling, drought assessment, and climate impact studies, which require accurate seasonal precipitation data.

The findings reinforce earlier studies that emphasize the importance of correcting raw GCM outputs to prevent issues such as misestimated precipitation totals and unreliable seasonal forecasts (Babaousmail et al., 2021; Kim et al., 2020).

Overall, the application of QDM substantially enhances the seasonal fidelity of precipitation simulations over Sumatra. These enhancements are critical for informing policy and adaptation strategies in climate-sensitive sectors such as agriculture, water resource management, and disaster risk reduction.

Building on the demonstrated benefits of QDM and ensemble approaches for improving precipitation simulations over Sumatra, future research should integrate high-resolution regional climate models (RCMs) with advanced bias correction techniques to better capture local-scale processes such as orographic rainfall and coastal dynamics. Extending the analysis to future climate scenarios would allow assessment of changes in drought frequency, onset, and intensity, especially in peatland dominated areas with high fire risk. Investigating compound events, such as drought associated fires, and incorporating vegetation-hydrology interactions could further enhance early warning systems and support more effective land-use and adaptation planning under a changing climate.

## 4. CONCLUSION

This study demonstrates that raw CMIP6 simulations tend to underestimate precipitation over western and northern part during the rainy seasons (SON and DJF), while overestimating precipitation during the dry season in most Sumatra. These biases persist despite overall improvements from CMIP5 to CMIP6 at the global scale, reflecting ongoing challenges in representing regional-scale processes influenced by Sumatra's complex topography and convective dynamics.

Bias correction significantly improves the accuracy of precipitation estimates. Among the methods evaluated, Quantile Delta Mapping (QDM) outperforms Linear Scaling (LS) by more effectively reducing both the magnitude and spread of seasonal and monthly biases. QDM achieves better agreement with observations during extreme precipitation periods, whereas LS tends to retain larger residual errors. Although both methods lead to more realistic precipitation patterns, QDM offers more consistent performance across models and seasons.

In conclusion, QDM is the preferred approach for improving CMIP6 precipitation outputs over Sumatra, providing more reliable data for hydrological modeling, drought monitoring, and climate impact studies in this climate sensitive region.

## ACKNOWLEDGEMENT

The authors gratefully acknowledge the anonymous reviewers for their constructive comments and valuable suggestions, which greatly enhanced the quality and clarity of this manuscript. This research was supported by the RIIM LPDP Grant and the National Research and Innovation Agency (BRIN), Grant No. 106/IV/KS/11/2023).

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