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Original Research Article

Bias-Corrected CORDEX-SEA Projections for Future Hydroclimatology Dynamics in Reservoir Systems

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Abstract

Climate change has significantly altered hydrological processes, particularly in tropical regions, where precipitation variability and atmospheric water demand are highly dynamic, affecting the performance of water resource systems such as the Selorejo Reservoir. This study aimed to project the hydro-climatological conditions of the reservoir for the short term (2025–2030) while improving the accuracy of climate model outputs. Climate data from CORDEX-SEA under RCP4.5 and RCP8.5. Model outputs were evaluated against baseline data (1995–2024) and corrected using a combination of linear scaling and quantile mapping to adjust mean values and distributions. Model performance was assessed using the correlation coefficient, Nash–Sutcliffe efficiency, root mean square ratio, and percent bias. The results indicate significant performance improvement following bias correction. Projections show that precipitation retains its seasonal pattern but exhibits higher extreme event intensity, particularly under the RCP8.5 scenario. Conversely, PET values are projected to increase by approximately 25–45 mm. Overall, the bias-corrected data provide scenario-based preliminary information to support the operation of the Selorejo Reservoir, although residual biases remain, and the data do not fully encompass the entire range of uncertainty in climate projections.

Keywords: Bias correction; climate change; CORDEX-SEA; potential evapotranspiration; precipitation

1. Introduction

Global climate change has emerged as a critical issue that significantly influences the dynamics of the hydrological cycle, particularly in tropical regions (Fu and Wu, 2024; He et al., 2024). These impacts are reflected in increasing precipitation variability, shifting seasonal patterns, and intensification of extreme events, such as heavy precipitation and droughts (Dollan et al., 2022; Donat et al., 2016; Sreeparvathy and Srinivas, 2022). In addition, rising air temperatures affect potential evapotranspiration (PET), a key component of the hydrometeorological system (Ding and Peng, 2021; Milly and Krista, 2016). The combined alterations in precipitation and PET contribute to growing uncertainty in future hydroclimatic conditions, highlighting the importance of climate projection-based approaches to assess potential long-term trends (Kim et al., 2026; Yang et al., 2025).

Selorejo Reservoir, located in East Java, serves as a multipurpose water resource system supporting irrigation, hydropower generation, and flood control. Based on historical data from Perum Jasa Trita I, the authority for managing Selorejo Reservoir, the average annual inflow has decreased from approximately ±13 m^3/s during the 2010-2014 period to ±10 m^3/s in recent five years (2020-2024), accompanied by a reduction in hydropower production from ±32 million kWh/year to ±28 million kWh/year. These trends suggest a shift in hydrometeorological conditions, likely influenced by changes in precipitation patterns and atmospheric processes.

In tropical watersheds, such as the Selorejo Reservoir, hydrological processes are heavily influenced by precipitation variability between the wet and dry seasons. This is supported by studies on tropical and regional climates, which indicate increased irregularity in precipitation patterns and a higher frequency of extreme hydroclimatic events (Ferreira et al., 2025; Hannan et al., 2026; Jackson et al., 2025). In addition, rising air temperatures contribute to increased PET rates, which enhances atmospheric water loss (Ramachandran et al., 2026; Yahaya et al., 2024). As precipitation and PET represent the primary input and output components of the reservoir water balance, their combined changes directly influence inflow dynamics, storage behavior, and overall system reliability. Therefore, an integrated assessment of these variables is essential to better understand future hydroclimatic responses at the reservoir scale.

To assess future climate conditions, model-based approaches are widely employed. Global Climate Models (GCMs) provide large-scale projections but are limited in their ability to represent local-scale variability because of their coarse spatial resolution. Regional Climate Models (RCMs), such as those developed for the Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA), offer improved spatial detail through dynamical downscaling (Tangang, Chung, Juneng, Supari, Salimun, Ngai, Jamaluddin, Mohd, Cruz, Narisma, Santisirisomboon, Ngo-Duc, et al., 2020; van Vuuren et al., 2014). However, despite these advancements, CORDEX-SEA outputs often contain systematic biases arising from discrepancies between simulated and observed data, which may reduce their applicability to local hydrological analyses (Nur et al., 2021). Consequently, bias correction methods, including linear scaling (LS) and quantile mapping (QM), are required to enhance the reliability of climate-projection data.

Previous studies have demonstrated the applicability of CORDEX-SEA for climate projection in Southeast Asia. Examples include regional-scale research covering areas such as Indonesia, Malaysia, Singapore, and the Philippines that utilized CORDEX-SEA models to examine future extreme precipitation trends and drought indices (Marzuki et al., 2026; Narulita et al., 2023), precipitation index variability and uncertainty (Qin, 2023), and the impact of sea surface temperatures on the climate (Magnaye et al., 2023). However, recent local-scale studies focusing on reservoirs in Indonesia (Anggraini et al., 2026; Hastina et al., 2025; Satria et al., 2025) generally analyze precipitation data using only single or isolated bias correction techniques. However, assessing reservoir system vulnerability requires a comprehensive evaluation of the water balance, which is influenced not only by precipitation but also by PET. Research integrating both precipitation and PET variables using a combined bias correction method at the local reservoir scale remains scarce. This limitation affects the reliability of climate-informed water resource assessments, particularly at the reservoir scale, where water balance components are strongly interdependent.

Therefore, to address this gap, this study aimed to answer two fundamental questions regarding the Selorejo Reservoir catchment area. First, it evaluated the performance of a bias correction approach that combines LS and QM in enhancing the quality of CORDEX-SEA climate model outputs (CNRM-CERFACS-CNRM-CM5/RCA4). Second, it utilized the bias-corrected datasets to project future changes in precipitation and PET under RCP4.5 and RCP8.5 scenarios. This study offers three main contributions: (a) an integrated assessment of precipitation and PET as key components of reservoir water balance; (b) a comparative evaluation of bias correction methods for improving projection reliability; and (c) an application at the reservoir scale to support climate-resilient water resource management. The results are

expected to provide a more robust basis for understanding future hydroclimatic trends in the Selorejo Reservoir and to enhance the usability of climate projection data in regional water management planning.

2. Methods

2.1 Study Location

This study focuses on the Selorejo Reservoir, a strategic reservoir located at the foot of Mount Kelud, precisely in Ngantang District, Malang Regency, East Java Province. Geographically, the reservoir is located at coordinates 07°52'25.15" South latitude and 112°21'23.37" East longitude. The Selorejo Reservoir is part of the Brantas River basin, and its water supply comes from precipitation, both falling directly on the reservoir surface and flowing through the river basin. The watershed contributing to the reservoir covers an area of approximately 236 km², while the reservoir's inundation area is approximately 4 km². The main inflows into the reservoir come from several rivers: the Konto River, the Pinjal River, and the Kwanjangan River.

Functionally, the Selorejo Reservoir is a multipurpose reservoir that provides irrigation water, generates hydroelectric power (PLTA), controls floods, supports fisheries, and promotes tourism. This reservoir serves the Siman Irrigation Area (D.I), which covers the Kediri and Jombang Regencies and has a total service area of approximately 23,060 ha. In addition, the installed hydroelectric power plant has a capacity of 4.5 MW and a significant annual electricity generation potential. In its operations, the Selorejo Reservoir is managed in an integrated manner by Perum Jasa Tirta I, in collaboration with "Pembangkit Jawa Bali" and provincial-level water resource management agencies. Figure 1 illustrates the geographical context of the study, showing the Selorejo Reservoir catchment area.

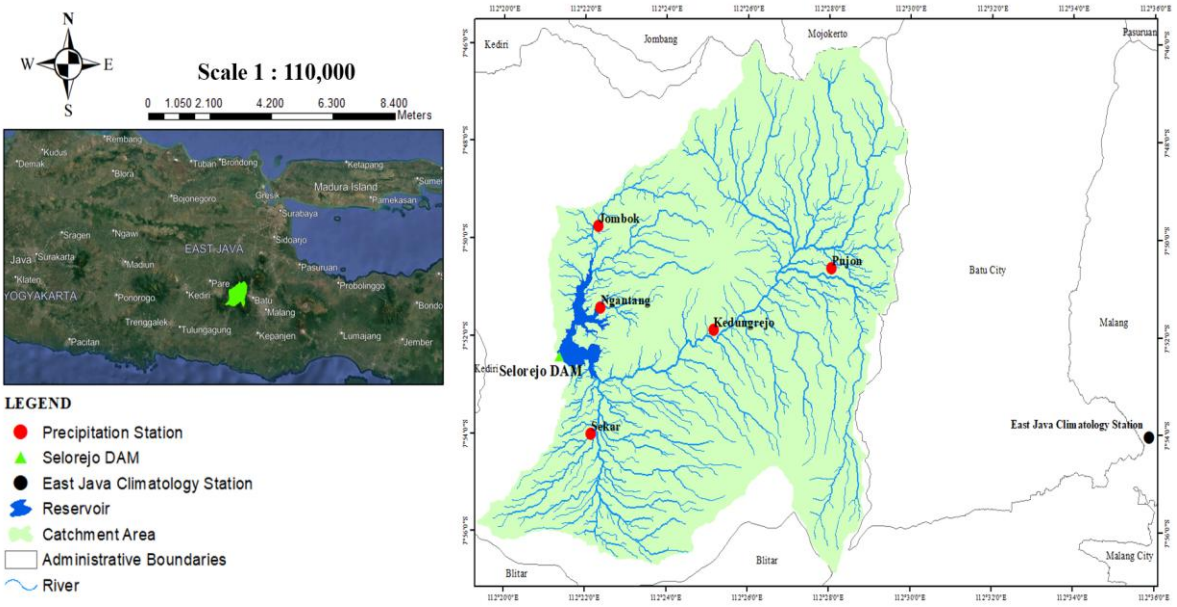


Figure 1. Selorejo Reservoir catchment area

2.2 Research Data

The observational data in this study consist of precipitation and climatological data. These represent the hydroclimatological conditions in the Selorejo watershed. Precipitation data were obtained from five stations: Jombok, Kedungrejo, Ngantang, Pujon, and Sekar. The observation period spanned 1995–2024, and data were sourced from the Public Works and Water Resources Agency of Malang Regency. Climatological data, including air temperature, relative humidity, sunshine duration, and wind speed, were obtained from the BMKG for the East Java region. These were collected during the same period. These climatological data will be analyzed to determine PET. The analysis will use the modified Penman method. The formula for this method is shown in Eq. (1) (Infantri Yekt et al., 2020).

$$Eto = c \times (WR_n + (1 - W)f(u)(e_a - e_d)) \quad (1)$$

In Eq. (1), *Eto* is potential evapotranspiration (mm/day), *C* is the Penman correction number obtained from the correction factor table in accordance with climatological conditions, *W* is a factor related to temperature obtained from a table based on air temperature and location elevation, *Rn* is sunshine duration (mm/day): *Rn = Rns – Rnl* (the difference between shortwave and longwave radiation), *f(u)* is a function of wind speed (km/day): $f(u) = 0.27(1 + 0.864u)$, *ea* is saturation vapor pressure (mbar) obtained from the saturated vapor pressure table based on air temperature, and *ed* is apparent vapor pressure (mbar): $ed = ea\left(\frac{RH}{100}\right)$, *RH* is relative humidity (%).

To analyze climate change and project future hydro-climatological trends, this study utilizes the CORDEX-SEA regional climate projection dataset, which is based on the CMIP5 framework and employs Representative Concentration Pathways (RCP4.5 and RCP8.5) scenarios. The RCP4.5 scenario was selected to represent a relatively realistic intermediate emission pathway, while RCP8.5 was chosen to represent an extreme or worst-case emission scenario (Moss et al., 2010). The study employs the CNRM-CM5 GCM, which is dynamically downscaled using the RCA4 RCM at a spatial resolution of 0.22° × 0.22° (±22 km) (Tangang, Chung, Juneng, Supari, Salimun, Ngai, Jamaluddin, Mohd, Cruz, Narisma, Santisirisomboon, Ngo-Duc, et al., 2020). Although the global climate community is currently transitioning toward the CMIP6 framework—incorporating Shared Socioeconomic Pathways (SSP) scenarios, the use of the CMIP5-based CORDEX-SEA dataset remains highly relevant and is maintained in this study, as CMIP6 regional downscaling products for Southeast Asia are currently in the preliminary experimental stage regarding physical configurations (Ngo-Duc et al., 2024). The selection of the CNRM-CERFACS-CNRM-CM5/RCA4 configuration was based on the model's performance in representing climate variability across Southeast Asia. An evaluation of nine CORDEX-SEA models by Aminoto et al., demonstrated that CNRM exhibited the best performance among individual models, making it a suitable configuration for climate projection analysis in the region (Aminoto et al., 2024). Nevertheless, relying on a single CMIP5 GCM–RCM combination presents a limitation, as it does not account for inter-model uncertainty or allow for direct comparison with CMIP6/SSP projections. Therefore, the projection results in this study should be understood as specific projections based on the CNRM-CERFACS-CNRM-CM5/RCA4 model and RCP4.5–RCP8.5 scenarios, utilizing variables, specifically precipitation and PET extracted from CORDEX data. All model data were obtained via the official Earth System Grid Federation (ESGF) portal at https://esgfdata.dkrz.de/search/cordex-dkrz/. The study area falls within the influence zone of four CORDEX-SEA grid points (Figure 2).

The CORDEX-SEA climate model data cover both a baseline period (1995–2024) and a short-term projection period (2025–2030). The selection of this projection period aimed to ensure that the CORDEX-SEA model outputs were sufficiently relevant for reservoir-scale water balance operations, allowing them to be directly integrated into risk mitigation strategies for drought or flooding within a timeframe meaningful to policymakers and practitioners. Therefore, the analysis results are limited to the conditions projected during the study period and cannot be used to identify long-term climate change trends. While climate change studies typically employ long-term horizons, such as the mid-to-late 21st century, to distinguish between emission scenarios, long-term projections entail increasingly complex uncertainties that can lead to less reliable outputs or overestimations (Gillett, 2024; Lehner et al., 2023; Lempert et al., 2024). The IPCC's 6th Assessment Report (AR6) emphasizes the need to focus on short-term risks and adaptation actions (2021–2040), noting that the uncertainties associated with end-of-century projections often complicate the formulation of current operational decisions regarding infrastructure (Portner et al., 2022).

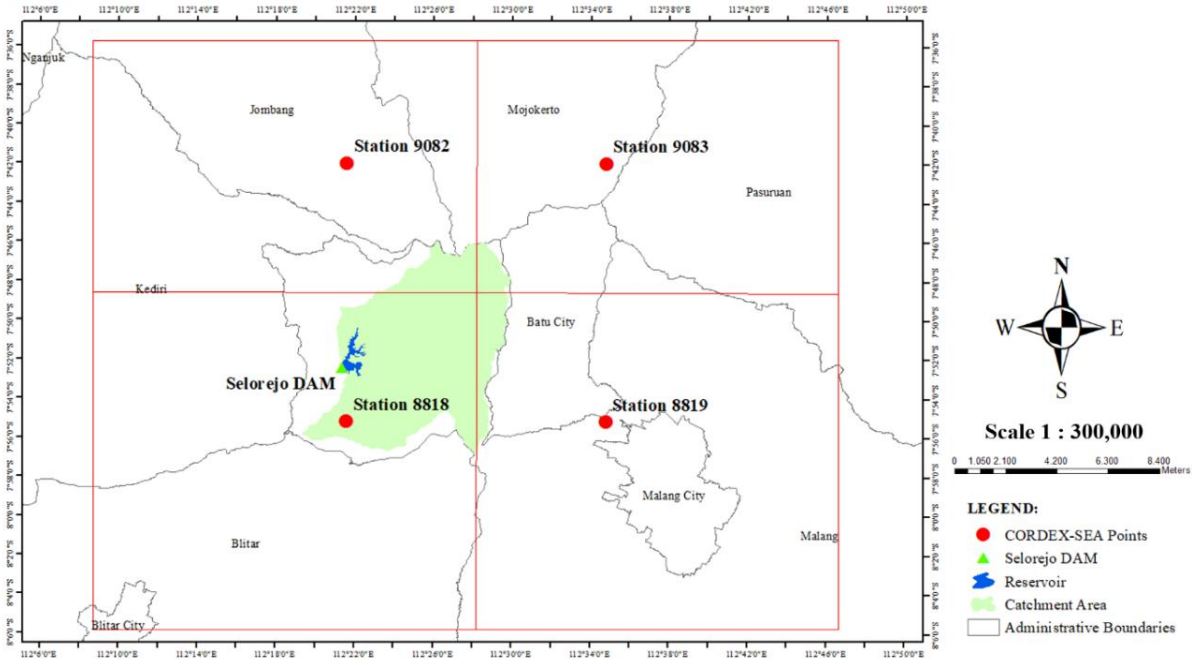


Figure 2. Influential CORDEX-SEA points

2.3 Research Method

This study comprises four main stages: data quality assessment, hydroclimatological processing, bias correction and evaluation, and future projection. The reliability of the observational and climate model data (1995–2024) was first evaluated using double-mass curve analysis for consistency, F-tests and t-tests for stationarity, and persistence tests. Regional precipitation data derived from both observations and the CORDEX-SEA climate model were determined using the Thiessen polygon method. For the observational data, polygons were constructed based on the locations of five stations. For the model data, polygons were constructed separately based on the locations of four CORDEX-SEA grid points that encompass and surround the Selorejo Reservoir watershed. The weight assigned to each station or grid point is determined by the ratio of the area of its corresponding polygon segment to the total area of the watershed. Differences in the locations and number of points resulted in varying weights between the two datasets. Nevertheless, both sets of weighted results represent the average precipitation over the same watershed area and time interval, making them suitable for use in bias correction and the evaluation of the model against observational data. Observed PET data were calculated using the modified Penman method, as presented in Eq. (1), incorporating local climatological parameters such as air temperature, sunshine duration, air humidity, and wind speed. PET data from the climate model were obtained directly by extracting CORDEX-SEA dataset values.

Bias correction was performed in stages, with LS applied first to adjust the monthly mean values, followed by QM to refine the distribution characteristics. During the bias correction phase, the data were split into a training period (80%; 1995–2018) for parameter estimation and a testing period (20%; 2019–2024) for validation. Bias correction performance was evaluated using four standard metrics: the correlation coefficient (CC), Nash–Sutcliffe Efficiency (NSE), the ratio of RMSE to the standard deviation of observations (RSR), and percent bias (PBIAS). Finally, the validated correction parameters were applied to CORDEX-SEA outputs to project precipitation and PET for the 2025–2030 period under RCP4.5 and RCP8.5 scenarios.

2.4 Bias Correction

Bias correction in this study combines LS-QM methods sequentially. The LS method is first applied to correct bias in mean values, aligning the central tendency of CORDEX-SEA model simulations with field observational data. Subsequently, the QM method is employed to adjust the statistical distribution of the data, addressing aspects ranging from variability to the frequency of extreme events, which simple correction methods often fail to adequately capture. This combined approach is expected to yield a more comprehensive correction regarding both mean values and probability distributions. Relying on a single method is often insufficient to mitigate the full range of bias characteristics in tropical regions with high climate variability. Integrating mean and distribution adjustments aligns with the findings of Teutschbein and Seibert, Ngai et al., and Zhang et al., who demonstrated the advantages of combining LS-QM to represent tropical monsoon precipitation characteristics (Ngai et al., 2017; Teutschbein and Seibert, 2012; Zhang et al., 2024). Furthermore, studies in Indonesia confirmed that combining mean-based and quantile-based methods produced a more accurate representation of hydro-climatological patterns compared to single-method scenarios (Hidayat and Taufik, 2025). However, the preservation of the climate change signal still requires a separate evaluation, as the empirical LS-QM method does not explicitly guarantee it. This includes examining changes between periods and values in the tails of the distribution, while accounting for the effects of bias correction.

2.4.1 Linear Scaling (LS)

The LS method is one of the simplest and most widely used bias correction techniques in hydrological and climate change research. The basic principle of this method is to adjust the mean value of the climate model output data to match the average observed data for the reference period. Thus, this method effectively corrects systematic bias at the mean scale, although it is not yet fully capable of correcting the data distribution or extreme events in the data. The LS method is expressed as follows: (2) (Teutschbein and Seibert, 2012).

$$P_{corr} = P_{sim} \times \frac{\overline{P_{obs}}}{\overline{P_{sim}}} \quad (2)$$

In Eq. (2), P_{corr} is the corrected data, P_{sim} is the model simulation data, $\overline{P_{obs}}$ is the average observation, and $\overline{P_{sim}}$ is the average model simulation.

2.4.2 Quantile Mapping (QM)

The QM method is a distribution-based bias correction technique that aims to align the cumulative distribution of model data with the distribution of observed data. This method works by mapping quantiles from simulated data to the corresponding quantiles in the observed data, thus correcting not only the mean but also the variability, distribution shape, and extreme events. Mathematically, the quantile mapping method is expressed in Eq. (3) (Gudmundsson et al., 2012).

$$P_{corr} = F_{obs}^{-1}(F_{sim}(P_{sim})) \quad (3)$$

In Eq. (3), P_{corr} is the corrected data, P_{sim} is the model simulation data, F_{sim} is the cumulative distribution function (CDF) of the simulated data, and F_{obs}^{-1} is the inverse CDF of the observed data.

2.5 Evaluation Model

This evaluation phase aims to ensure that the applied bias correction process improves the alignment of the model data's statistical characteristics, specifically regarding patterns, variability, and value trends, so that the corrected data can be reliably used for subsequent stages. The combination of four statistical indicators—CC, NSE, RSR, and PBIAS—represents a recommended standard approach for evaluating hydrological model performance, as it provides a comprehensive assessment of various aspects of model error. CC assesses the strength of the linear relationship, NSE evaluates the model's ability to represent data variability, RSR measures the magnitude of error relative to the standard deviation of

observations, and PBIAS identifies the model's bias tendency. Utilizing this combination of indicators is considered effective because the parameters complement one another in characterizing overall model performance. This aligns with the views of Hoshin et al. and Krause et al., who state that hydrological model evaluation should employ multiple criteria to avoid biases arising from interpretations based on a single indicator, and that no single parameter can fully represent all characteristics of model performance (Hoshin et al., 2009; Krause et al., 2005).

2.5.1 Correlation Coefficient (CC)

CC analysis is a statistical method commonly used to determine the relationship between two variables. This analysis measures the linear relationship between the observed and corrected data. The CC equation is presented in Eq. (4) (Sugiyono, 2013). Performance was evaluated based on CC parameters, with several indicator classifications shown in Table 1.

$$CC = \frac{(n)(\sum P_{obs}P_{sim})-(\sum xP_{obs})(\sum P_{sim})}{\sqrt{\left(n\times\sum {P_{obs}}^2-\sum(P_{obs})^2\right)\times\left(n\times {P_{sim}}^2-\sum(P_{sim})^2\right)}} \quad (4)$$

In Eq. (4), P_{sim} is the model simulation data, P_{obs} is the observation data, and n is the total number of data points in the dataset.

Table 1. Classification of the CC

Value	Category
0.8 – 1.00	Very Strong
0.6 – 0.79	Strong
0.4 – 0.59	Medium
0.2 – 0.39	Low
0.00 – 0.19	Very Low

2.5.2 Nash-Sutcliffe Efficiency (NSE)

Similarly, the NSE assesses the predictive accuracy of the model by comparing the variance of the model errors to the variance of the observed data. The NSE is computed using the equation shown in Eq. (5) (Moriasi et al., 2007). The performance was evaluated based on the NSE parameters, with several indicator classifications shown in Table 2.

$$NSE = 1 - \frac{\sum_{i=1}^{N}(P_{obs}-P_{sim})^2}{\sum_{i=1}^{N}(P_{obs}-\overline{P_{obs}})^2} \quad (5)$$

In Eq. (5), P_{sim} is the model simulation data, P_{obs} is the observation data, $\overline{P_{obs}}$ is the average observation, and n is the total number of data points in the dataset.

Table 2. Classification of the NSE

Value	Category
0.76 – 1.00	Very Strong
0.66 – 0.75	Strong
0.51 – 0.65	Satisfactory
≤ 0.50	Unsatisfactory

2.5.3 Root Mean Square Ratio (RSR)

The RSR standardizes the RMSE using the standard deviation of the observed data and incorporates an error index. The RSR is calculated using the ratio of the RMSE and the standard deviation of the observations. The RSR is computed using the equation shown in Eq. (6) (Moriasi et al., 2007).

Performance was evaluated based on the RSR parameters, with several indicator classifications shown in Table 3.

$$RSR = \sqrt{\frac{\sum_{i=1}^{N}(P_{obs}-P_{sim})^2}{\sum_{i=1}^{N}(P_{obs}-\overline{P_{obs}})^2}} \quad (6)$$

In Eq. (6), P_{sim} is the model simulation data, P_{obs} is the observation data, $\overline{P_{obs}}$ is the average observation, and n is the total number of data points in the dataset.

Table 3. Classification of the RSR

Value	Category
0.00 – 0.50	Very Strong
0.51 – 0.60	Strong
0.61 – 0.70	Satisfactory
≥ 0.70	Unsatisfactory

2.5.4 Percent Bias (PBIAS)

PBIAS is a quantitative measure that reflects the tendency of the average model simulation to be above or below the observed data. PBIAS is often used as an indicator of model performance because of its ability to directly indicate the presence of systematic bias towards the average volume or value. The PBIAS is computed using the equation shown in Eq. (7) (Moriasi et al., 2007). Performance was evaluated based on the PBIAS parameters, with several indicator classifications shown in Table 4.

$$PBIAS = \frac{\sum_{i=1}^{N}(P_{obs}-P_{sim})\times 100}{\sum_{i=1}^{N}P_{obs}} \quad (7)$$

In Eq. (7), P_{sim} is the model simulation data, P_{obs} is the observation data, and n is the total number of data points in the dataset.

Table 4. Classification of the PBIAS

Value	Category
≤ ±10	Very Strong
±10 – ±15	Strong
±15 – ±25	Satisfactory
≥ ±25	Unsatisfactory

2.6 Projected Future

The analysis of future precipitation and PET projections in the Selorejo Reservoir was conducted based on the output of the CORDEX-SEA regional climate model, using a combination of the GCM CNRM-CERFACS-CNRM-CM5 and the RCM RCA4. Projected precipitation and PET data for the 2025–2030 period obtained from CORDEX-SEA have undergone a bias correction process to improve their agreement with observed data. Furthermore, the corrected data were analyzed to characterize their magnitude, variability, and seasonal patterns. A descriptive comparison between the RCP4.5 and RCP8.5 scenarios was conducted based on the model outputs. These short-term differences may be influenced by internal climate variability and model uncertainty; therefore, they cannot be directly attributed to differences in emission pathways (Lempert et al., 2024). Further analysis focuses on the short-term hydroclimatological characteristics and their application as inputs for reservoir water balance simulations in the study area.

3. Result and Discussion

3.1 Comparison Between Observed Data and CORDEX-SEA Climate Model During the Baseline Period (1995–2024)

The baseline period (1995–2024) serves as a crucial reference for evaluating the performance of the CORDEX-SEA climate model against observational data. Prior to analysis, both the observational and model datasets underwent quality assessments, confirming their reliability, stability, and suitability for the subsequent stages. Pre-processing was then conducted to derive regional or watershed-scale precipitation values using the Thiessen polygon method, while PET was calculated using the modified Penman method. These regional precipitation and PET results subsequently served as the basis for comparing CORDEX-SEA outputs under the RCP4.5 and RCP8.5 scenarios during the baseline period.

As shown in Figure 3(a), the observed regional precipitation exhibited high temporal variability, characterized by significant fluctuations and intermittent extreme events across 10-day intervals. In contrast, CORDEX-SEA precipitation data displayed a bias, particularly under the RCP8.5 scenario, which tended to overestimate extreme events, evidenced by peak values exceeding those of the observational data. Conversely, during periods of low precipitation, the model sometimes failed to accurately represent dry conditions, indicating limitations in capturing the full range of precipitation variability. The PET comparison presented in Figure 3(b) revealed a more consistent pattern between the observational and model data. The temporal variations in PET were relatively smoother than those in precipitation, and the CORDEX-SEA model generally succeeded in reproducing both the trends and value ranges of the observed PET. Despite minor deviations during specific periods, the differences between the modelled and observed PET were not substantial.

Overall, the climate model demonstrated better performance in simulating PET than precipitation. Although the model captures general hydrometeorological patterns, the observed discrepancies indicate the presence of systematic biases in the CORDEX-SEA output. Such biases may arise because climate models have limitations in simultaneously representing various atmospheric physical processes and local characteristics (Liu et al., 2023; Magnaye et al., 2023). Differences in representing these processes can cause model simulation results to deviate from observed conditions. Consequently, if left uncorrected, these biases could significantly impact the accuracy of subsequent analyses.

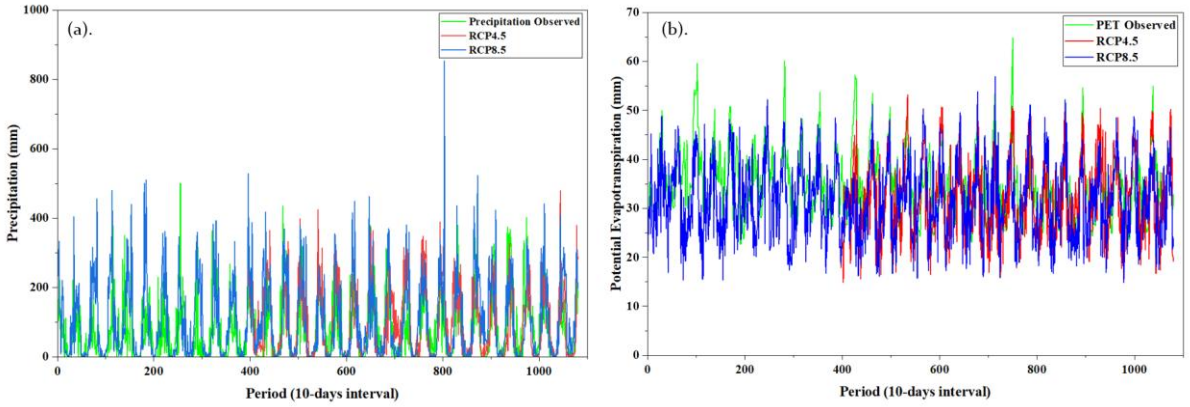


Figure 3. Baseline period (1995-2024): (a). Precipitation and (b). PET

3.2 Bias Correction Climate Model CORDEX-SEA

Based on the comparison results in the previous subsection, the CORDEX-SEA model output still shows discrepancies with the observed data, particularly for the precipitation variable, which has high variability. Therefore, an approach is needed to reduce this discrepancy so that the model data can better represent actual conditions. In this study, the bias correction process was carried out using a combination of LS-QM methods, which aimed to adjust the average value and statistical distribution of the model data

to the observed data. These methods were implemented using Python to ensure efficient and consistent data processing, utilizing a baseline dataset from the training period (80%, 1995–2018) with 10-day resolution. All 10-day data from the training period were combined to derive the LS factor and QM mapping, without grouping the correction functions separately by month.

The LS step was performed by multiplying the model data by the ratio of the mean of the observations to the mean of the model outputs during the training period. Subsequently, the QM is established using the scaled training-model distribution as a reference and the training-observation distribution as the target. The percentile for each input value was calculated based on its empirical rank using the `percentileofscore` function with the `rank` option in Python. These percentiles were then mapped onto the observation distribution using the `scoreatpercentile` function with linear interpolation in Python. Input values falling outside the range of the reference model distribution are mapped to the minimum or maximum values of the calibration observations, with no extrapolation of the distribution tails.

The results of the bias correction for the precipitation variable are shown in Figure 4(a). In general, the precipitation data after correction exhibit a fluctuation pattern that still follows seasonal characteristics, with high variability between 10-day periods. The corrected precipitation values still exhibit extreme events, with some peaks reaching over 400 mm, but with a more distributed frequency throughout the observation period. Furthermore, precipitation intensities in the low-to-medium categories (around 50–250 mm) appear more dominant and form a consistent recurring pattern, reflecting a more stable hydrological cycle. Temporally, there is no significant phase shift between wet and dry periods, thus maintaining the seasonal pattern. However, variations between scenarios are still visible, with RCP8.5 tending to show slightly higher fluctuation amplitudes than RCP4.5, particularly during certain periods, indicating potential increased precipitation intensity. This pattern indicates that despite the adjustments, the complex and nonlinear characteristics of precipitation variability remain a key feature of the data.

Figure 4(b) shows the results of the bias correction for the PET variable. In contrast to precipitation, the PET pattern after correction shows relatively more stable and continuous fluctuations throughout the observation period. PET values generally range from ±20 to ±45 mm per 10-days period, with variations that tend to be uniform across time. No significant extreme spikes were observed; therefore, the PET temporal pattern appears smoother and more controlled. Furthermore, the distribution of PET values shows a more homogeneous trend, with values dominating in the mid-range (around 25–35 mm), reflecting relatively consistent atmospheric conditions. Differences between scenarios (RCP4.5 and RCP8.5) are also not too striking, although in some periods, RCP8.5 shows slightly higher values. This indicates a stronger influence of climatic factors, such as temperature, in this scenario, but remains within reasonable limits of variation. Overall, the resulting PET pattern exhibits greater temporal stability than precipitation.

Overall, the application of the LS-QM combination demonstrates improvements in the CORDEX-SEA model output for both precipitation and PET variables. Theoretically, LS adjusts the difference in mean values between model output and observations, whereas QM corrects the data distribution by mapping model values based on quantiles corresponding to the observations. Thus, combining these two methods can reduce bias in central values while simultaneously improving the distributional characteristics of the model output. Chen et al. demonstrated that the LS and QM methods effectively reduced bias in temperature and precipitation simulations; furthermore, Ngai et al. state that the application of QM to CORDEX-SEA has been shown to reduce bias and inter-model variation in precipitation simulations across Southeast Asia (Chen et al., 2022; Ngai et al., 2022). However, visual and distributional improvements alone are insufficient to confirm that bias correction has significantly enhanced model performance. Therefore, further evaluation using various statistical indicators is required to quantitatively assess changes in model performance before and after the application of LS-QM, as discussed in the following subsection.

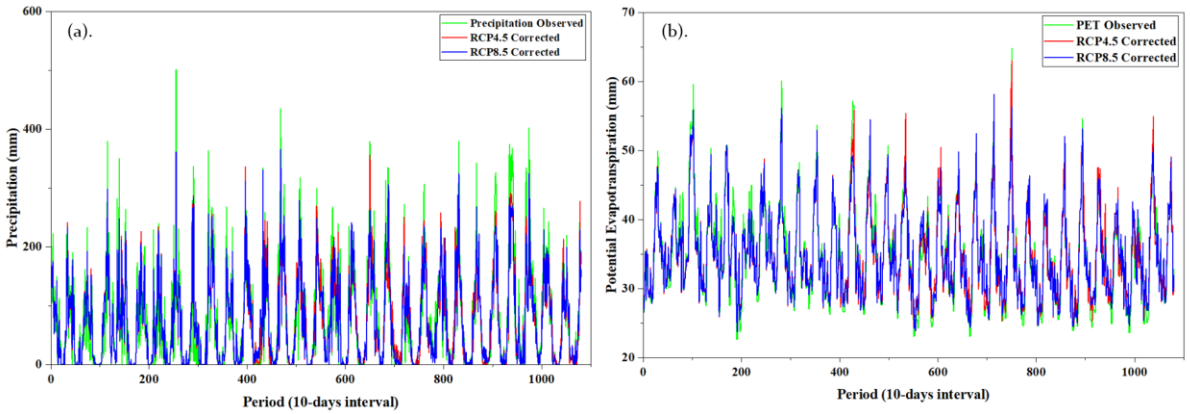


Figure 4. Baseline period (1995–2024) after bias correction: (a). Precipitation and (b). PET

3.3 Evaluation Climate Model CORDEX-SEA

The CORDEX-SEA climate model was evaluated to quantitatively assess the extent to which bias correction improves the agreement between model outputs and observed data. This assessment employs four widely used statistical indicators: CC, NSE, RSR, and PBIAS, each representing different aspects of model performance, including linear association, predictive accuracy, relative error magnitude, and systematic bias. The model evaluation stage also utilizes Python to ensure efficient and consistent data processing, utilizing a baseline dataset from the testing period (20%, 2019–2024). By comparing pre- and post-correction results under both RCP4.5 and RCP8.5 scenarios, this evaluation provides a robust basis for determining the reliability of the corrected datasets for subsequent hydro-climatological analysis (Table 5).

Table 5. Evaluation climate model CORDEX-SEA

Method	Precipitation				PET			
	RCP4.5		RCP8.5		RCP4.5		RCP8.5	
	Before Corrected	After Corrected	Before Corrected	After Corrected	Before Corrected	After Corrected	Before Corrected	After Corrected
CC	0.49	0.95	0.48	0.94	0.44	0.96	0.38	0.97
NSE	-0.35	0.89	-0.54	0.88	-0.51	0.92	-0.62	0.93
RSR	1.16	0.34	1.24	0.34	1.23	0.28	1.27	0.27
PBIAS	90.40	11.12	94.93	11.55	19.45	4.14	19.68	3.86

The evaluation results for the precipitation data component show significant improvement following the bias correction stage, despite certain remaining limitations. The CC value increased from “Medium” to “Very Strong” category, indicating a significant improvement in the correlation between the model and observations. Similarly, the NSE value shifted from negative (indicating “Unsatisfactory”) to positive with a "Very Strong" category, demonstrating that the corrected model effectively captures observational variability with high accuracy. The RSR value also dropped drastically from >1.00 “Unsatisfactory” to 0.34 “Very Strong” category, reflecting a reduction in model error relative to the standard deviation of the observations. PBIAS decreased significantly from a level of severe overestimation with “Unsatisfactory” category to approximately 11–12% “Strong”. These results indicate that the combined LS–QM approach is effective for correcting bias in precipitation data, although there is still some bias, as indicated by a PBIAS value of approximately 11–12%. The initially high PBIAS value indicates a tendency for the model output to significantly overestimate precipitation. This result aligns with the findings of Nguyen et al., who observed that the CORDEX-SEA model tends to exhibit a wet bias in precipitation simulations for Southeast Asia; this bias is associated with increased local and large-scale moisture supply, as well as enhanced convective precipitation, particularly during extreme events relative to observations (Nguyen et al., 2022). The improved relationship following bias correction highlights the

importance of adjusting both mean values and variability, given that precipitation is highly sensitive to local climate variability and extreme events. Regarding scenario comparisons, both RCP4.5 and RCP8.5 exhibited very similar performance after bias correction, indicating that the correction method is robust across different emission scenarios.

A similar pattern was observed for PET, where all performance indicators showed improvement following bias correction. The CC value increased from a “Low” or “Medium” category to a “Very Strong” category, indicating a near-perfect linear fit after correction. The NSE value followed a similar pattern, rising from negative to positive with a "Very Strong" category, reflecting excellent performance. Furthermore, the RSR value decreased from >1.20 to approximately 0.28 and 0.27 “Very Strong” category, indicating a significant reduction in relative error. Additionally, PBIAS improved from the "Satisfactory" category to "Very Strong” (~±4%), demonstrating that systematic bias was effectively minimized. Compared to precipitation, PET exhibited a relatively lower bias even prior to correction. This result aligns with Chen et al., who demonstrated that climate models, specifically regarding surface air temperature generally display bias characteristics that are more structured, whereas precipitation exhibits biases that are more complex and more difficult for climate models to represent. (Chen et al., 2022). However, applying LS followed by QM maximized distribution improvements, bringing PET mean values and variability closer to observed data. This is crucial because PET determines atmospheric water demand, which directly influences reservoir water balance dynamics. As with precipitation, no significant differences were found between the RCP4.5 and RCP8.5 scenarios for PET following correction; this indicates that model performance is driven more by the bias correction procedure than by the emission scenarios themselves.

Overall, the study results confirm that the sequential application of LS and QM methods significantly enhances the reliability of CORDEX-SEA climate model outputs for both precipitation and PET, as reflected in the improvements in CC, NSE, and RSR. Although the PBIAS for precipitation remains around 11–12%, indicating the presence of residual bias, this value falls within a tolerable range according to the PBIAS classification provided in Table 4. Consistent improvements across all statistical indicators demonstrate that bias correction is essential for reducing uncertainty in climate projections, particularly at the local scale. Consequently, these corrected datasets provide a more robust foundation for subsequent hydro-climatological analyses, including water balance modelling and climate change impact assessments for the Selorejo Reservoir.

3.4 Projection Future Climate Model CORDEX-SEA (2025-2030)

Based on the bias correction and model evaluation results from the previous subsection, applying the LS-QM combination demonstrated an ability to adjust the CORDEX-SEA model outputs to more closely align with observed conditions. This improvement was quantitatively evidenced by changes in the evaluation indicator values, which show enhanced performance following bias correction. Thus, the evaluation results for the baseline period not only demonstrate the success of the correction in reducing bias but also provide insight into the characteristics of patterns, variability, and distributions of precipitation and PET produced by the model. Once the model's bias characteristics during the baseline period were established, the correction function derived from the relationship between the model data and observations was applied to the model outputs for the projection period (2025–2030). This approach allows for the correction of future CORDEX-SEA outputs based on bias patterns identified during the baseline period, without overwriting the climate change information generated by the model. A similar approach was employed by Zhao et al., who applied a bias correction method to the baseline period of CORDEX-SEA models and subsequently applied the selected method to projection-period outputs to estimate future precipitation changes (Zhao et al., 2021). This demonstrates that correction functions calibrated based on baseline period characteristics can be applied to model outputs for the projection period. Consequently, the bias patterns identified during the baseline period can serve as the basis for applying the LS-QM correction function to model outputs for the projection period (2025–2030).

The projection of future precipitation for the period 2025–2030, as presented in Figure 5(a), indicates that both the RCP4.5 and RCP8.5 scenarios maintain a highly fluctuating temporal pattern with pronounced variability across 10-day intervals. Peak precipitation events remained significant, with several instances exceeding 250 mm and even reaching above 300 mm, particularly under the RCP8.5 scenario. Both scenarios showed alternation between relatively wet and dry periods. Higher peak values under RCP8.5 reflected the differences in the model output throughout the study period. However, these differences are insufficient to indicate a sustained increase in precipitation or a systematic influence resulting from varying emission pathways. Furthermore, the values presented represent 10-day accumulated precipitation. Therefore, they do not directly indicate changes in the intensity or frequency of extreme precipitation.

In contrast, the projected PET shown in Figure 5(b) demonstrates a relatively smoother and more stable temporal pattern compared to precipitation. PET values generally range between approximately 25 mm and 45 mm per 10-day period, with gradual fluctuations and no extreme spikes. Both scenarios exhibit relatively similar temporal patterns, with the RCP8.5 output showing slightly higher values throughout the analysis period. This discrepancy is interpreted as a characteristic of the short-term projections derived from the model output employed. A six-year period does not yet provide sufficient evidence to conclude that there is a sustained increase in PET or a persistent divergence between the two scenarios.

A primary limitation of this analysis is the short projection period. Fluctuations between 2025 and 2030 may be influenced by internal climate variability as well as model uncertainties. Given these limitations, the projections for precipitation and PET serve as conditional inputs for evaluating the water balance response of the Selorejo Reservoir over the selected planning horizon. Projected precipitation can inform anticipation of periods with high potential inflow, while PET can indicate rising water demand during dry periods. However, directly applying these projections to reservoir operating rules requires further study, taking into account inflow projections, storage conditions, water demands, and operational limits. Thus, this research can provide preliminary information to support reservoir management that is more adaptive.

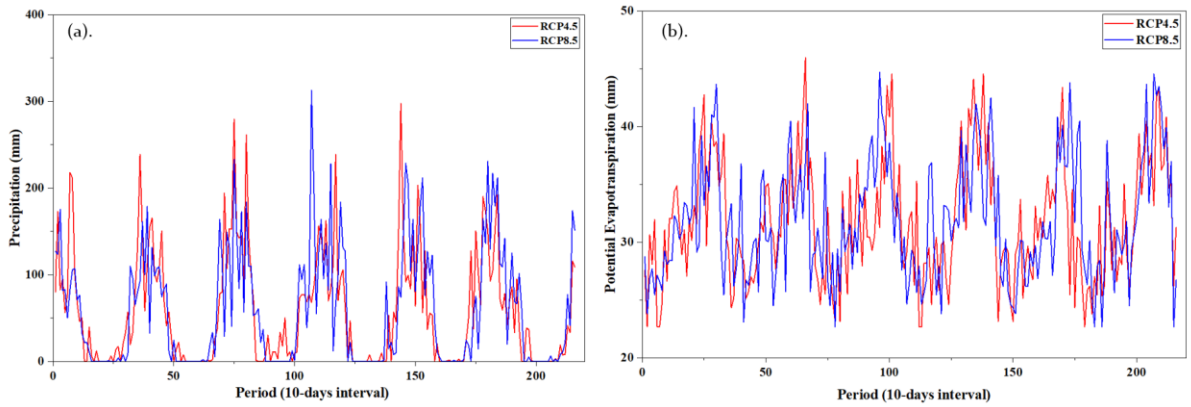


Figure 5. Projection future climate model CORDEX-SEA (2025-2030) after bias correction: (a). Precipitation and (b). PET

4. Conclusions

This study highlights the importance of bias correction in improving the reliability of CORDEX-SEA climate model outputs for hydroclimatological analysis. The initial evaluation showed notable discrepancies between model outputs and observations, particularly for precipitation, while PET exhibited relatively better agreement. Following the application of the LS-QM methods, the model performance improved substantially, with most statistical indicators reaching a "very strong" category. Nevertheless, residual biases exceeding 3% persisted, reaching 11–12% for precipitation, although these remained within an acceptable range. Future projections for the 2025–2030 period indicate temporal

variations under both the RCP4.5 and RCP8.5 scenarios. Precipitation exhibited fluctuations across 10-day intervals, while PET displayed a smoother pattern. The differences between the scenarios are described in terms of model output characteristics. However, they are insufficient to draw definitive conclusions regarding an overall increase in extreme events linked to long-term climate change. The bias-corrected CORDEX-SEA projection data were utilized as conditional inputs for water balance simulations of the Selorejo Reservoir to assess potential water availability conditions. These results represent a single realization based on the CNRM-CM5/RCA4 model combination and do not encompass the full range of uncertainty inherent in climate projections. Consequently, the findings provide preliminary, scenario-based information to support reservoir operations, while accounting for the limitations of the models and the projection period.

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Ethics Statement

The manuscript entitled "Bias-Corrected CORDEX-SEA Projections for Future Hydroclimatology Dynamics in Reservoir Systems" is an original work, free from plagiarism, fabrication, and copyright infringement. This manuscript has not been previously published and is not currently under review in any other journal. I take full responsibility for the entire content of the manuscript and agree to its publication in Jurnal Presipitasi: Media Komunikasi dan Pengembangan Teknik Lingkungan.

CRediT Author Statement

Dania Triwika Febrianti: Research Design, Data Curation, Formal Analysis, Investigation, and Manuscript Draft. **Sri Wahyuni**: Idea Development, Result Verification, Resources, Supervision, Manuscript Review and Revision. **Mohammad Bisri**: Result Verification, Manuscript Review and Revision, Visualization, and Supervision. **Yuangga Rizky Illahi**: Investigation, Formal Analysis, and Manuscript Draft.

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