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Evaluation of Bias Correction Techniques for RCA4 Model of CORDEX-Africa Precipitation and Temperature Data in Case of Omo Gibe River Basin, Ethiopia

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Abstract

The accurate assessment of climate change that impacts on water resources is fundamental to sustainable development. While Regional Climate Models (RCMs) are essential tools for this task due to their high resolution, their outputs contain significant biases that must be corrected. This is particularly critical in data-scarce regions like East Africa where the selection of optimal Bias Correction Methods (BCMs) remains largely unexplored and often relies on generalized recommendations. This study addresses this research gap by evaluating and identifying the most suitable BCM for the Omo Gibe River Basin in Ethiopia. The observed climate data (1990–2020) from 35 stations and precipitation and temperature variables from the Rossby Center regional Atmospheric Mode for African domain (RCA4) RCMs of the CORDEX-Africa project were utilized. The finding of the study demonstrated that the delta-change method outperformed other techniques, achieving exceptional performance metrics for bias-corrected historical data: for temperature Root-mean-square error (R^2) is 0.95, Nash Sutcliffe efficiency (NSE) is 0.97, Coefficient of determination (RMSE) is 0.0028 and for precipitation (R^2 = 0.9, NSE = 0.95, RMSE = 0.0025). The study concluded that the delta-change method is the most robust approach for correcting both historical and future climate projections in the basin. Its application is therefore highly recommended for subsequent climate change impact studies on hydrology in the Omo Gibe Basin and similar regions in East Africa.

Keywords: RCM, bias correction; climate variables; Omo Gibe River Basin.

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1. INTRODUCTION

Climate change is unequivocally altering fundamental climate parameters, with temperature and precipitation being among the most significant. Understanding the subsequent impact on hydrological systems is critical for water resource management, agricultural planning, and disaster preparedness. To project these future impacts, scientists rely on hydrological models driven by climate variables such as temperature, precipitation, and water vapour—simulated by General Circulation Models (GCMs). However, a significant limitation arises from the coarse spatial resolution of GCMs, which typically ranges from 100 to 500 km. This scale is inadequate for regional impact studies as it fails to capture the detailed, regional-scale physiographic features necessary for accurate watershed-scale analysis (Grotch & MacCracken, 1991, Manatsa *et al.*, 2008, Morgan, 2004).

To bridge this scale gap, RCMs have been developed as pivotal tools. RCMs dynamically downscale the large-scale atmospheric conditions from GCMs to finer resolutions of 25–50 km, providing climate information that is far more relevant to regional topography and hydrology. Initiatives like the Coordinated Regional Downscaling Experiment (CORDEX), under the auspices of the World Climate Research Program (WCRP), have been instrumental in standardizing and advancing these downscaling approaches. CORDEX provides a robust framework for generating regional climate data, which is essential for investigating environmental vulnerabilities, climate change impacts, and adaptation strategies particularly in data-sparse regions like Africa (Giorgi *et al.*, 2009, Gutowski *et al.*, 2016).

Despite their utility, RCM-simulated climate variables are not free from inaccuracies and exhibit significant systematic biases when compared to observed data. These biases stem from imperfections in model conceptualization, parameterization, and the spatial averaging within grid cells (Christensen *et al.*, 2008, Teutschbein & Seibert, 2010a, Varis *et al.*, 2004). Consequently, using raw RCM output directly in hydrological impact studies can lead to misleading results. To address this, BCMs have become a standard pre-processing step. These methods, which range from simple scaling to sophisticated distribution mapping techniques, are employed to minimize the discrepancies between simulated and observed climate data, thereby producing more reliable inputs for hydrological models (Teutschbein & Seibert, 2012). Furthermore, to account for model uncertainty and inter-model variability, the use of multi-model ensembles incorporating multiple RCMs and GCMs is widely recommended (Déqué *et al.*, 2007).

While the application of BCMs is now commonplace, their performance is not universal. The efficacy of a given method can vary significantly depending on the region, the climate variables, and the local topography. In the context of Ethiopian river basins, several studies have applied bias correction techniques to temperature and precipitation data (Abera *et al.*, 2018, Bekele *et al.*, 2019, Chaemiso *et al.*, 2016, Feyissa *et al.*, 2024, Gebrechorkos *et al.*, 2019, Gebremeskel & Kebede, 2018, Gismu Chakilu *et al.*, 2024, Kassaye *et al.*, 2024). However, these studies often rely on methods suggested in global literature without a comprehensive basin-specific evaluation to identify the most suitable technique for a particular hydrological and climatic context. This has created a critical research gap at the individual river basin level, including the Omo Gibe River Basin, where a systematic assessment of BCMs has not yet been conducted (Fentaw *et al.*, 2018, Mengistu *et al.*, 2023, Yifru *et al.*, 2021). Identifying the most appropriate bias-correction technique is a prerequisite for any robust assessment of climate change impacts on the water resources of the basin.

Therefore, this study aims to fill this gap by conducting a systematic evaluation of various bias correction approaches for correcting precipitation and temperature datasets from the RCA4 regional climate model (part of the CORDEX Africa AFR-44 domain). The primary objective is to identify the most effective bias correction method for tailoring RCM-simulated climate parameters to the specific conditions of the Omo Gibe River Basin, thereby establishing a reliable foundation for subsequent climate change impact and hydrological studies in the region.

2. MATERIALS AND METHODS

2.1. Study area

Omo Gibe River Basin is one of the largest river basins in Ethiopia. The area coverage of the river basin is 79678 km^2. The basin is situated between 34^{0}0’0’’ - 39^{0}0’0’’ E and 4^{0}0’0’ - 10^{0}0’0’ N. The river basin topography ranges from 3596m to 335m. The high variation of topography of the river basin impacts climate variables and hydrological process of the catchment (Gelebo *et al.*, 2022, Jillo *et al.*, 2017). The river basin drains to Lake Turkana at its downstream end. The river basin currently has 35 climate station repesented as “Omo-Climate-stat” in legend of the Fig. 1 spread over the catchment.

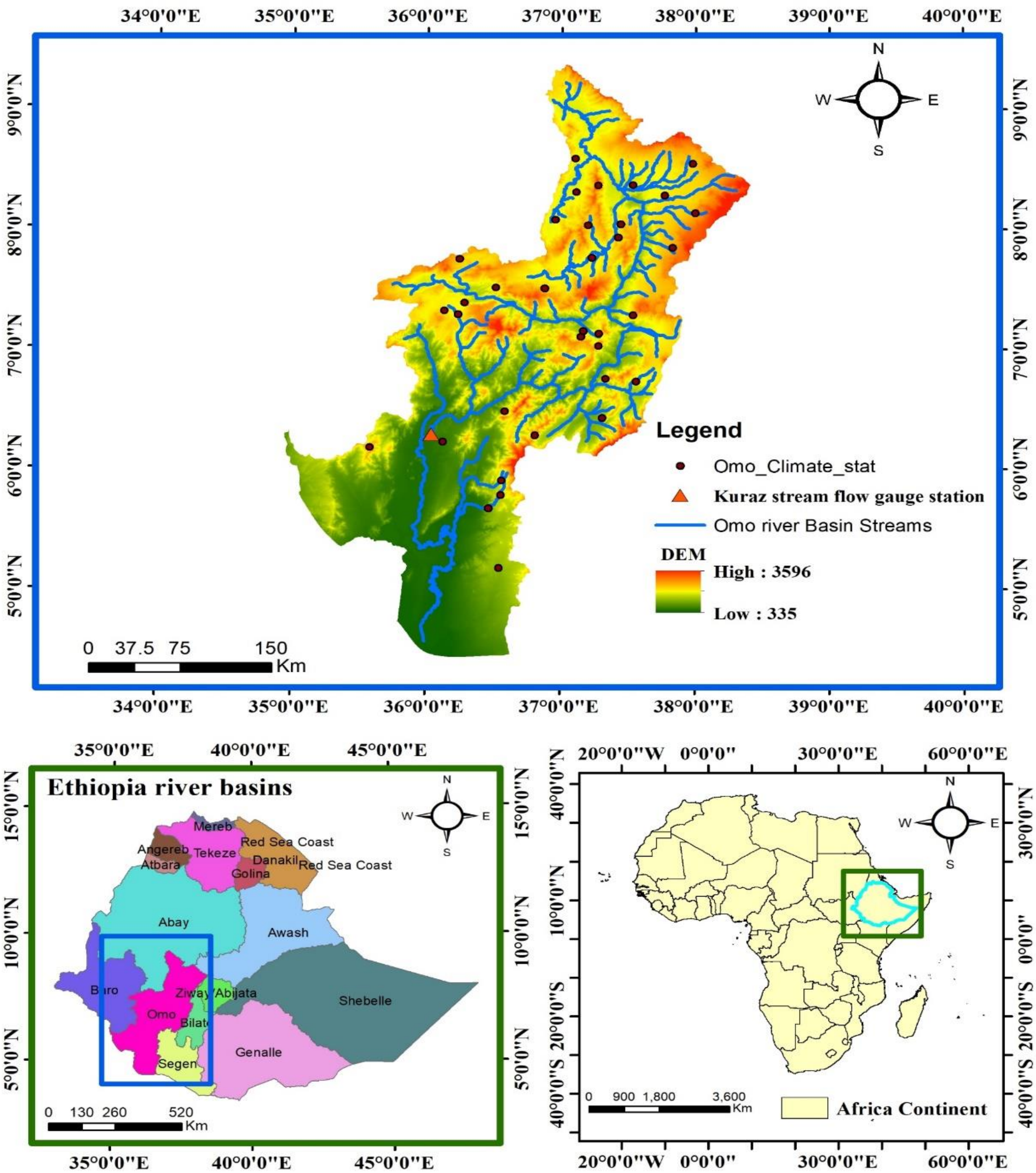

Fig. 1 Study area

2.2. Data process and models description

The climate datasets from downscaled regional climate model of Swedish Meteorological and Hydrological Institute (SMHI) and RCA4 were preferable and effective for investigating climate change effects on hydrological systems in African. The dynamic downscaling of subsets of GCMs from CMIP5 project under a large ensemble of regional climate simulations was produced at the Rossby Centre for Coordinated Regional Climate Downscaling Experiment (CORDEX) (Samuelsson *et al.*, 2015). The CORDEX was initiated by the World Climate Research Program (WCRP) to produce high-resolution datasets for climate scenarios over various regions worldwide (Gutowski *et al.*, 2016). All datasets of CORDEXwere archived at Earth System Grid Federation (ESGF). The software used in ESGF allowed users to transparently access all data archived (Juckes *et al.*, 2013). The CORDEX-Africa climate data were retrieved from the website https://esg-dn1.nsc.liu.se/search/cordex/.

The observed (baseline) climate variables such as temperature and rainfall data for the period of the year 1990 to 2020 for 35 climate stations in the river basin were collected from the National Metreology Agency (NMA) currently replaced by Ethiopian Meteorological Institute (EMI). The high-resolution simulated climate data of temperature and precipitation were generated from RCMs within the CORDEX-AFR-44 initiative for Africa. These RCM were driven from ten different Global Climate Models (listed in Table 1), creating a robust multi-model foundation for Africa. This dataset intially subjected to bias correction to improve its accuracy, and was then used to produce an ensemble of climate variables for enhancing the reliability of the projections.. All CORDEX Regional Climate Models (CORDEX_RCMs) spatial resolution grid sizes were set to 0.44◦ longitude and 0.44◦ latitude, in which the models work at the equatorial domain under a quasi-constant spatial resolution of approximately 50 by 50 km (Nikulin *et al.*, 2012). The RCA4 historical and future climate data such as daily temperature and precipitation was obtained from SMHI-NSC Sweden Institute of climate project from ESGF – CORDEX framework (Diatta *et al.*, 2020).

Table 1 depicts all driving models available for Africa domain RCM models in CORDEX dataset. All driving models for obtaining downscaled RCM climate data were identified for the study area (Table 1). The experiment family such as historic and RCP scenarios (RCP4.5 and RCP8.5) using the r1i1p1 ensemble method in the study area was considered for the investigations. The CMhyd model was initially trained for all driving models for identifying appropriate driving models for the study area. The Driving model such as CSIRO-QCCCE-CSIRO-Mk3-6-0, IPSL-IPSL-CM5A-MR and MIROC-MIROC5 satisfy the condition to be used in the Omo Gibe River Basin, East Africa.

The identified RCA4 regional climate models for the study area historic and future climate data were used for evaluation of bias correction methods. The Representative Concentration Pathways (RCP) climate change scenarios such as RCP4.5 and RCP8.5 were considered in the study area. The details of CORDEX data driving models of RCA4 used in this study are presented in Table 1.

Table 1. CORDEX data driving models in Africa region for regional climate model of RCA4

Driving model	**RCM model**	**Resolution**	**Historic and future climate data time range**
CSIRO-QCCCE-CSIRO-Mk3-6-0	RCA4	50km	1951 – 2005 and 2006 - 2100
IPSL-IPSL-CM5A-MR	RCA4	50km	1951 – 2005 and 2006 - 2100
MIROC-MIROC5	RCA4	50km	1951 – 2005 and 2006 - 2100
CCCma-CanESM2	RCA4	50km	1951 – 2005 and 2006 - 2100
CNRM-CERFACS-CNRM-CM5	RCA4	50km	1951 – 2005 and 2006 - 2100
ICHEC-EC-EARTH	RCA4	50km	1951 – 2005 and 2006 - 2100
MOHC-HadGEM2-ES	RCA4	50km	1951 – 2005 and 2006 - 2100
MPI-M-MPI-ESM-LR	RCA4	50km	1951 – 2005 and 2006 - 2100
NCC-NorESM1-M	RCA4	50km	1951 – 2005 and 2006 - 2100
NOAA-GFDL-GFDL-ESM2M	RCA4	50km	1951 – 2005 and 2006 - 2100

2.3. Bias Correction Methods

The bias correction of climate model data of daily climate parameters such as temperature and precipitation and their monthly ensemble average could be used for analysis of future climate chnage effect on spatio-temporal variation of water balances and hydrological process of the river basin. The Climate Model data for hydrologic modelling (CMhyd model) tool was used for estimating the corrected climate variables. CMhyd is designed to provide bias-corrected simulated climate data representing the gauges' location available in the watershed(Rathjens *et al.*, 2016). In addition, an ensemble approach is highly recommended to be used in line with bias correction. The approach supports in averaging numerous bias-corrected climate models and climate variables outputs for minimizing deviations in simulated RCMs (Teutschbein & Seibert, 2010b, 2012). Table 2 depicts9 methods of bias correction algorithms executed into CMhyd tool. The details about the bias correction methods, mathematical formulation, and explanation were presented by previous researchers (Mendez *et al.*, 2020, Teutschbein & Seibert, 2012). The three effective ensembled GCMs driving models downscaled by RCA4 regional climate model were used for generating bias-corrected historical and future climate variables data. The bias correction methods in the CMhyd model were preferred based on their compatable consideration of existing 35 climate stations. The bias correction methods such as (1) delta change correction (multiplicative), (2) linear scaling (multiplicative), (3) precipitation local intensity scaling, and (4) power transfer of precipitation were the best fit for analysis of bias correction of downscaled precipitation climate outputs in the CMhyd model. While bias correction methods such as (1) delta change correction (additive), (2) linear scaling (additive), and (3) variable scaling of temperature are compatible for bias correction of temperature for each gauge station in the Omo Gibe River Basin (Table 2).

Table 2. Common bias correction methods in CMhyd Model (Rathjens *et al.*, 2016, Teutschbein & Seibert, 2010b, 2012)

Precipitation	**Temperature**
Linear scaling (multiplicative)	Linear scaling (additive)
Delta-change correction (multiplicative)	Delta-change correction (additive)
Precipitation intensity local scaling	Variable scaling
Power transformation	Distribution (Quantile) mapping
Distribution (Quantile) mapping	

1) **Linear Scaling (LS)**

   The Linear Scaling (LS) method is a simple technique that corrects climate model data, like rainfall, using monthly adjustment factors. For precipitation, it calculates a monthly correction factor by dividing the observed average rainfall by the simulated average. This factor is then applied to each daily rainfall value within that month to produce a corrected dataset. In adition, this method corrects temperature data using an additive term based on the difference between observed and simulated mean tempreature. The detail of the emperical formulation is available on the previous works (Mendez *et al.*, 2020, Sha *et al.*, 2021, Teutschbein & Seibert, 2012).

2) **Local Intensity Scaling**

The Local Intensity (LI) method is commonly used to correct the daily precipitation data simulated by GCMs and RCMs. This correction adjusts both the frequency of rainy days and the intensity of the rain produced. While the original model data often overestimates daily rainfall compared to observations, the LI method recalibrates the thresholds for defining a "wet day" to better match projected future rainfall patterns. The detail of the threortical formulations was presented by previous studies (Dinku & Gibre, 2024, Nikulin *et al.*, 2012, Teutschbein & Seibert, 2012).

3) **Power Transformation of Precipitation**

Precipitation is highly variable across space and time and behaves nonlinearly. The Power Transformation (PT) method addresses this by nonlinearly correcting both the mean and variance of precipitation data (Teutschbein & Seibert, 2012). This correction uses an exponential formula, P*= $\mathbf{a \times P^b}$, where P* corrected precipitation, parameters *a* and *b* are calculated monthly. The method is applied by comparing observed data from a station to simulated data from the nearest Regional Climate Model (RCM) grid point, treating the grid point as a virtual station. Parameters a and b are estimated by equalizing the coefficient of variation (CV) of the corrected simulations and the CV of the observed values. The detail of formulation and relation of parameters and procedures for estimating the corrected precipitation (P*) are presented by (Teutschbein & Seibert, 2012).

4) **Variance Scaling of Temperature**

While the Power Transformation (PT) method effectively adjusts the mean and variance of precipitation, it is unsuitable for temperature data. This is because temperature follows a normal distribution unlike the nonlinear distribution of precipitation (Bhatti et al. 2016). For normally distributed variables like temperature, a different method and the detial of the emperical theortical formulation were presetented by previous studies (Dinku & Gibre, 2024, Teutschbein & Seibert, 2012)

5) **Delta Change Method**

The Delta Change (DC) method generates future climate scenarios by applying simulated anomalies from RCMs to observed data. This approach operates on the assumption that bias at the regional level remains constant over time (Das et al., 2022). Despite being widely discussed in scientific literature (Ashraf *et al.*, 2022, A. Das *et al.*, 2022, Hassan *et al.*, 2022, Teutschbein & Seibert, 2012, Yifru *et al.*, 2021), the performance of the method is formally quantified using the equation presented by previous studies (P. Das *et al.*, 2022, Dinku & Gibre, 2024, Teutschbein & Seibert, 2012).

6) **Distribution Mapping**

The Distribution Mapping (DM) technique corrects bias by aligning the statistical distribution of simulated data with that of observed data. There are two primary DM variants: Empirical Quantile Mapping (EQM) and Theoretical Quantile Mapping (TQM). EQM is a non-parametric method that directly matches the cumulative density functions (CDFs) of historical model output and observed records (Teutschbein & Seibert, 2010a, 2012). In contrast, TQM fits the CDF of the model to a theoretical distribution (e.g., gamma) assumed for the observations. This assumption is a drawback, as it can introduce new biases if the chosen distribution does not perfectly fit the observed data (P. Das *et al.*, 2022, Dinku & Gibre, 2024, Teutschbein & Seibert, 2012).

2.4. Model Performance Evaluation Techniques

The performance of bias correction methods was evaluated using Nash Sutcliffe efficiency (NSE), root-mean-square error (RSME) and regression coefficient (R^2). The bias-corrected and observed climate variables were used for evaluation of preformances of the BCMs. The performance evaluation methods are described empirically as follows.

1) ***Coefficient of determination (R^2):***

$$\boldsymbol{R^2 = 1 - \frac{SS_{residual}}{SS_{Total}}} \qquad (1)$$

where $SS_{residual}$ is the sum of the square of residuals and SS_{Total} is the total sum of squares

2) ***Nash Sutcliffe efficiency (NSE):***

$$\boldsymbol{NSE = 1 - \frac{\sum_{i=1}^{n}[O_i - S_i]^2}{\sum_{i=1}^{n}[O_i - \overline{O}]^2}} \qquad (2)$$

where $\boldsymbol{\overline{O}}$ is the average of observed climate variables, $\boldsymbol{S_i}$ is simulated climate variable and $\boldsymbol{O_i}$ is observed climate variable. The suffix *i* refers to corresponding days.

3) Root-mean-square error (RSME)

$$\boldsymbol{RSME = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}}} \qquad (3)$$

where S_i is the simulated climate variable, O_i is the observed climate variable, and n is the total number of time series data.

The performance of bias correction methods presented in Table 2 was evaluated by CMhyd software (Rathjens *et al.*, 2016). The bias correction method was based on the established principle of deriving a transfer function between historical RCM simulations and observed station data, which is then applied to future climate projections (Lafon *et al.*, 2013, Maraun, 2016, Maraun & Widmann, 2018, Teutschbein & Seibert, 2012). As long as the correction algorithm is calibrated exclusively on the historical period and is independent of the future emission scenario, the performance of the method can be adequately assessed using bias-corrected data from either RCP 4.5 or 8.5 of any station of the basin (Lafon *et al.*, 2013). Thus, in this study the bias corrected RCP 8.5 and observed temprature and precipitation data of Agena climate station of the river basin was prefered for evalaution of BCMs.

The conceptual frame developed for all methods adopted to meet the objectives of the study are presented in Fig. 2.

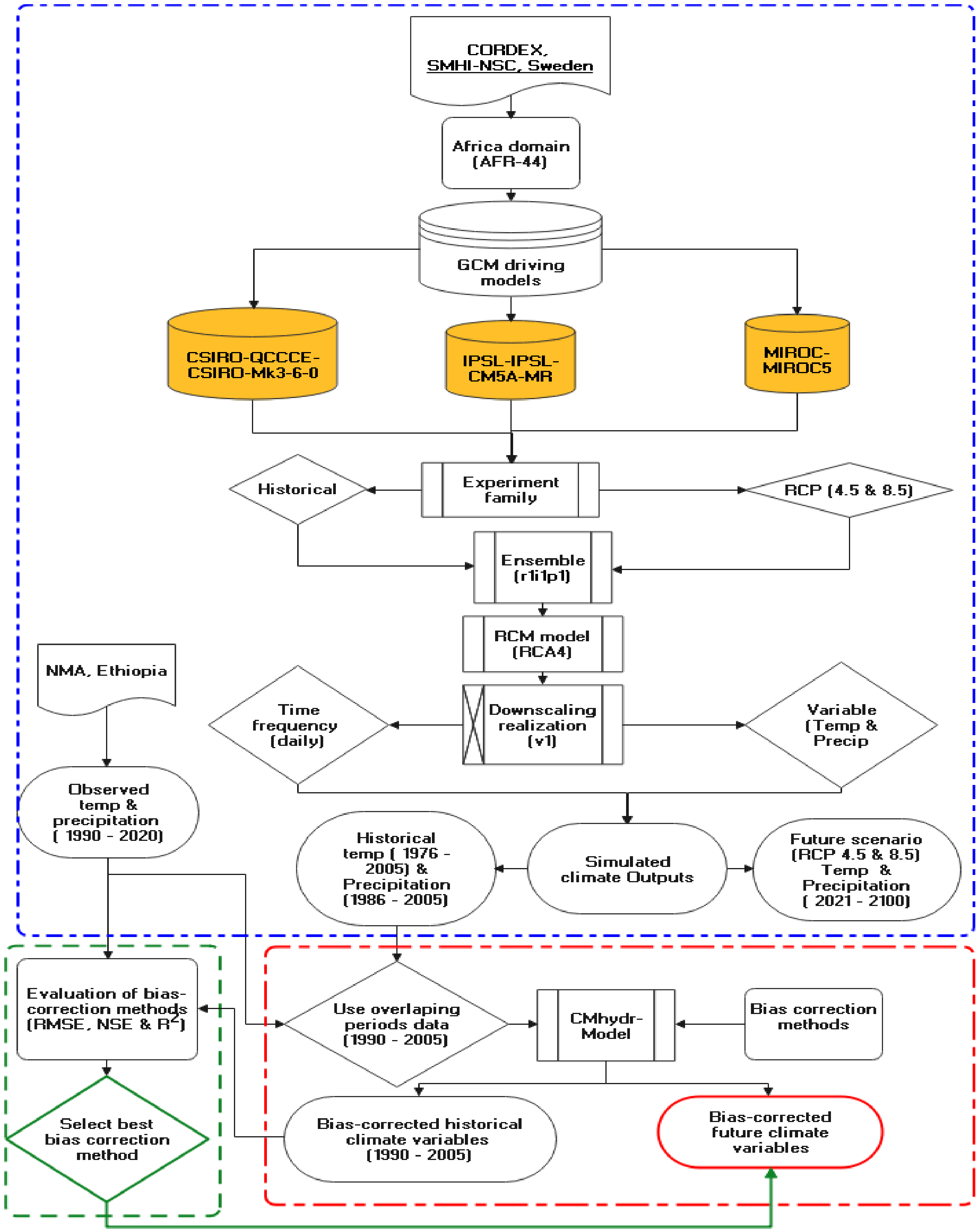

Fig. 2 Conceptual framework

3. RESULTS AND DISCUSSION

Whole bias correction techniques had the capacity to correct daily climate parameters such as temperature and precipitation. The results and discussion are presented as follow.

3.1. Evaluation of Bias-Correction Methods for Temperature

This study evaluated the performance of several bias-correction methods in reconciling historical temperature simulations from a regional climate model (RCM) with observed data in the Omo Gibe River Basin.

The results demonstrated significant variation in performance among the methods. The Linear Scaling Method showed a considerable discrepancy between the bias-corrected historical temperature and the observed records (Fig. 3) because Linear Scaling applies a constant monthly-based correction factor which fails to capture the full complexity of the systematic bias of the model particularly its dependence on temperature magnitude or the occurrence of extreme values. Its simplistic approach, while computationally efficient, often proves insufficient to accurately adjust daily temperature series in complex terrains like river basins (Teutschbein & Seibert, 2012).

In contrast, both the Delta-change Correction and Variable Scaling Additive methods produced bias-corrected temperature series that exhibited a high degree of similarity with the observed values. The quantitative metrics strongly support this visual and qualitative assessment. The superior performance of the Delta-change and Variable Scaling Additive methods is underscored by high-performance indicator values.

Delta-change Correction Method achieved an exceptional fit, with an R^2 of 0.95, an NSE of 0.97, and a very low RSME of 0.0028. An R^2 of 0.95 indicated that 95% of the variance in the observed data was explained by the bias-corrected model data, reflecting a very strong linear relationship (Fig. 3). An NSE value of 0.97 (where 1.0 represents a perfect match) was outstanding, signifying that the corrected data is a predictor of the observations with minimal residual variance. The near-zero RSME further confirmed that the magnitude of errors was negligible (Ashraf *et al.*, 2022, A. Das *et al.*, 2022, Hassan *et al.*, 2022, Teutschbein & Seibert, 2012, Yifru *et al.*, 2021) .

Variable Scaling Additive Method also performed robustly, yielding an R^2 of 0.93, an NSE of 0.96, and an RSME of 0.28 (Fig. 3). The R^2 and NSE values were only marginally lower than those of the Delta-change method, confirming its high skill in replicating observed conditions. The RSME value of 0.28, while higher than the Delta-change's metric, remained low in the context of temperature. This result showed an average error of less than 0.3°C and often acceptable for climate impact studies (Mendez *et al.*, 2020, Sha *et al.*, 2021, Teutschbein & Seibert, 2012).

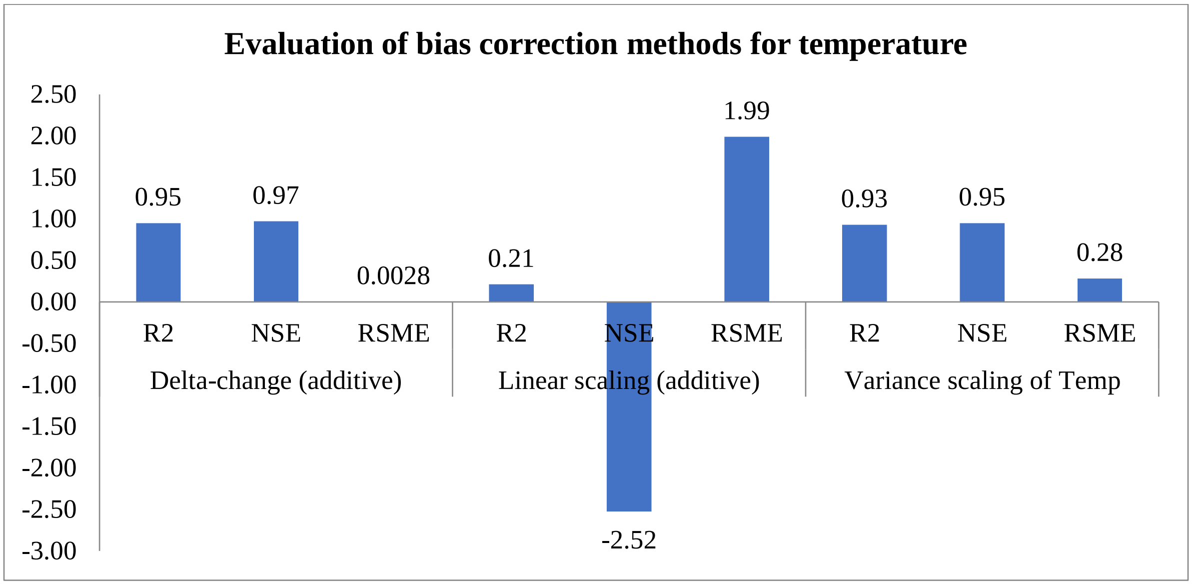

Fig. 3. Evaluation of bias correction methods for temperature

The finding showed that both Delta-change and Variable Scaling Additive methods are highly operative BCMs for correction of climate models Temperature data. While the Delta-change method showed marginally better statistical scores, its fundamental principle must be considered (Fig. 4). The Delta-change method calculates relative changes (deltas) between future and historical model runs and applies these to observed data (Das et al., 2022). It is therefore primarily used for future projections and its application here to the historical period is a validation of its internal consistency. Its excellent performance suggests that the model accurately captures the trend and pattern of change even if the absolute values are biased (Ashraf *et al.*, 2022, A. Das *et al.*, 2022, Hassan *et al.*, 2022, Teutschbein & Seibert, 2012, Yifru *et al.*, 2021). The Variable Scaling Additive method directly adjusts the historical values of the model to match the observed distribution. Thus, it served as a true bias-correction technique for the baseline period (Fig. 4). Its high performance confirmed its utility for producing a corrected historical baseline (Bhatti et al. 2016).

For subsequent studies in the Omo Gibe River Basin focusing on future climate projections, the choice between these two top-performing methods depended on the objective of the study. If the goal is to analyze future changes in climate signals with minimal influence from the baseline bias of the model, the Delta-change method is robust as suggested by previous studies world wide. If the goal is to work with bias-corrected daily time series for hydrological or ecological modeling that require realistic absolute values, the Variable Scaling Additive method is highly recommended (Andréasson *et al.*, 2004, Bosshard *et al.*, 2013, Graham *et al.*, 2007, Hay *et al.*, 2000, Teutschbein & Seibert, 2012).

The poor performance of Linear Scaling suggests that it should be avoided for temperature correction in this basin. These results provided a critical foundation for selecting appropriate methods to generate reliable climate data for impact assessments and water resource management planning in the region (Andréasson *et al.*, 2004, Bosshard *et al.*, 2013, Teutschbein & Seibert, 2012).

Therefore, the Delta-change Correction and Variable Scaling Additive Bias Correction methods can be preferable for bias correction of historic and predicted climate variables of regional climate models which support examination of climate change scenarios in Omo Gibe River Basin.

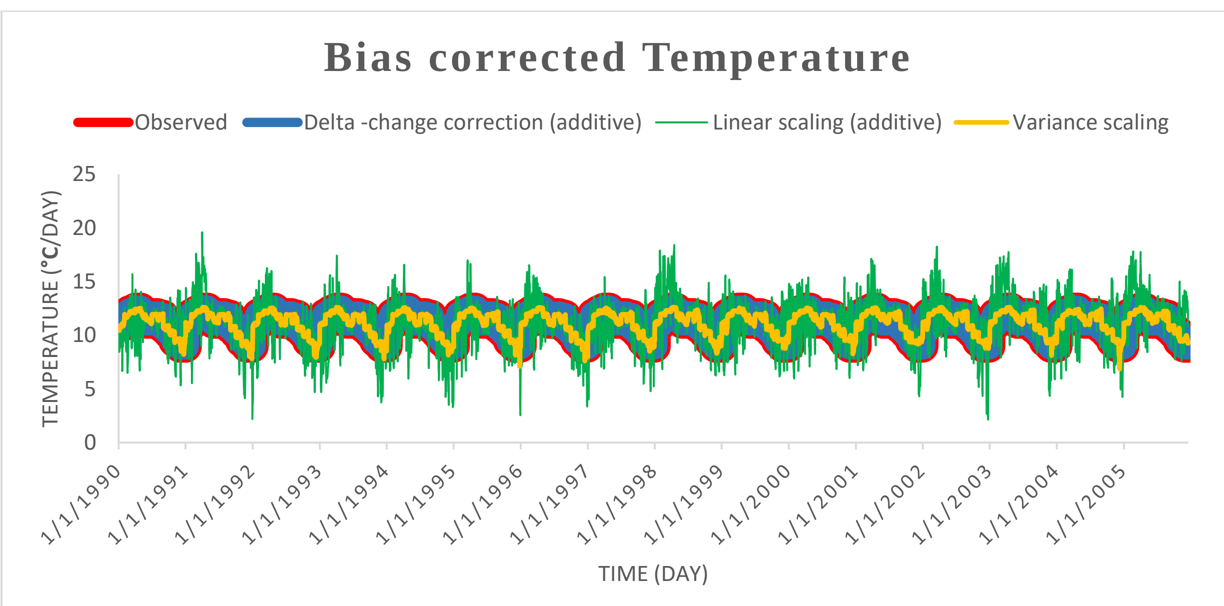

Fig. 4 Temperature bias correction methods & outputs

3.2. Evaluation of Bias-Correction Methods for Precipitation

The analysis revealed significant disparities in the performance of the different techniques. Methods such as Linear Scaling (Multiplicative) and Precipitation Local Intensity Scaling (PLIS) produced bias-corrected precipitation time series that exhibited considerable deviation from the observed station records (Dinku & Gibre, 2024, Nikulin *et al.*, 2012, Teutschbein & Seibert, 2012). These methods, while useful for certain applications, appeared insufficient to accurately replicate the statistical properties and distribution of the observed precipitation in this specific regional context. Their outputs showed notable residual biases, indicating a less effective calibration of the raw RCM data (Mendez *et al.*, 2020, Sha *et al.*, 2021, Teutschbein & Seibert, 2012).

In contrast, the Delta Change Correction (Multiplicative) and Power Transformation methods demonstrated superior performance. The precipitation series generated by these techniques aligned remarkably with the observed data, capturing both the temporal variability and the intensity distribution of actual precipitation events with high fidelity (Teutschbein & Seibert, 2012).

The quantitative validation of these findings is presented in Fig. 5, which compares the best-performing bias-corrected data against observations. The agreement is exceptionally strong as evidenced by near-perfect statistical metrics. Coefficient of Determination (R^2) = 0.9 & 0.92 for Delta Change Correction and Power Transformation, respectively (Fig. 5). This indicated that 90% of the variance in the observed precipitation was explained by the bias-corrected model outputs, signifying a very strong linear relationship. The NSE was 0.95 for both methods which was close to 1.0. This denoted almost perfect match between the simulated and observed hydrographs, affirming the excellence of the model in predicting the magnitude and timing of precipitation. The RMSE was 0.0025 for both approaches and extremely low RMSE value confirmed that the average magnitude of the prediction errors was negligible, further underscoring the accuracy of these methods.

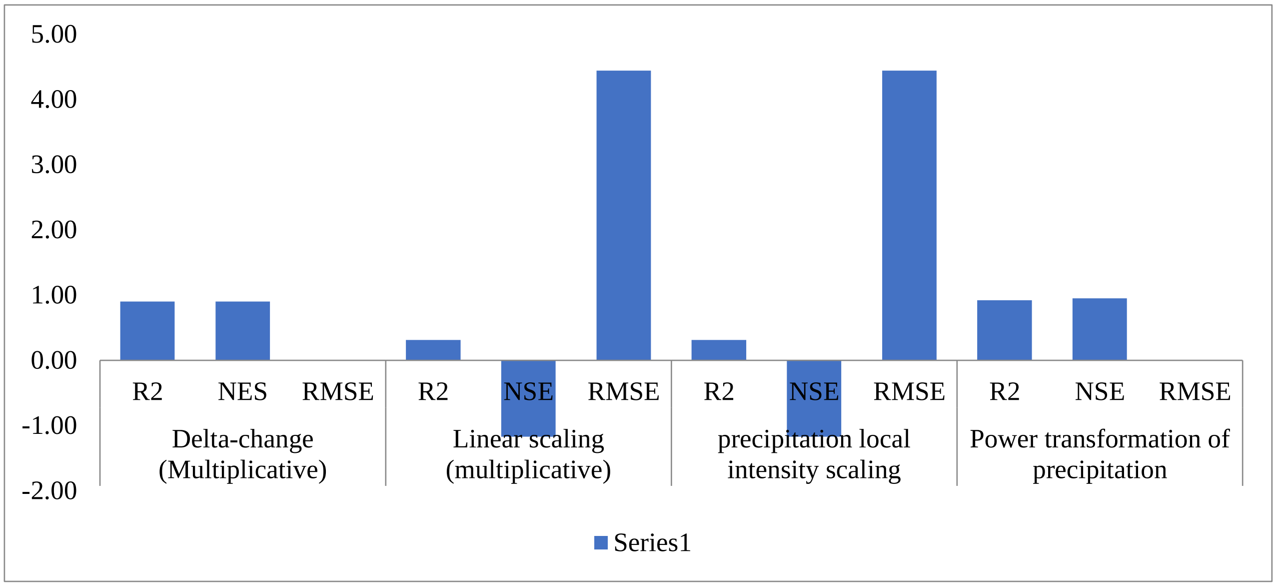

Fig. 5 Evaluation of precipitation bias correction methods

The demonstration conducted in this study conclusively identified Delta Change Correction (Multiplicative) and Power Transformation as the most robust and effective techniques for correcting systematic biases in simulated RCM precipitation for the studied region. A comparative summary of all method performances is illustrated in Fig. 6.

The finding showed that the Delta Change method was particularly effective. This was strongly supported by the broader scientific literature. This method is widely adopted and validated globally for the bias correction of both historical and future climate projections. Our results aligned with the work of numerous researchers such as (A. Das *et al.*, 2022, Fang *et al.*, 2015, Mendez *et al.*, 2020, Teutschbein & Seibert, 2012) who had successfully applied and endorsed this approach. The consistency between our findings and those of established international studies not only validated the results presented but also reinforced the reliability and transferability of the Delta Change Method. The Power Transformation Method similarly proved to be a powerful tool as it non-linearly adjusting the intensity distribution of precipitation which is crucial for representing extreme events.

In conclusion, it is strongly recommended that future climate projections be bias-corrected using either the Delta Change Correction (Multiplicative) or Power Transformation methods to ensure the highest degree of data integrity and realism. This might apply for any subsequent climate impact analysis of particularly hydrological modeling, water resource management, and drought or flood risk assessment within this catchment.

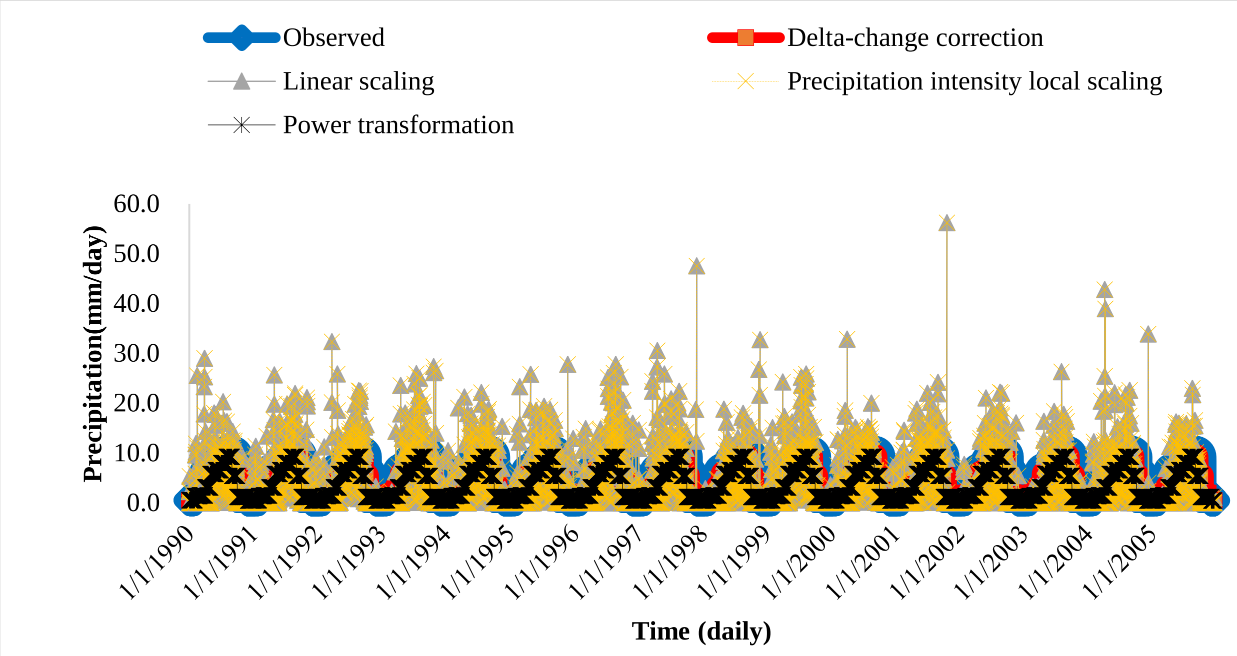

Fig. 6 Precipitation bias correction methods & outputs

4. CONCLUSION AND RECOMMENDATIONS

This study conclusively demonstrated that the performance of bias-correction methods was highly variable and method-dependent in the Omo Gibe River Basin. For temperature, the Delta-change Correction and Variable Scaling Additive methods were superior, effectively reconciling RCM simulations with observed data while Linear Scaling was inadequate. For precipitation, the Delta Change Correction (Multiplicative) and Power Transformation methods were the most robust, accurately replicating observed statistical properties and distributions. The strong performance of the Delta-change method across both variables validated the internal consistency of the model in capturing climate change signals.

The choice of the optimal bias-correction method should be guided by the specific variable and the objective of the study. This study suggested that the Delta-change Correction method should be used for studies focusing on future *changes* in climate signals. The study suggested to use the Variable Scaling Additive method for impact studies (e.g., hydrological or ecological modeling) that required realistic absolute daily temperature values for the historical or future baseline. The findings of this study suggested that either the Delta Change Correction (Multiplicative) or Power Transformation method should be used for all applications of hydrological modeling and drought/flood risk assessment. Based on the evaluation made by CMIP5 (CORDEX RCA4) for an African basin, the study suggested that the Linear Scaling method was unsuitable for temperature and precipitation correction. Hence, the Precipitation Local Intensity Scaling method was not recommended for precipitation. It should be noted that the analysis was limited to CMIP5. Therefore, future researches are recommended to compare both CMIP5 and CMIP6 projections while evaluating bias correction methods.

Conflicts of Interest: No, there is no conflict of interest.

Data Availability Statement: The data will be available if the corresponding author is requested.

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Code availability: Upon reasonable request to the corresponding author, computer simulation codes developed for the modeling will be shared for research purposes.

Ethics approval: This study did not involve humans and animals, and hence no ethical approval was required.

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