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COMPARATIVE ANALYSIS OF BIAS CORRECTION APPROACHES FOR CLIMATE PROJECTIONS OVER MALAMPUZHA CATCHMENT

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ABSTRACT

Climate change significantly influences hydrological systems, particularly in reservoir-based irrigation regions where temperature and rainfall variability directly affect water availability. This study evaluates the performance of different bias correction for improving the accuracy of Global Climate Model (GCM) projections over the Malampuzha reservoir catchment area in Kerala, India. The CNRM-CN6-1 model from CMIP6 was used to simulate precipitation, maximum and minimum temperatures for the historical period (1990-2014). Observed data was used to assess model biases. Three bias correction techniques-Linear Scaling (LS), Variance Scaling (VS) and Distribution Mapping (DM) were applied to temperature data, while precipitation was corrected using Linear Scaling, Local Intensity Scaling (LOCI), Power Transformation (PT) and Distribution Mapping methods. Statistical evaluation and Taylor diagram analysis revealed that variance scaling performed best for temperature by correcting both mean and variance, while power transformation showed superior performance for precipitation correction. The Power transformation technique was applied to the precipitation data and Variance scaling was applied to temperature data for bias correcting the climate data for the historical period as well as for the future under three SSP scenarios (SSP126, SSP245 and SSP585). Maximum temperature is projected to increase by approximately 1.5°C, 3.0°C, and over 4.0°C under SSP126, SSP245 and SSP585, respectively by 2100. Minimum temperature exhibited a similar increasing trend, while precipitation displayed greater interannual variability, particularly under SSP585. Overall, the study highlights the importance of applying suitable bias correction techniques to enhance climate model accuracy and provides valuable insights into future climatic shifts impacting the Malampuzha reservoir area.
Keywords **:** CMIP6, Bias correction, SSPs, Climate change.

Introduction

Climate change poses a significant challenge to the sustainability and management of water resources, particularly in regions that depend heavily on reservoir-based irrigation systems. Reservoirs are the manmade structures used to store the inflow volume of water from upstream catchment area and later released to the downstream command area for different purposes. The increasing variability in temperature and precipitation patterns has a direct influence on the hydrological cycle, leading to uncertainty in water availability, reservoir storage, and crop water demand. Assessing the future impacts of climate change on such systems requires accurate projection and correction of climate model data. The present study focuses on the Malampuzha reservoir catchment area in Kerala. In recent years, the reservoir has faced challenges in meeting irrigation water requirements during all seasons, largely due to erratic rainfall and rising temperature trends. Understanding how future climatic variations may influence these parameters is therefore vital for effective reservoir operation and long-term water resource planning. Global Climate Models (GCMs) serve as essential tools for simulating future climate under different greenhouse gas emission scenarios (Gado *et al.*, 2022). However, GCM outputs often contain systematic biases when compared with observed local data, due to their coarse spatial resolution and simplified representations of physical processes (YoosefDoost *et* al., 2018; Visweshwaran, 2021; Parmas *et al.* 2023). Consequently, bias correction becomes necessary to refine GCM simulations and make them suitable for local-scale impact assessments, particularly in hydrological and reservoir modelling applications (Dinku and Gibre (2024); Daniel, 2023). The following sections describes in detail the data sources, bias correction techniques, and analytical approach adopted to evaluate the climate change impacts on temperature and precipitation over the Malampuzha reservoir region (George and Athira, 2020).

Materials and Methods

This study was conducted to understand the climate change impact on weather parameters of Malampuzha reservoir catchment area situated in Palakkad district of Kerala, India. It is considered as one of the largest reservoirs in Kerala having gross storage capacity of around 226 Mm^3. The culturable command area of the reservoir is around 22000 ha. Recent studies revealed the inability of reservoir to satisfy the crop water demand in all seasons. So, this study was undertaken to evaluate the effect of climate change on the precipitation and temperature in the area.

Global Climate Models (GCMs) are powerful tools used to simulate future climate under different emission scenarios. However, their outputs often contain systematic biases when compared to observe local data due to several reasons, such as coarse spatial resolution, simplified physical processes, and regional climatic heterogeneity. These biases, if uncorrected, can lead to significant errors in climate impact studies, especially in hydrological modelling, reservoir operation, and water resource planning, which require accurate rainfall and temperature inputs. Hence, bias correction is essential to adjust GCM outputs to better represent local climatic conditions before their use in further analysis. Several bias correction techniques are available for different weather parameters. All the bias correction techniques applied in this study were taken from Teutschbein and Seibert (2012).

Shared Socioeconomic Pathways (SSPs)

From the latest sixth assessment report of IPCC, a new set of emission scenarios, which explain how socio-economic trends along with climate forcing levels describe possible future global developments that influence greenhouse gas (GHG) emissions and climate change. SSPs provide a consistent framework to study how socioeconomic choices influence future climate conditions, enabling researchers to assess the impact of climate change on hydrology, agriculture, and water resources under different possible futures. These include, a world of sustainability-focused growth and equality (SSP1) to a world of rapid and unconstrained growth in economic output and energy use (SSP5). SSP126, SSP245 and SSP585 scenarios were considered in this research to get future understanding of the weather parameter changes.

In this study CNRM-CN6-1 GCM model predictions were considered as it showed better performance for south Asian region (Hemanandhini and Vignesh, 2023). Four bias correction techniques such as Linear Scaling (LS), Local Intensity Scaling (LOCI), Power Transformation (PT) and Distribution Mapping (DM) for precipitation (Jaiswal *et al.*, 2022) and three bias correction techniques such as Linear Scaling (LS), Variance Scaling (VS) and Distribution Mapping (DM) for maximum and minimum temperature were applied to the raw simulations of the CNRM-CM6-1 GCM. The linear scaling technique corrects the mean bias of temperature data on a monthly basis. The distribution mapping method corrects not only the systematic mean bias but also the variance (or spread) of GCM data to match the observed distribution. The variance scaling technique adjusts both the mean and the variance of the GCM-simulated temperature data to match those of the observed data. The methodology followed is shown in the Fig.1. The observed data of precipitation, maximum and minimum temperature was collected from the Malampuzha Irrigation Division Office, Palakkad. The bias correction techniques were applied to the simulations of CNRM-CN6-1 model and best bias correction was selected based on statistical criteria and Taylor plots. The selected bias correction techniques will be applied for the different future scenarios to get the future climate data.

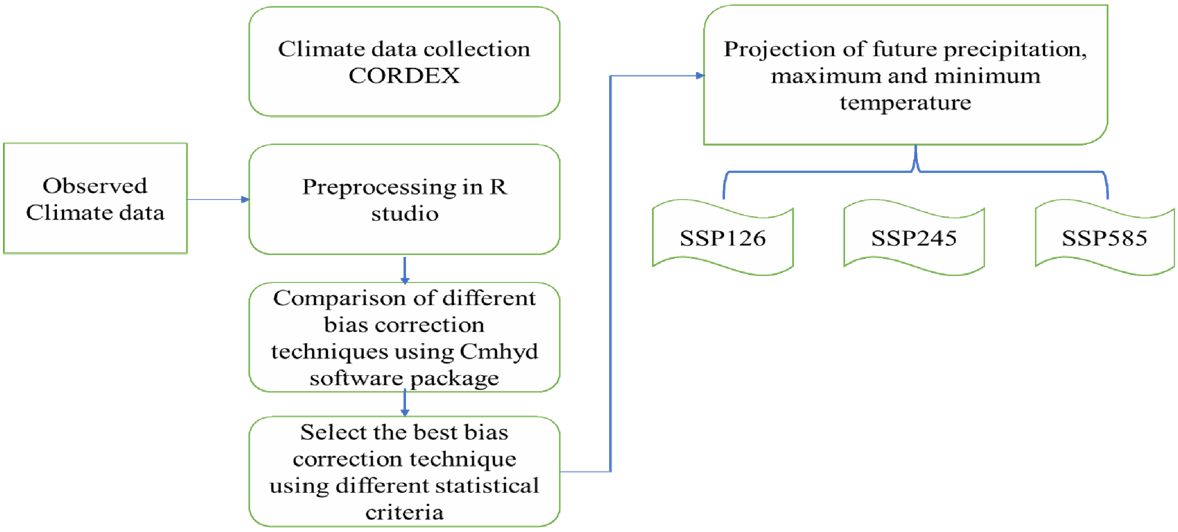

Fig. 1 : Methodology chart

Results and Discussion

Rainfall, maximum and minimum temperature data of CNRM-CN6-1 GCM model for the period 1990-2014 was downscaled to the study area. Different bias correction techniques were applied to identify the best technique that can improve the raw simulations. The selected bias correction technique will be applied to the different SSP scenarios to get climate change projections.

Statistical evaluation of bias correction techniques

The bias correction results of the maximum and minimum temperature were presented in Table 1 and Table 2. Positive values indicate that the GCM underestimated the temperature compared to observed data. Hence, the GCM temperature values are increased by the given amount for that month, whereas negative values indicate that the GCM overestimates the temperature. From Table 1, it was observed that the bias correction factors showed clear seasonal variation throughout the year. During the winter months (November to February), both maximum and minimum temperatures exhibited high positive bias correction values (ranging from 3.2°C to 4.8°C), indicating that the GCM significantly underestimates the observed temperatures during this period.

In contrast, during the pre-monsoon and monsoon months (April to June), the correction factors were negative or very low, suggesting that the GCM slightly overestimates the temperature during the summer season. The post-monsoon period (July to October) showed moderate positive biases (around 1.5°C to 3°C), implying a tendency of the GCM to simulate somewhat lower temperatures compared to observations.

Table 1: Monthly bias correction factor for Temperature (Linear scaling)

Month	T_{max}[°C]	T_{min}[°C]
1	3.42	4.85
2	0.79	3.74
3	0.08	2.91
4	-0.11	1.22
5	-0.5	1.18
6	-1.02	0.67
7	1.58	1.45
8	2.07	2.68
9	2.49	2.38
10	3.21	2.76
11	3.38	3.94
12	4.4	3.87

Table 2: Monthly mean and SD of temperature (Distribution mapping)

Month	Mean				Standard Deviation (SD)			
	$T_{max,obs}$	$T_{max,sim}$	$T_{min,obs}$	$T_{min,sim}$	$T_{max,obs}$	$T_{max,sim}$	$T_{min,obs}$	$T_{min,sim}$
1	33.536	30.113	20.474	15.619	11.36	2.093	2.31	1.967
2	34.534	33.745	21.249	17.511	1.399	1.763	2.258	2.19
3	35.711	35.631	23.738	20.831	1.759	1.963	15.135	1.786
4	34.986	35.095	24.342	23.122	1.654	2.208	1.895	1.032
5	33.445	33.943	24.423	23.239	2.471	2.937	1.658	1.156

6	30.219	31.236	23.159	22.487	2.067	3.582	1.483	1.04
7	29.143	27.563	22.705	21.252	1.631	2.705	1.217	0.85
8	29.449	27.383	23.554	20.875	1.537	1.928	11.16	0.758
9	30.588	28.093	23.033	20.648	1.573	1.914	1.006	1.056
10	31.225	28.016	22.992	20.235	1.628	1.56	1.135	1.287
11	31.794	28.414	22.281	18.343	1.384	1.809	1.531	1.95
12	32.134	27.735	20.796	16.924	1.117	2.123	2.421	2.573

From Table 2, it was evident that for most months the simulated (GCM) mean temperatures are lower than the observed means, indicating an underestimation bias, particularly during the winter months (November–February). The standard deviation values reveal that the GCM generally underrepresents variability, as the observed SDs are mostly higher than simulated ones. Similarly, the bias correction results for precipitation were presented in Table 3. From Table 3, both Linear scaling and Local intensity scaling showed similar monthly bias correction trends, with higher correction factors during the monsoon months (March–July) and relatively low corrections during the dry months (October–February). This indicates that GCMs tend to underestimate precipitation during the wet season, requiring an upward adjustment of up to 5-6% in peak rainfall months. In contrast, the Distribution mapping method showed considerable variation in both scale and shape factors between observed and simulated data which controls the variability and skewness of rainfall, respectively.

Table 3: Monthly bias correction values (%) for precipitation

Month	Linear Scaling Factor	Local Intensity Scaling Factor	Distribution Mapping			
			Scale factor		Shape factor	
			Obs	Sim	Obs	Sim
1	0.34	0.6	4.375	4.52	1.174	2.155
2	1.77	2.35	14.899	2.744	0.643	1.67
3	4.99	5.61	14.161	2.77	0.907	0.839
4	4.75	5.05	13.961	3.763	0.92	0.676
5	2.26	2.49	23.503	5.833	0.754	1.219
6	3.51	3.52	22.356	9.328	0.919	0.63
7	2.87	2.89	22.453	7.892	0.988	0.974
8	1.69	1.75	17.609	4.899	0.876	1.799
9	1.45	1.62	18.766	3.035	0.882	3.368
10	1.09	1.24	20.121	2.754	0.862	5.108
11	0.78	0.99	19.546	2.641	0.75	5.608
12	0.33	0.62	15.842	3.454	0.839	6.408

Taylor diagrams were developed to compare these bias corrected simulations with observed as well as raw simulations of GCMs. Taylor diagrams are the graphical representation of three statistical criteria such as coefficient of correlation, standard deviation and root mean squared deviation. In the diagram, the parameter which is close to the observed one, considered to be the best. Taylor plots for precipitation, maximum and minimum temperatures are presented in Fig 2., Fig. 3 and Fig 4 respectively.

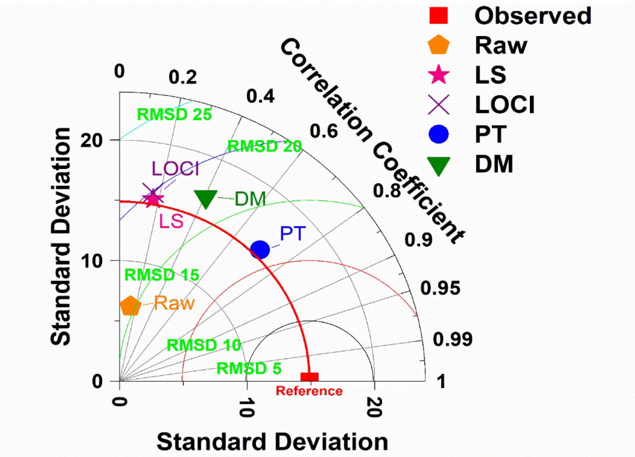

Fig. 2 : Taylor diagram- Comparison of several bias correction techniques in simulating observed precipitation

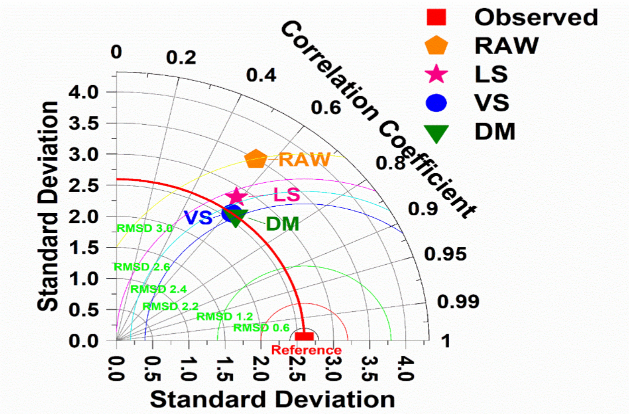

Fig. 3 : Taylor diagram- Comparison of several bias correction techniques in simulating observed maximum temperature

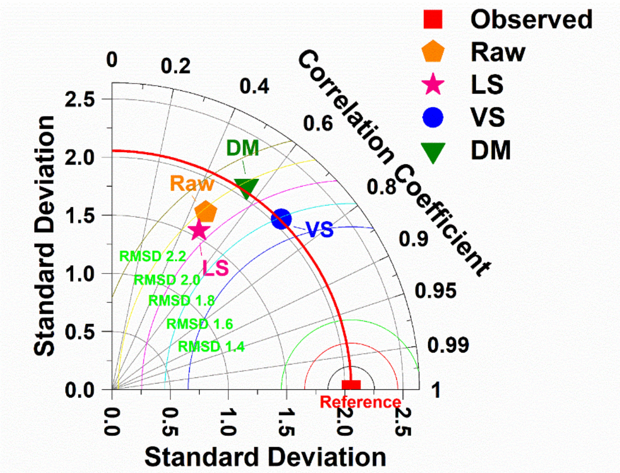

Fig. 4 : Taylor diagram- Comparison of several bias correction techniques in simulating observed minimum temperature

From the Taylor plots, it was clear that all bias correction techniques have significantly improved the raw simulations of GCMs. For precipitation, Power transformation technique showed superiority over other methods. The performance of Distribution mapping technique was also accepted for precipitation. In case of maximum and minimum temperature, Distribution mapping and Variance scaling techniques outperformed Linear scaling (LS) in reproducing observed minimum and maximum temperature characteristics because of the reason that Linear scaling only shifts the mean but doesn't adjust variability or distribution. Variance scaling technique adjust both mean and variance and leads to better alignment with the observed data than both of the other techniques.

Climate change projections

The Power transformation technique was applied to the precipitation data and Variance scaling was applied to maximum and minimum temperature data. Fig. 5, 6 and 7 illustrates the bias corrected average annual maximum temperature, minimum temperature and precipitation trends for historical period, and three SSPs: SSP126, SSP245 and SSP585, extending from 1990 to 2100. The historical period serves as the baseline and spans from 1990 to 2014, after which the future projections begin.

During the historical period, the maximum temperature fluctuated between approximately 31.5°C and 33°C, with minor inter annual variability. SSP126 predicted a mild increase in maximum temperature over time. By the end of the 21st century, maximum temperature projected by SSP126 scenario, stabilize around 33.5°C to 34°C, indicating a controlled warming of about 1.5°C above the historical average. A continues rising trend was observed for both SSP245 and SSP585 scenarios. SSP245 projected a more increase in maximum temperature approximately 34.5°C to 35°C by the end of century. This represents a warming of around 2.5°C to 3°C compared to the historical baseline. SSP585 scenario predicted a rapid continuous rise in maximum temperature throughout the century, and it is predicted that by 2100, temperature may rise to around 37°C, which is an increase of more than 4°C above the historical levels.

From Fig. 6, it is clear that during historical period, the minimum temperature over Malampuzha reservoir system ranges between 21°C to 24°C. Similar to maximum temperature, a mild increase was predicted by SSP126 where minimum temperature reaches 24.5°C by the end of century. The warming from the SSP245 predictions is more pronounced than in SSP126 but not as steep as in SSP585. SSP585 predicted a significant and consistent rise in minimum temperature, exceeding 26.5°C by 2100, which is more than 4°C above the historical average.

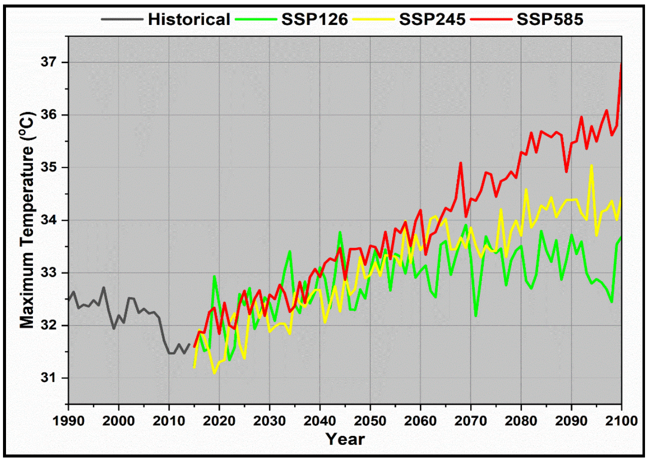

Fig. 5 : Average annual maximum temperature (°c) in Malampuzha from 1990 to 2100.

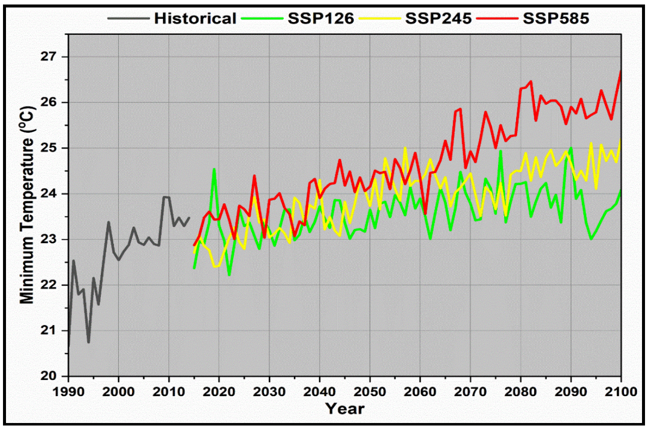

Fig. 6 : Average annual minimum temperature (°c) in Malampuzha from 1990 to 2100.

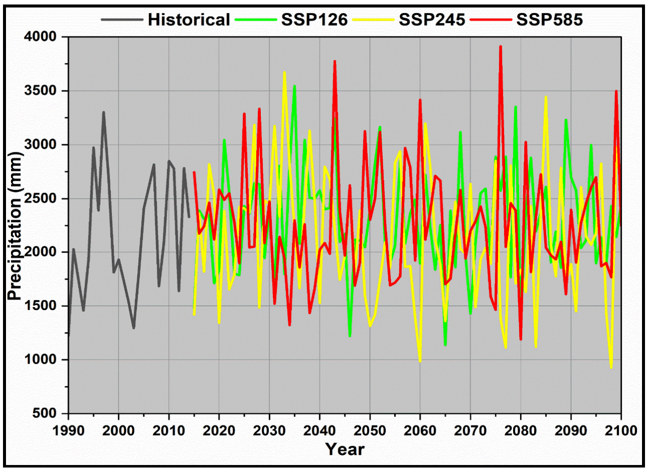

Fig. 7 : Average annual precipitation (mm) in Malampuzha from 1990 to 2100.

The historical data from Fig. 7 indicates an average annual precipitation over Malampuzha shows significant variability (2000 to 3200 mm). The precipitation variability was expected to increase in future, especially under SSP245 and SSP585. SSP126 predicted a moderate variability in the precipitation ranging between 1800 mm to 3300 mm. SSP245 scenario predicted high variability in precipitation particularly in the second half of the century. SSP585 scenario predicted high variability in precipitation. SSP585 exhibits the most erratic behavior with extreme highs (>3500 mm) and lows (~1200 mm). Precipitation as well as maximum and minimum temperatures exhibited a rising trend from 2015 to 2100 under different scenarios. Both temperatures were projected to rise continuously under SSP245 and SSP585. However, the temperatures were predicted to rise slightly just before the mid-century and fall gently later (around 2075) under SSP126.

Conclusion

This study evaluated the performance of various bias correction techniques in improving CMIP6 GCM (CNRM-CM6-1) simulations of temperature and precipitation over the Malampuzha reservoir region. Linear Scaling, Variance Scaling, Power Transformation, Local Intensity Scaling, and Distribution Mapping methods were tested using observed data (1990–2014). The analysis revealed that GCMs generally underestimated both maximum and minimum temperatures, particularly during the winter months, with seasonal bias corrections ranging from –1.0°C to +4.8°C. Among the techniques, Variance Scaling and Distribution Mapping provided superior results for temperature, effectively adjusting both the mean and variability. The performance of Variance scaling was better than Distribution mapping and hence was used for bias correction of future data. For precipitation, Power Transformation showed the best performance, followed by Distribution Mapping, successfully correcting wet-season underestimations of up to 6%. Power transformation was used for bias correction of future data. Future climate projections indicated a consistent warming trend across all SSPs, with maximum temperature increases of 1.5°C (SSP126), 2.5–3.0°C (SSP245), and >4°C (SSP585) by 2100. Minimum temperature followed a similar pattern, rising by more than 4°C under SSP585. Precipitation displayed increased variability and intensity, especially under SSP245 and SSP585 scenarios.

Overall, the study highlights the critical role of bias correction in improving GCM performance for local hydrological applications and emphasizes the potential warming and precipitation variability risks that future water resource management strategies must address in the Malampuzha reservoir area.

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