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Original Article

Climate Change Vulnerability Assessment of a River Basin on Precipitation Applying CMIP6 Climate Model

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Abstract - *The hydrological impact is evaluated by downscaling huge-scale climate variables (predictors) simulated and modelled by a Global Climate Model. Hydro-meteorological variations illustrate the use of the Statistical Downscaling technique to enhance precipitation resolution. In this investigation, we introduce a statistical precipitation model utilizing three distinct approaches that are the Delta technique, the Quantile Mapping technique, and the Empirical Quantile Mapping technique. To investigate the statistical downscaling method, the weather stations Chaskaman, Paragon, Sakhar, and Shirur were chosen as research sites to evaluate the approach for precipitation. All the stations are situated within the Bhima River Basin. To identify patterns from historical observations and subsequently apply them to both historical and Shared Socioeconomic Pathway (SSP) periods (Shared Socioeconomic Pathway to describe possible future development). Future projections based on climate scenarios utilize CMIP6 data and the global climate model CNRM-CM6-1. The statistical downscaling results indicate that the SDGCM (Statistical Downscaling Global Climate Model) performs best in predicting daily precipitation. In the future period (2021-2100), the SDGCM model predicts an increase in average yearly rainfall at all four locations in the context of SSP245 and a substantial rise in average yearly rainfall at all four locations in the context of SSP585.*

Keywords - *Climate change, GCMs, Rainfall, SDGCM, Statistical downscaling.*

1. Introduction

Climate change profoundly affects water resources through shifts in water availability, glacier retreat, rising sea levels, and alterations in the hydrological cycle. Precipitation and temperature are pivotal variables immediately influencing climate change. Forecasting and projecting future climate changes in the atmosphere is essential.

After various literature surveys, a significant gap remains in the region-specific vulnerability assessment, especially concerning precipitation patterns in river basins. Many studies have focused on larger and global-scale assessment. However, regional basins like the Bhima River basin in India require detailed analysis using the latest advancements in climate modelling, such as CMIP6 (Coupled model intercomparison project phase 6).

Most previous assessments have relied on older CMIP phases (e.g. CMIP5) is valuable but may not capture the full range of projected climate change due to their lower resolution and outdated socioeconomic scenarios. The understanding of how changing precipitation patterns will affect local water availability, agriculture, and communities is still evolving. There is a limited number of studies that incorporate both high resolution and climate projection and local vulnerability indicators like socioeconomic factors and infrastructure. The detail vulnerability assessment integrating CMIP6 projection is necessary to inform local adoption strategies.

Climate change has emerged most pressing global challenge. River basins are vulnerable to these changes as they are often highly dependent on seasonal precipitation patterns. Alteration in rainfall due to climate change can lead to significant disruption including flood, drought and water availability. The Bhima River Basin, a critical water source in Maharashtra, is particularly susceptible to these shifts due to its dependence on the southwest monsoon.

The CMIP6 models, which provide improved resolution and incorporate updated socioeconomic pathways (SSPs), offer a new opportunity to project future climate impacts with greater accuracy. Translating these model outputs into actionable vulnerability assessments remains a challenge. This study seeks to bridge that gap by applying CMIP6 climate projections to evaluate how future precipitation changes will affect the Bhima River Basin's water resources.

The goal is to identify the most vulnerable areas and sectors, helping policymakers and local stakeholders develop more effective adaptation strategies. Global Climate Models

(GCMs) are a crucial tool for evaluating the potential result of climate shift effects on hydrological assets and resources and other environmental aspects.

The output from GCMs requires analysis and interpretation before it can be directly utilized. GCMs operate on a global scale, with grid resolutions typically ranging from 250 to 500 kilometres. This coarse resolution is insufficient for capturing local variations in watershed modelling. The downscaling technique is employed to transform coarse resolution into finer resolution (Wilby & Wigley, 1997; Hashmi et al., 2009).

Downscaling is categorized into two ways: statistical and dynamic Downscaling. Statistical downscaling involves establishing a statistical linkage between broad-scale climate factors (such as precipitation) simulated by GCMs and their corresponding small-scale climate factor.

Typically, this relationship is established by using past data and GCM output (Huang et al., 2011). Statistical downscaling involves creating a quantitative link between global atmospheric parameters (predictors) and small-scale variables (predictors). The software SDGCM V2.0, developed by Agrimetsoft, facilitates this system (Wilby et al., 2004). This paper focuses on assessing the suitability of SDGCM for downsizing precipitation and providing regional climate information based on future emission projections (SSP245, SSP585) for ongoing hydrological impact assessments related to climate change (Wilby et al., 2004).

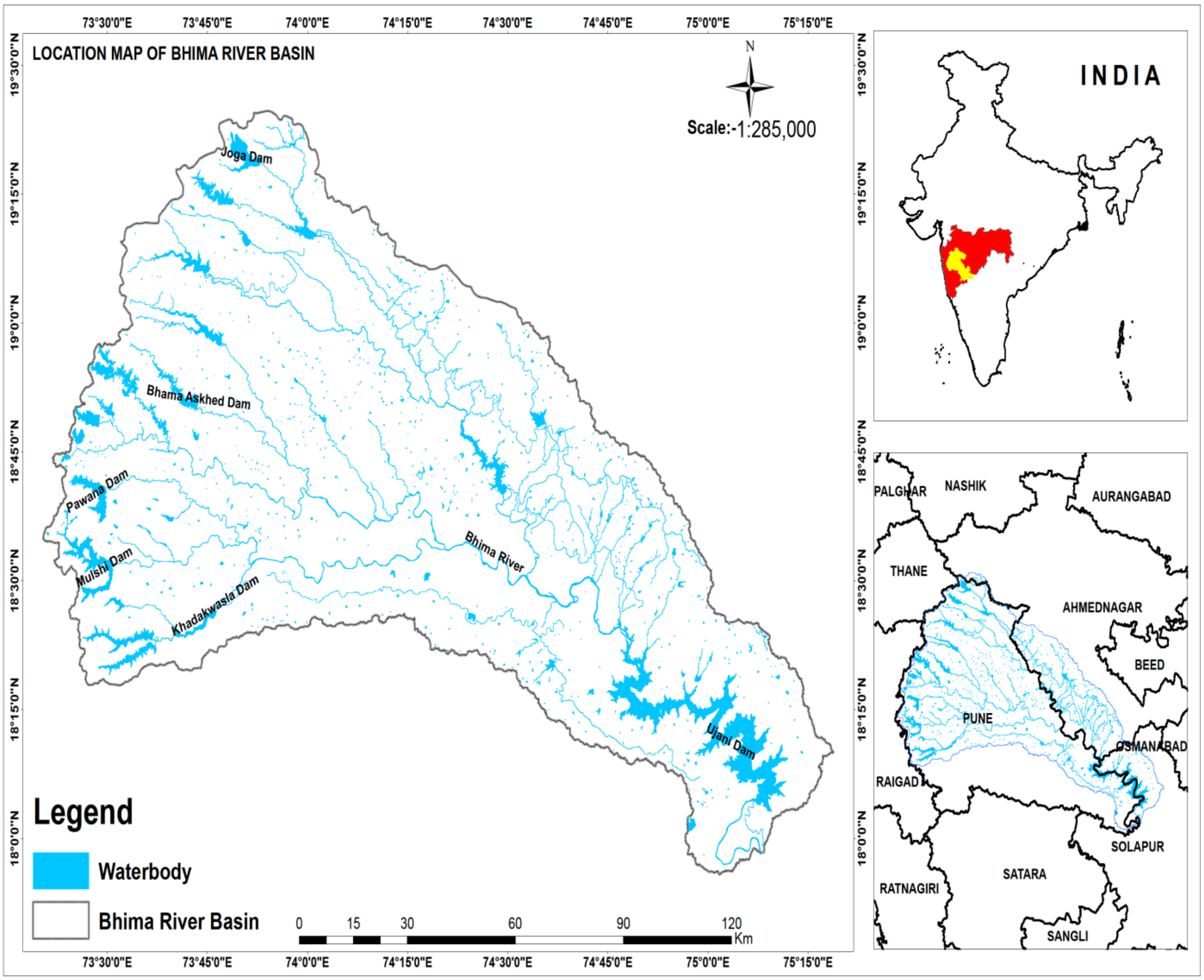

Fig. 1 Study area showing Bhima river basin with dam

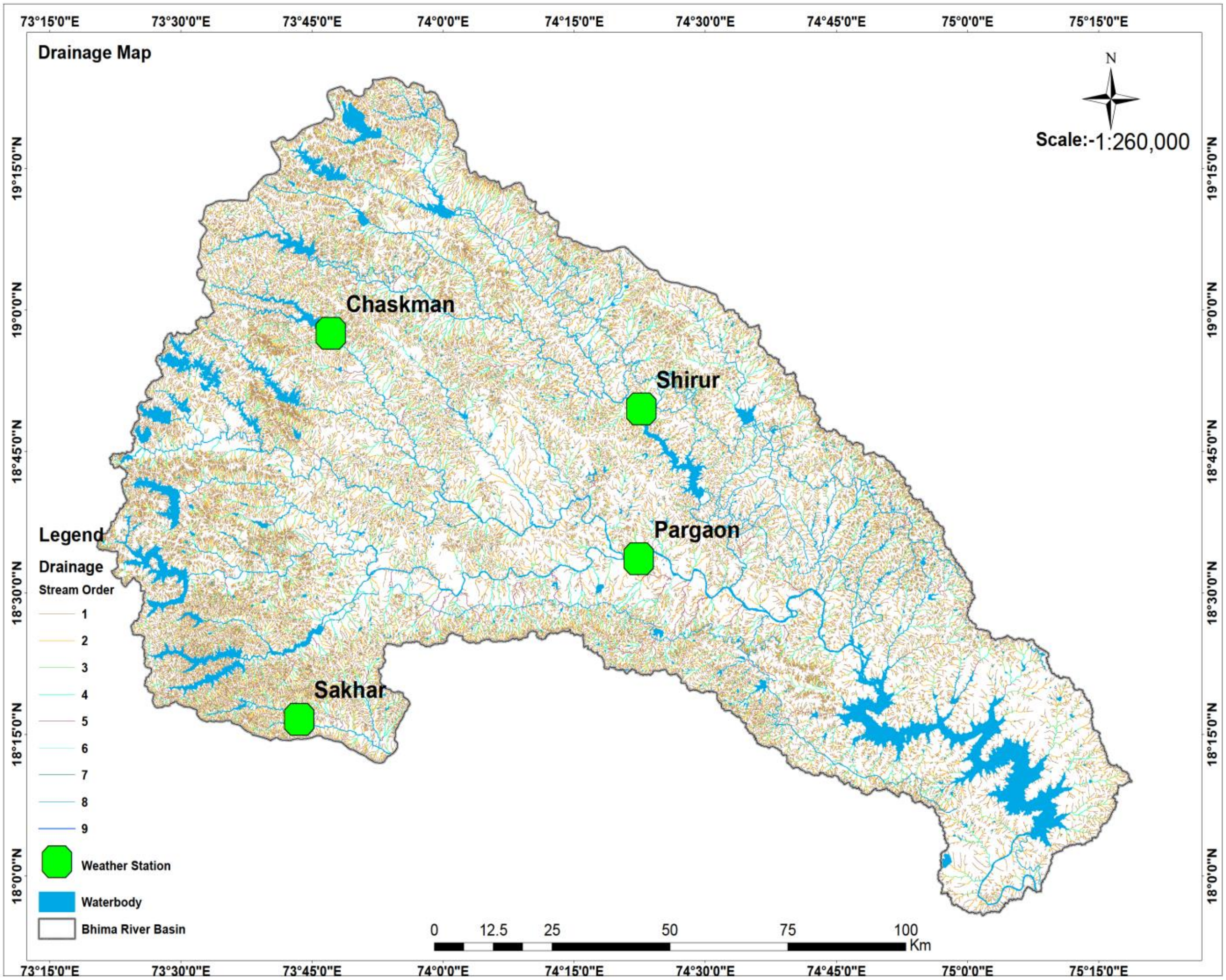

Fig. 2 Drainage map showing the weather monitoring station as chaskaman, paragon, sakhar, shirur

2. Study Area

The Bhīma River has its source in the dry zone area of the Sahyadri Ghats in India. The Upper Bhīma basin extends geographically from 73°15'E to 75°15'E and from 18°0'N to 19°15'N, in an area of 15859 km2 (Figure 1). The drainage map (Figure 2) displays comprehensive information about villages and stations. The Bhīma basin has features of a meandering landscape, with variations in elevations from 499 meters to 1,298 meters above ocean level. The west side section of the catchment is highly rocky terrain. The central area is characterized by rolling hills and a gentle slope, while the east side section features undulating terrain and a low-lying area (Central Water Board, Water Resources Department). The watershed experiences a tropical wet and dry climate, with temperatures reaching a high of around 38°C in April and a low of about 11°C in January. It receives an average rainfall of 1,233 mm annually, primarily from the summer monsoon. The west section of the watershed gets over 3,000 mm of precipitation and slowly reduces to 600 mm towards the basin exit point (Samal et al. 2015).

The Bhīma River provides a large volume of water flow, mainly due to its closeness to the West section of the Ghats. Four stations, namely Chaskaman, Paragon, Sakhar, and Shirur, are chosen within this river basin. Thus, studying the effects of climate change will provide valuable insights for making informed and effective decisions regarding the development of water resources for future growth. The primary meteorological data utilized in the study is precipitation. Historical precipitation data was sourced from Hydrological Data User Group (HDUG) in Nashik. The basin's landscape has undergone rapid urbanization in recent years, driven by the expanding Pune metropolitan region. This has garnered attention from scholars and scientists (Wagner et al., 2013, 2019) who are analysing the effect of climate shift on availability and water governance.

3. Methodology

Global Climate Model (GCM) data downscaling involves several steps, where the predictor is the GCM output and the predictor is the observed station value. Precipitation data is employed as the dataset, selected through correlation analysis, and subjected to statistical downscaling using multilinear regression (Kannan et al., 2011). The model is applied to estimate daily precipitation for each station in both present and future scenarios. Monthly and annual precipitation totals are derived from the daily precipitation series (Srivastava et al., 2008). The Bhima River basin is prone to variations in monsoon patterns, which are highly sensitive to climate change and also experience periodic water scarcity. This study could provide insight into sustainable water management strategies under future climate scenarios. The flow chart of progressive steps in this investigation is as below.

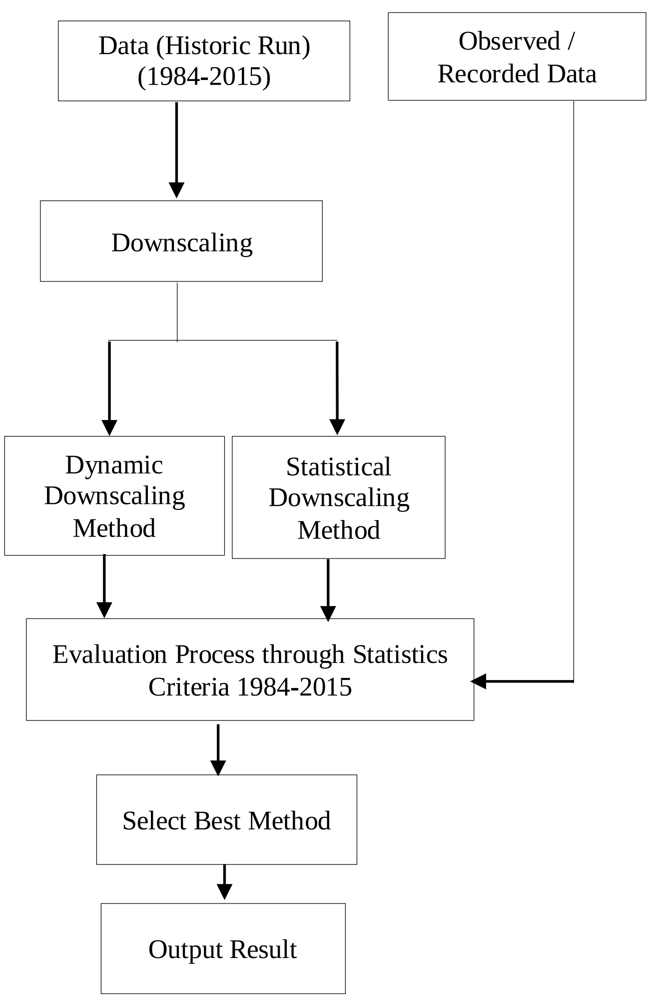

Fig. 3 Showing detailed methodology of downscaling

3.1. Statistical Downscaling

The model is utilized to project daily precipitation for each station under current and future conditions. Monthly and annual precipitation computed depends on the daily rainfall time series (Srivastava et al., 2008). The developed statistical correlation is implemented to project climate model simulations to predict future hydrological parameters. The climate model's projected variables (predictor) and recorded precipitation values (predictand) are statistically correlated using a mathematical process employing the delta method for statistical downscaling. This approach is widely adopted, utilizing GCM output as a predictor (Marun et al., 2010; Kang et al., 2016; Kim et al., 2016). According to Marun et al. (2010), the delta approach does not correct biases in climate models. Instead, it utilizes the model's reaction to climate shift to refine observation, serving as a valuable reference point for the elimination of bias. The delta method approach builds upon the climate change signal derived from GCM data and applies it to observational data (Hay et al., 2000). In this approach, precipitation downscaling is determined as follows:

$$P_{stat,downscaling} = P_{MOD}, \text{daily x } (P_{OBS}/P_{MOD})$$

Where $P_{stat.downscaling}$ = downscaled precipitation data

P_{OBS} = mean observed precipitation

P_{MOD}= mean precipitation data of GCM historical. For projecting future data, the equation incorporates the future period. The SD-GCM software tool (Agrimetsoft SD-GCM 2017) is specifically employed to execute the delta technique, facilitating the downscaling of CMIP6 model data across different Shared Socioeconomic Pathways (SSPs) scenarios. The observed data and GCM output are stored in Excel format files. The SD-GCM tool offers three statistical downscaling approaches: the delta approach, the quantile mapping approach (QM) (Brier et al., 1968), and the Empirical Quantile Mapping approach (EQM) (Boe et al., 2007).

A database is created to apply CMIP6 models under SSP245 and SSP585 scenarios. The SD-GCM tool includes options for manually entering input data, provided in a separate file. The CMIP6 models, such as the CNRM-CM6-1 model, follow a specific naming format. The SD-GCM software includes an evaluation data option, enabling the assessment of CMIP6 model performance against observational data over a concurrent period. The observational data is stored in an Excel sheet file. During the evaluation phase, the efficiency criteria are assessed using metrics such as Pearson correlation, Root Mean Squared Error (RMSE), Spearman correlation, Nash-Sutcliffe efficiency, Mean Absolute Error (MAE), and d (index of agreement).

3.2. Downscaling Concept

Downscaling transforms global climate model data to achieve finer regional projections and detailed assessments of climate change impacts in specific areas. Raw outputs from GCM simulations lack the detail required for hydrological impact studies. Because of the inadequate and broader spatial resolution of GCM output data (typically 250 km), downscaling techniques are employed. Downscaling narrows the disparity between coarse data and detailed climatic information at smaller scales.

Downscaling can address geographical and time-related aspects of climate prediction. High-resolution mapping involves techniques to enhance resolution from a coarser to a finer scale. This can include refining data from a 25-kilometer grid cell to a 500-kilometer resolution or a specific geographical location (Fowler et al., 2007).

Dynamical Downscaling involves complex computational processes, limiting its application in climate impact studies. Dynamical Downscaling (DD) requires a Regional Climate Model (RCM) to project finer-scale details within the broader framework provided by GCM nodes (Ghosh et al., 2009). Numerous methods have been developed for Statistical Downscaling, all relying on establishing statistical interrelationships between big-scale predictors and local ground station predictands. Statistical reduction creates climate projections tailored to specific locations, a capability that Dynamical Downscaling lacks due to its analytical constraints within a 25–50 km range.

A key benefit of Statistical Downscaling methods is their reduced analytical complexity, enabling them to downscale numerous GCM or RCM climate projections efficiently. This approach is straight forward to implement and provides climate variables at station level from GCM-scale outcome (Yatagai et al., 2012). Statistical methods in downscaling are categorized into three main types: regression methods (Kang et al. 2007) and stochastic weather generators (Richardson, 1981). The most widely adopted approach is Bias Correction (BC), extensively utilized in climate change impact assessments worldwide (Payne et al., 2004).

The SD-GCM V1.0 tool is utilized for processing daily data from observational stations and GCM datasets. For monthly and daily data from CMIP6 or CORDEX, the SD-GCM V2.0 tool is employed.

3.3. Statistical Downscaling Methods in SD GCM V1.0 Tool

The Global Climate Model (GCM) outputs downscaling procedure is made easier for climate researchers by AGRIMETSOFT's SD GCM software, a specialist application. When performing Statistical Downscaling (SD) using different bias correction techniques, such as Delta, Quantile Mapping, and Empirical Quantile Mapping (EQM), this software is especially helpful. With its intuitive interface, users may efficiently handle and process huge datasets to conduct climate impact assessments at local or regional sizes.

The SD GCM software tool offers three statistical downscaling approaches: The Delta approach, the Quantile Mapping (QM) approach, and the Empirical Quantile Mapping (EQM) approach. The Delta Statistical Downscaling Method computes the delta, or difference, between historical climate simulations from a GCM and future climate projections. These computed deltas represent the relative changes in variables like temperature or precipitation.

Downscaled future climate projections are then obtained by applying these modifications to observed historical climate data at a finer spatial level. Because the method maintains the observed climate characteristics and offers a consistent way to apply climate change signals across locations, it is extensively utilized and computationally easy. One significant drawback is that it assumes that the relationship between large-scale climate and local-scale variability will not change in the future.

3.3.1. Delta Statistical Downscaling Approach (Dessu and Melesse, 2013)

Equation (1) is for the precipitation, and Equation (2) is for the temperature for the downscaling of GCM data.

$$P_{SD}^{Delta} = P_{GCM\ SSP} \times \frac{P_{obs}}{P_{GCM\ HIS}} \tag{1}$$

$$T_{SD}^{Delta} = T_{GCM\ SSP} + (T_{obs} - T_{GCM\ HIST}) \tag{2}$$

Where, P_{SD}^{Delta} is for precipitation and T_{SD}^{Delta} is for temperature data downscaling. P_{Obs} represents the mean measured and observed precipitation while $P_{GCM\ HIST}$ corresponds to the historical mean precipitation simulated by the GCM. The subscript GCM ssp denotes the GCM's SSP projections for future periods, and the subscript Obs refers to the observed values.

3.3.2. Quantile Mapping (QM) Statistical Downscaling Method

Quantile Mapping (QM) is used to address biases in climate model outputs, especially for variables like temperature and precipitation. By mapping the quantiles of the model outputs to the corresponding quantiles of observations, the approach modifies the distribution of predicted climatic variables to match the distribution of observed historical data. By doing this, it is guaranteed that the downscaled data's statistical characteristics, such as its mean, variance, and extremes, are in line with previous observations. According to Panofsky et al. (1968), Quantile Mapping comprises a downscaling technique. In Quantile Mapping, the equation calculates the transformation from the ratio of Modelled Probabilistic Distribution (MPD) and Observed Probabilistic Distribution (OPD). SD GCM employs equation 3 for evaluating criteria and Equation (4) for future downscaling.

$$P_t^{Eval} = \text{Inv CDF}\frac{Stat}{Pt-Cal}(\text{CDF}\frac{HIST}{Pt-Cal}\ (P_{t-Eval}^{GCM})) \tag{3}$$

$$P_t^{Predict} = \text{Inv CDF}\frac{Stat}{Pt-His}\ (\text{CDF}\frac{HIST}{Pt-His}\ (P_{t-SSP}^{GCM})) \tag{4}$$

In Equation (3), P_t^{Eval} is the Cumulative Distribution Function (CDF) of the observation data and GCM data over the supposed same period.

3.3.3. Empirical Quantile Mapping (EQM)

The statistical downscaling and bias correction technique used to modify climate model outputs is called Empirical Quantile Mapping, or EQM. By using empirical Cumulative Distribution Functions (CDFs) to map the quantiles of climate model outputs to those of observable data, it improves on the conventional quantile mapping method. By doing this variable-by-variable, it is ensured that the projected data of the model matches the observed statistical features, such as variance, mean values, and extremes, more precisely over the whole distribution.

Wetterhall (2012), in statistical downscaling methods, EQM utilizes the Empirical Cumulative Distribution Function (ECDF) as described in Equation (5), along with all the components utilized similarly by SD GCM. Eq. 5 is P_t^{Eval} for evaluation criteria, and Equation (6) is $P_t^{Predict}$ for future downscaling.

$$P_t^{Eval} = \text{InvECDF}\frac{Stat}{Pt-Cal}\,(\text{ECDF}\frac{HIST}{Pt-Cal}\,(P_{t-Eval}^{GCM})) \qquad (5)$$

$$P_t^{Predict} = \text{InvECDF}\frac{Stat}{Pt-His}\,(\text{ECDF}\frac{HIST}{Pt-His}\,(P_{t-SSP}^{GCM})) \qquad (6)$$

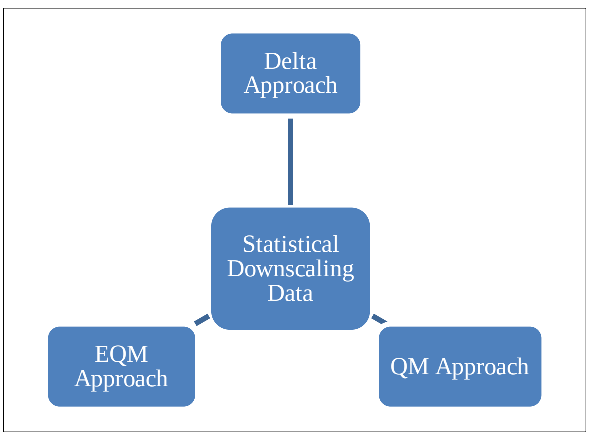

Fig. 4 Three statistical downscaling approaches in the SD GCM software tool

3.3.4. Comparative Analysis of Downscaling Techniques

Downscaling techniques are crucial in climate change research to convert coarse-resolution outputs from global climate models to finer scales appropriate for regional assessments. The Delta approach, Quantile Mapping (QM), and Empirical Quantile Mapping (EQM) are among the frequently used techniques.

The methodology, precision, and applicability of these methodologies vary, especially when it comes to predicting future precipitation patterns. A comparison of these three approaches is given in this section. One of the simplest and most used downscaling strategies is the delta method. It modifies observable data uniformly or by applying a delta based on changes predicted by Global Climate Models (GCMs).

In order to estimate future values, the delta is typically computed as the difference between the historical and future simulations from GCMs. This difference is then added to the observed past data. The Delta method's primary benefits lie in its computational efficiency and ease of use. Its main flaw, which ignores the variability and distributional changes in climate variables, is the assumption of uniform changes across time.

A more advanced method called Quantile Mapping (QM) aligns the distribution of modeled data with the observed data by adjusting for bias in climate model outputs. QM uses the statistical link between the quantiles of the simulated and observed variables to modify model outputs.

This approach effectively reduces biases since it takes into consideration the whole distribution of precipitation rather than simply the mean, especially for extreme events. Nonetheless, QM may have trouble with non-stationarity, a situation in which the relationship between simulated and observed data varies over time, and it may be sensitive to the size and caliber of observed datasets.

Building on the QM method, Empirical Quantile Mapping (EQM) applies bias correction using empirical distributions of modeled and observed data. EQM employs the empirical cumulative distribution functions (also known as CDFs) of observed and modeled precipitation directly, without making any assumptions about a particular distribution (such as normal or gamma).

Because of its adaptability, EQM is especially helpful in situations when the data's underlying distribution is complicated or uncertain. Similar to QM, EQM efficiently tackles distributional biases, such as those resulting from extreme precipitation occurrences. Nevertheless, it also has the drawbacks of being dependent on a large amount of data and possibly being less efficient in non-stationary scenarios.

Although the Delta approach is straightforward to use and computationally straightforward, it is unable to account for changes in the distribution of rainfall, especially at extremes. On the other hand, by modifying the complete distribution of climate model outputs, QM and EQM offer more realistic predictions of future precipitation patterns. EQM provides increased adaptability through the use of empirical distributions, which, in complicated climatic conditions, can result in more reliable bias correction. However, compared to the Delta technique, QM and EQM are computationally more demanding and need high-quality observational observations.

3.3.5. Input Station and GCM Data Downscaling

Three types of data are loaded and utilized: observational data, historical GCM data, and projected GCM data for future scenarios. An Excel file serves as the input format for uploading. Users can select weather data from a specific station by clicking on "Browse file." In the pop-up window, users can browse and choose the targeted file containing observation data (in-situ). The station data should be in daily intervals. Once the input file is selected, attributes of the station data need to be specified. After selecting the required input sheet, users should input details such as "Station Name, Latitude, Unit, and Longitude."

3.3.6. Statistical Downscaling in SD-GCM

The process begins by selecting the downscaling method for future data under specified Shared Socioeconomic Pathway (SSPs) scenarios. Three time periods, that is, station data, historical data (from GCM), and projected data, are designated. The target year for downscaling future data is manually chosen. Next, the appropriate statistical downscaling method is selected. During the evaluation phase, the Delta method is chosen. The downscaling procedure is executed via the downscaling tab, and by enabling the "Plot Observation Data" checkbox, users can visualize the time series graphically.

3.3.7. Selecion of GCM Model

Table 1 shows the details of the GCM model.

Table 1. Details of GCM model

Sr. No	Name of GCM Models	Climate Model Description	Resolution
1	CNRM-CM6-1	The climate model developed by the CNRM/CERFACS modelling group of CMIP6	AOGCM high resolution 0.25 degrees in the ocean and 0.5 degrees in the atmosphere

4. Statistical Analysis for Model Accuracy

4.1. Statistical Analysis for Model Accuracy

4.1.1. Root Mean Square Error (RMSE)

The RMSE quantifies the typical deviation between the predicted values from a statistical model and the actual observed values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i} - X_{model,i}\right)^2}{n}}$$

4.1.2. NRMSE

NRMSE computes the Normalized Root Mean Square Error by matching observed and prediction values, employing various normalization techniques.

$$NRMSE = \frac{RMSE}{X_0}$$

4.1.3. Pearson Correlation Coefficient

The Pearson Correlation Coefficient gauges the power of the linear relationship between two parameters measured on the same scale. It assesses how closely and in what direction two continuous variables are related.

$$r = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i-1}^{n}(O_i - \bar{O})^2}\ \sqrt{\sum_{i-1}^{n}(P_i - \bar{P})^2}}$$

4.1.4. M.A.E.

The Mean Absolute Error (MAE) is determined as the sum of all residuals (the discrepancies between actual and predicted values) divided by the total number of data points. Both MAE and RMSE span from 0 to ∞ and are insensitive to the direction of errors. These metrics are negatively driven, meaning lower scores indicate better performance. The MAE is determined using the following formula.

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} |O_i - P_i|$$

4.1.5. M.B.E.

The Mean Bias Error (MBE) calculates the mean deviation between two information sets. It retains the unit of the variable being measured. Values close to zero are ideal.

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)$$

4.1.6. Index of Agreement

The index of agreement suggests the ratio between the Mean Square Error (MSE) and the Potential Error (PE). The value of 1 signifies an ideal match, while a value of zero indicates no agreement.

$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2}, \quad 0 \le d \le 1$$

4.1.7. NSE

The Nash-Sutcliffe Efficiency (NSE) is a statistical metric used to assess the predictive accuracy of hydrological models. It evaluates how well the model replicates the observed data. NSE values can range from -∞ to 1.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(OBS_i - SIM_i)^2}{\sum_{i=1}^{n}(OBS_i - \overline{OBS})^2}$$

5. Result and Discussion

5.1. GCM Model CNRM-CM6-1

Table 2. Evaluation criteria for Village- Chaskaman

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe Model Efficiency
Delta	3.182	1.643	0.512	0.753	1.73	0.01	0.687	-0.356
QM	4.44	2.296	0.532	0.762	2.32	0.97	0.616	-1.652
EQM	4.767	2.458	0.508	0.747	2.45	1.14	0.584	-2.044

Table 3. Evaluation criteria for Village-Pargaon

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe Model Efficiency
Delta	2.4	1.86	0.331	0.644	1.43	-0.01	0.556	-0.524
QM	5.397	4.04	0.343	0.652	2.81	1.88	0.376	-6.110
EQM	5.644	4.214	0.327	0.652	2.91	2.04	0.354	-6.775

Table 4. Evaluation criteria for Village- Sakhar

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe Model Efficiency
Delta	6.705	1.466	0.646	0.773	3.556	-0.02	0.786	0.174
QM	7.337	1.604	0.667	0.782	3.876	1.02	0.785	0.013
EQM	7.695	1.682	0.653	0.775	4.046	1.18	0.768	-0.086

Table 5. Evaluation criteria for Village- Shirur

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe Model Efficiency
Delta	2.687	1.827	0.361	0.682	1.48	-0.01	0.586	-0.451
QM	5.995	4.077	0.371	0.682	3.08	2.162	0.397	-6.211
EQM	6.194	4.217	0.361	0.682	3.18	2.312	0.377	-6.711

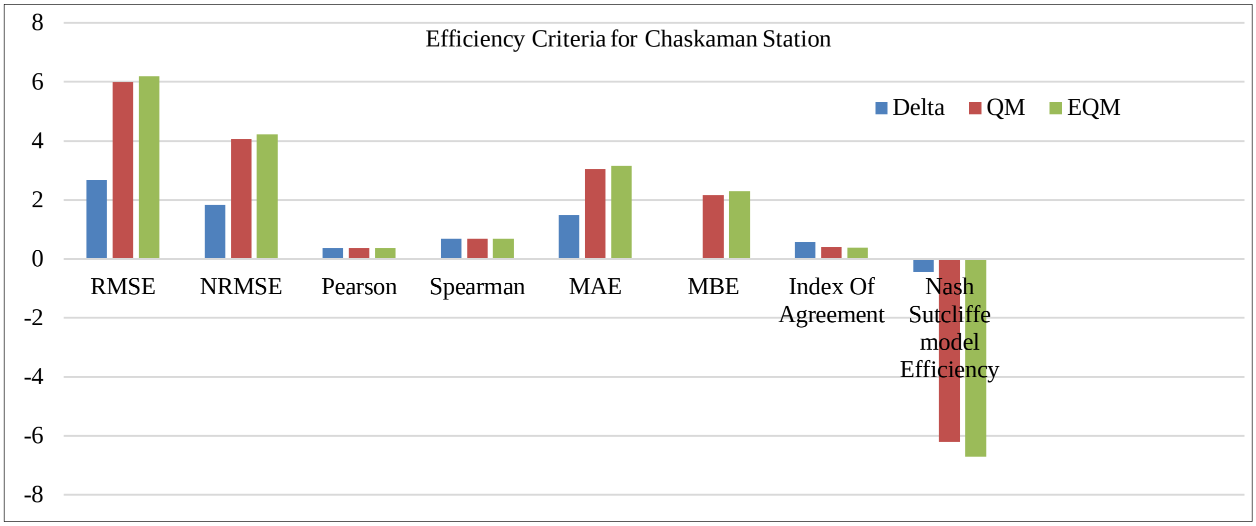

Fig. 5 Evaluation analysis of three methods for Chaskaman station

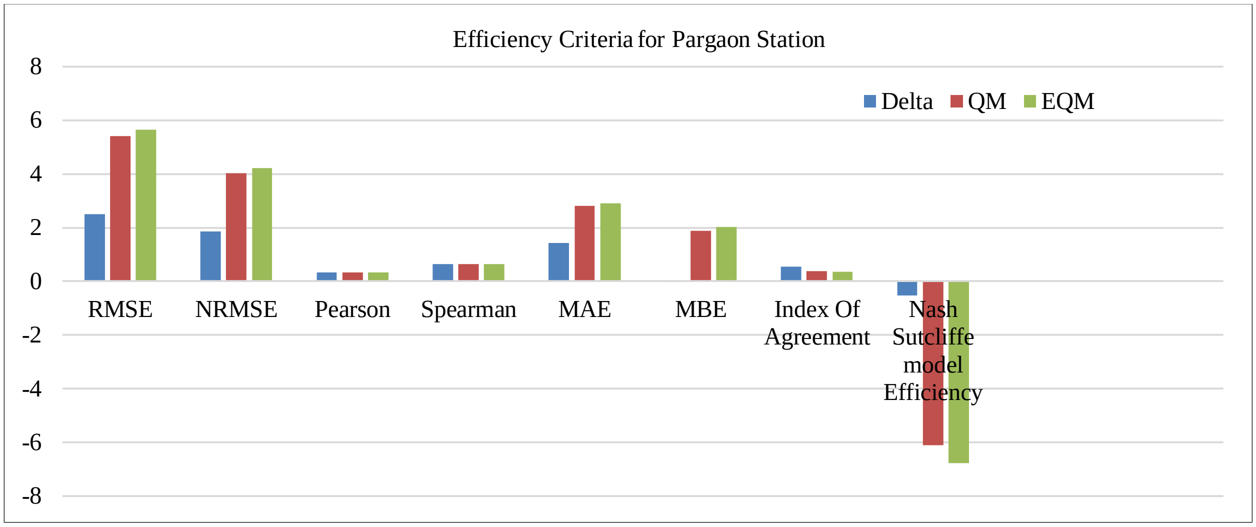

Fig. 6 Evaluation analysis of three methods for Pargaon station

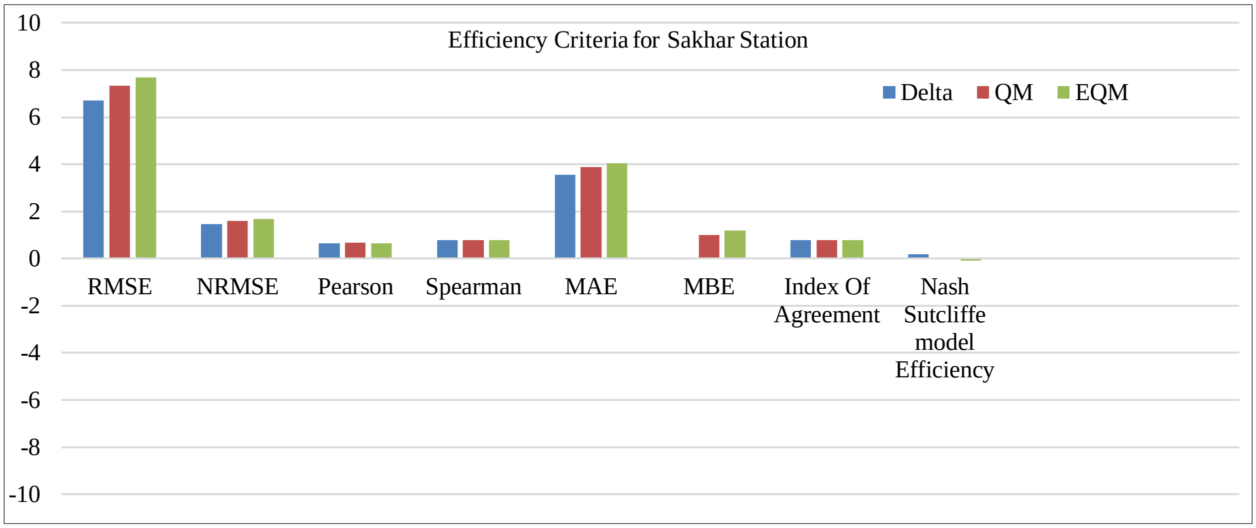

Fig. 7 Evaluation analysis of three methods for Sakhar station

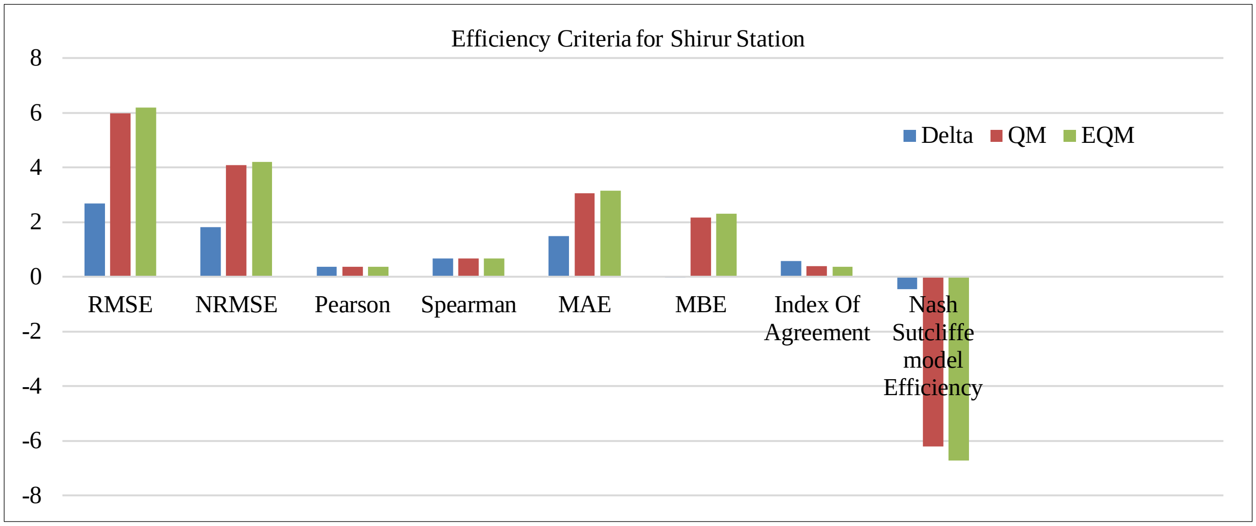

Fig. 8 Evaluation analysis of three methods for Shirur station

5.2. Evaluation Criteria

In this criterion, the effectiveness of statistical downscaling methods is evaluated during a shared time frame. The assessment involves three distinct periods: the station period, the past period, and the predicted period. The past period pertains to GCM historical data. SDGCM can choose a common base that aligns with both the station and historical data periods. In the "Evaluation" tab, the user will choose three periods: Station period, Historical period, and Predicted period (based on GCM). SD-GCM will then calculate the calibration period and evaluation period from these selected periods.

The calibration period is established based on the overlap between the Station period and the Historical period (it is recommended that the user selects the same period for both). The evaluation period is determined based on the Predicted period. In the downscaling process, there are four statistical downscaling methods, with three of them currently active: Delta, QM, and EQM. Once the data has been accurately downscaled, the efficiency criteria results can be reviewed. For evaluation comparisons, users can apply five efficiency criteria methods to compare the observed data with the past data from the GCM model.

An RMSE value of zero indicates a perfect fit for the model. Lessen RMSE values indicate a better model and good accuracy predictions, while higher RMSE values show a deviation from the residual to the benchmark label. In this context, since the Delta method has the lowest RMSE value, it is preferred.

The Normalized Root Mean Square Error (NRMSE) relates to the RMSE range of recorded values for the variable. It is stated as a portion of the total range that the model accounts for. In this scenario, the NRMSE value is the lowest, making the Delta approach the preferred choice.

A Pearson value close to +1 or -1 shows a perfect relation, as one parameter increases, the other also increases as well. If the coefficient value falls between ±0.50 and ±1, it signifies a strong correlation. In this instance, all values are approximately 0.35, but the Pearson value for the Delta method is slightly lower.

Spearman's rho is a nonparametric test used to check the power of the correlation of two parameters. When r = 1 denotes a perfect correlation (positive) when r = -1 shows a perfect correlation (negative). In this scenario, none of the values meet these criteria, so the Delta approach is selected.

When closer the Mean Absolute Error (MAE) is zero, the model is more accurate. Evaluation within the dataset reveals that the Delta approach, with its near-zero MAE, is more accurate and thus preferred.

Mean Bias Error (MBE) occurs when predictions consistently underestimate observed values. For a reliable model, the random error RMSE should approximate the systematic error RMSE, ideally approaching zero.

The Agreement index assesses the proportion of Mean Square Error (MSE) and Potential Error (PE). 1 indicates perfect agreement, while zero signifies no agreement.

The Nash-Sutcliffe Efficiency (NSE) is a standardized measure that compares the magnitude of residual variance. NSE ranges from 1 to -∞, where 1 represents a perfect fit, and 0 suggests the mean value achieves the same level of accuracy.

5.3. Observed and Simulated Precipitation by Delta Method

The evaluation result of the SDGCM Model downscaling of precipitation is as follows. (Delta method of downscaling).

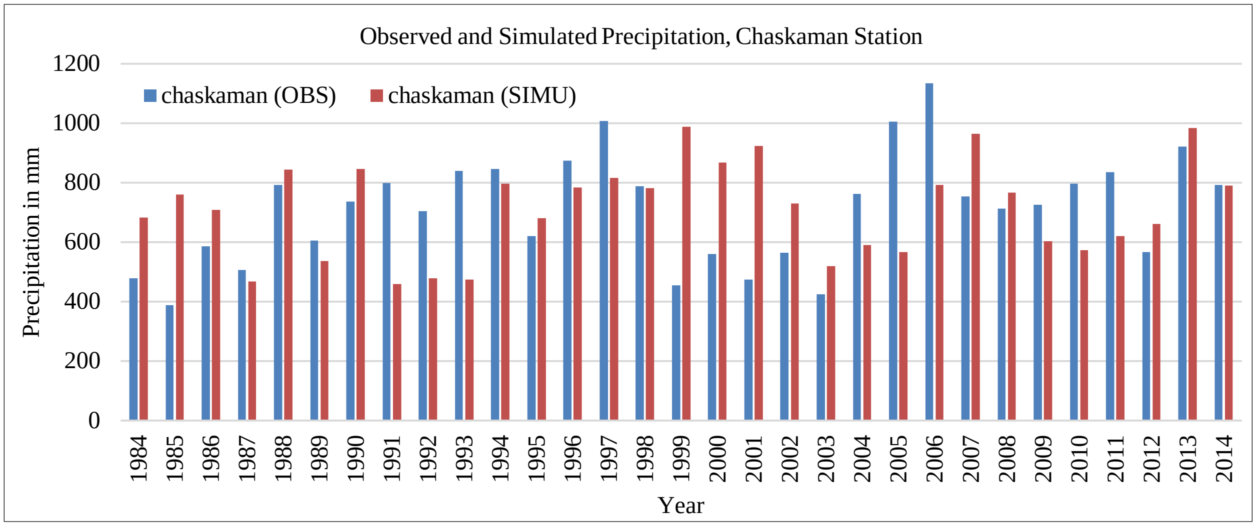

Fig. 9 The observed and simulated precipitation for Chaskaman station

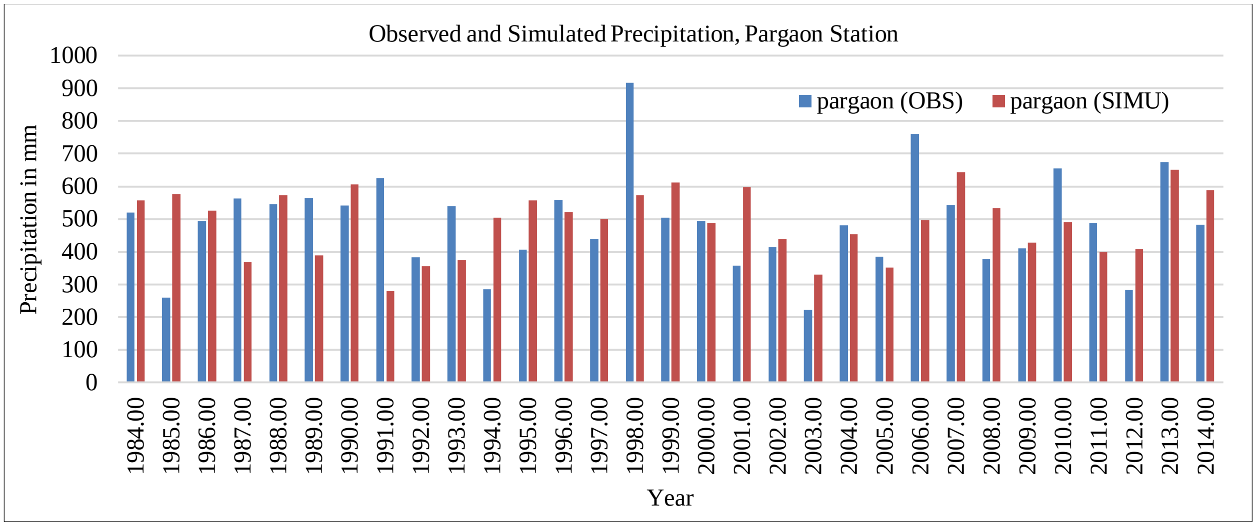

Fig. 10 The observed and simulated precipitation for Pargaon station

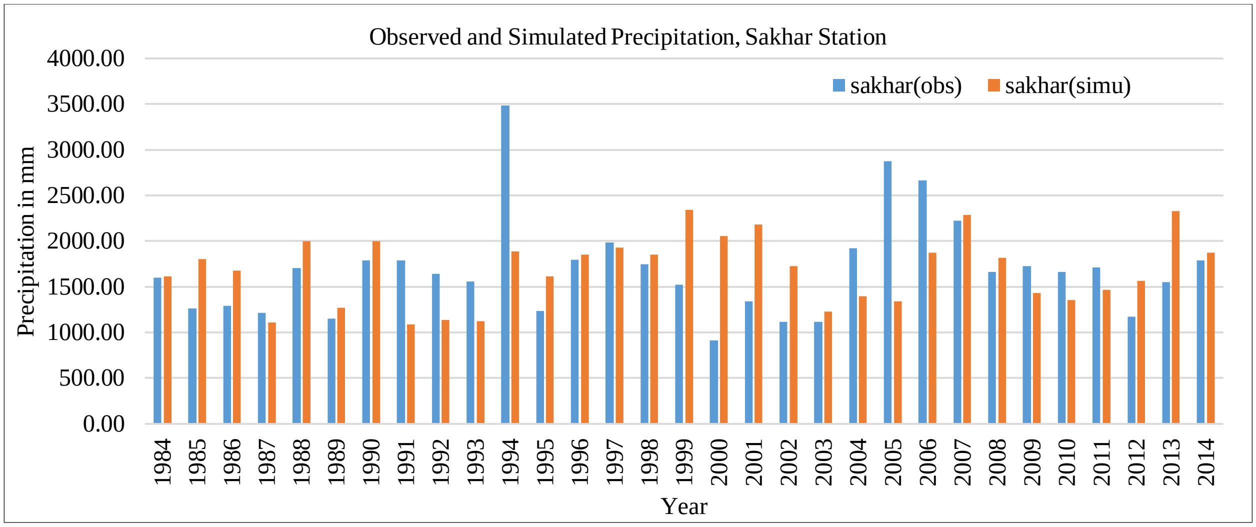

Fig. 11 The observed and simulated precipitation for Sakhar station

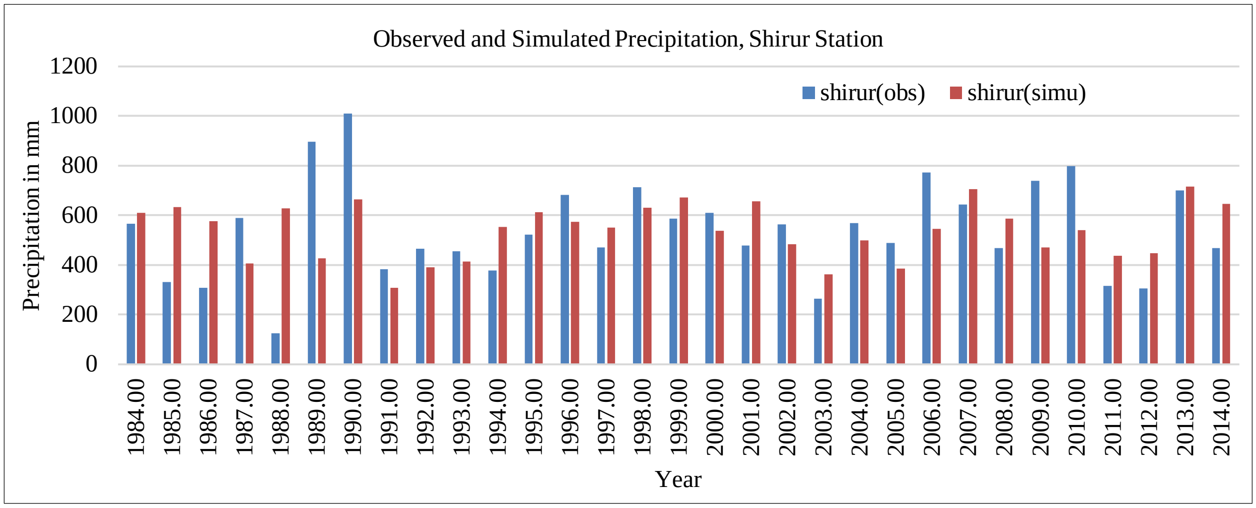

Fig. 12 The observed and simulated precipitation for Shirur station

5.4. Observed and Simulated Precipitation by EQM Method

The assessment outcome of the SDGCM Model's precipitation downscaling using the EQM method is as follows:

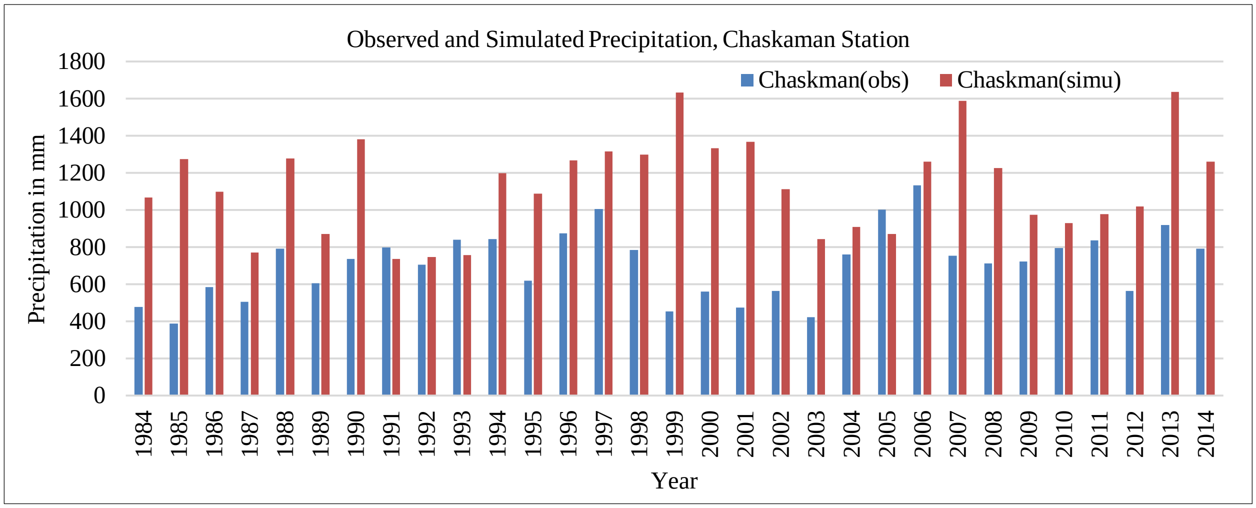

Fig. 13 The observed and simulated precipitation for Chaskaman station

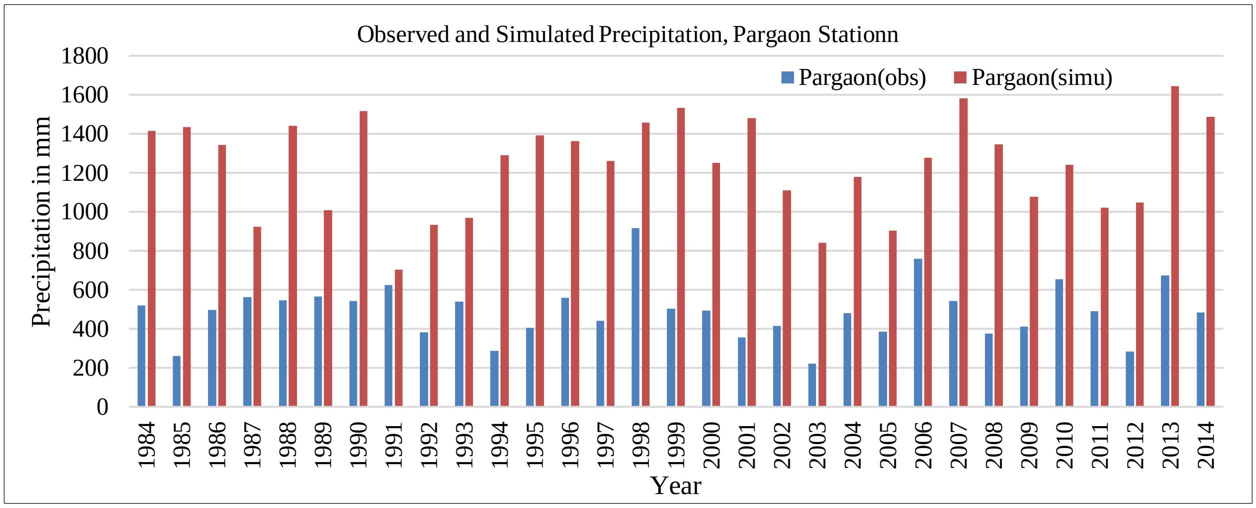

Fig. 14 The observed and simulated precipitation for the Pargaon station

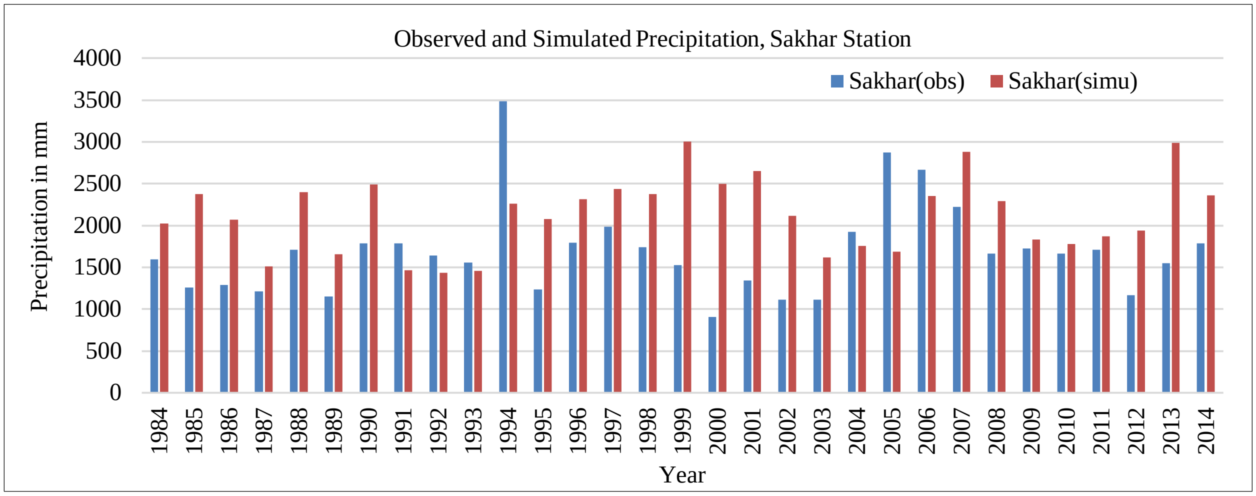

Fig. 15 The observed and simulated precipitation for Sakhar station

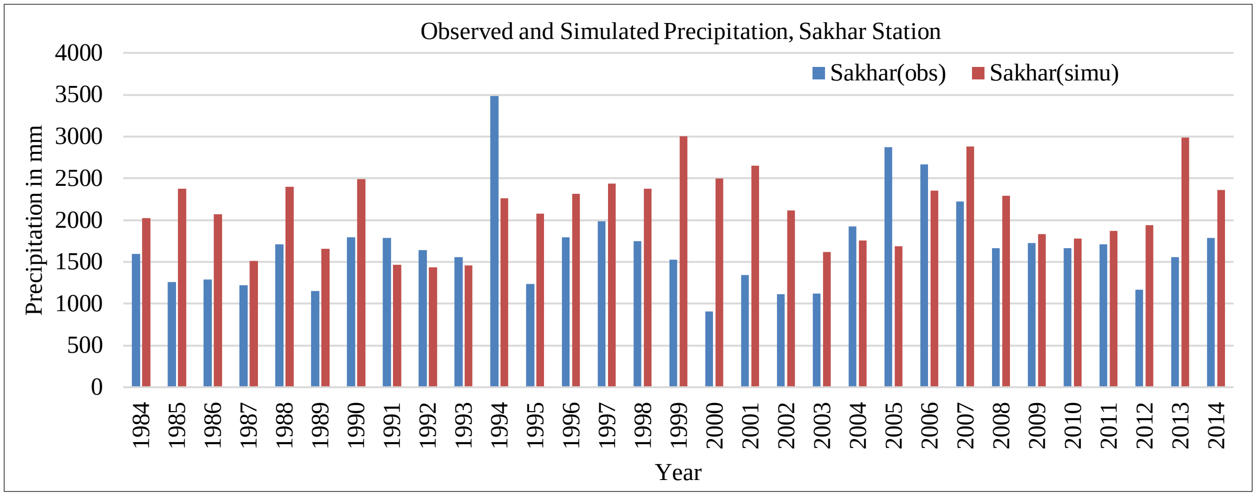

Fig. 16 The observed and simulated precipitation for Shirur station

5.5. Observed and Simulated Precipitation by QM Method

Here are the evaluation findings for precipitation downscaling using the Quantile Mapping method in the SDGCM Model. (Quantile Mapping method of downscaling).

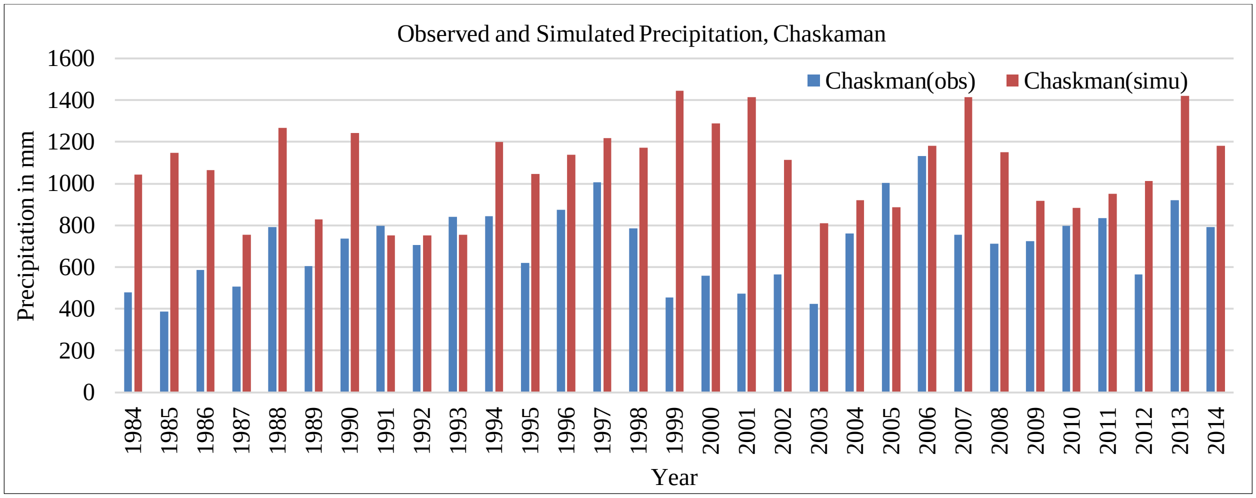

Fig. 17 The observed and simulated precipitation for Chaskaman station

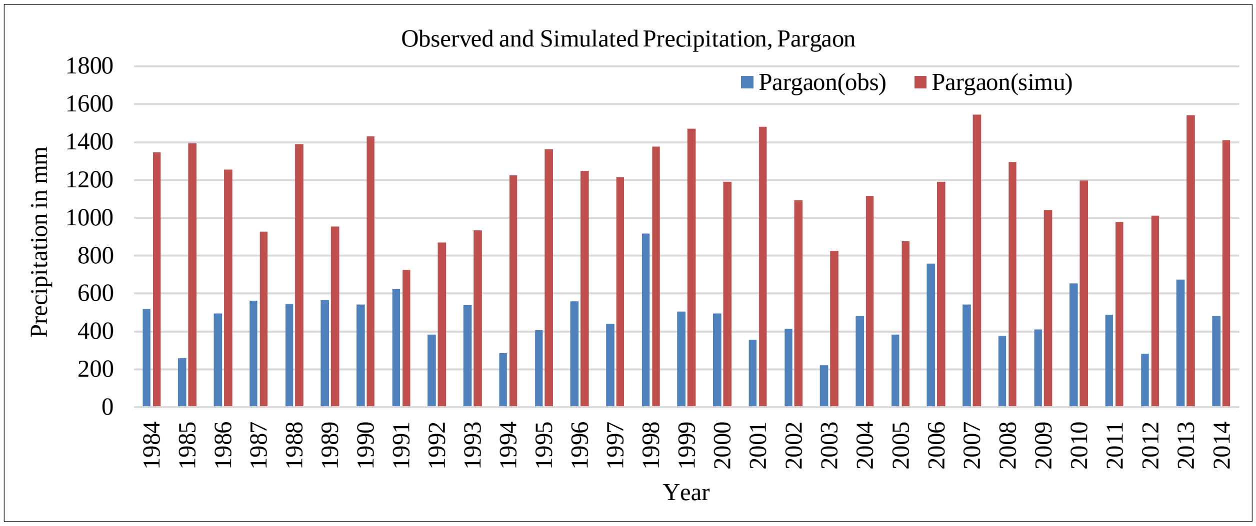

Fig. 18 The observed and simulated precipitation for the Pargaon station

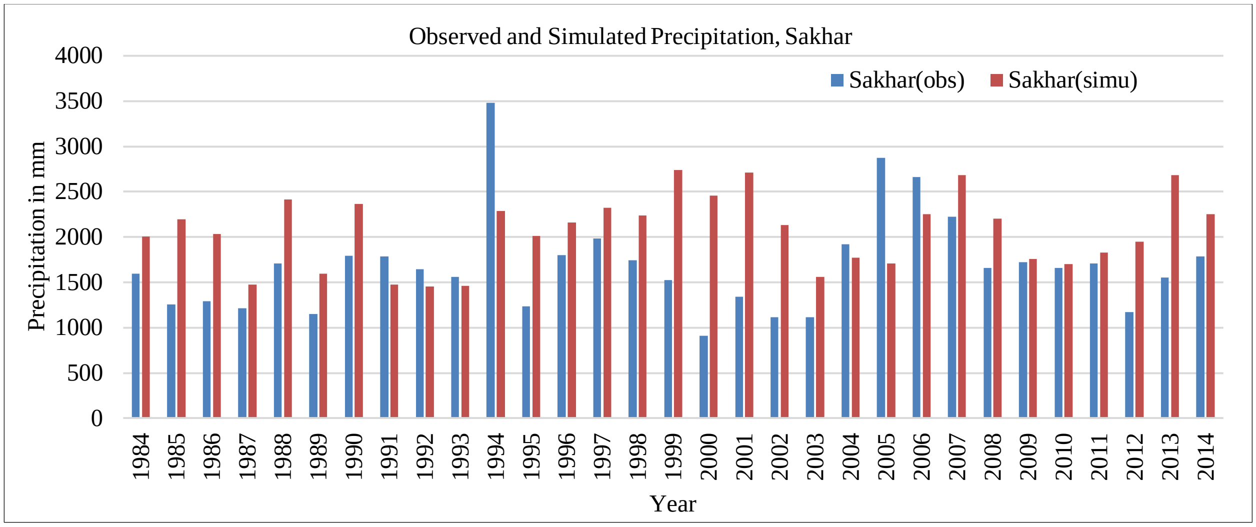

Fig. 19 The observed and simulated precipitation for Sakhar station

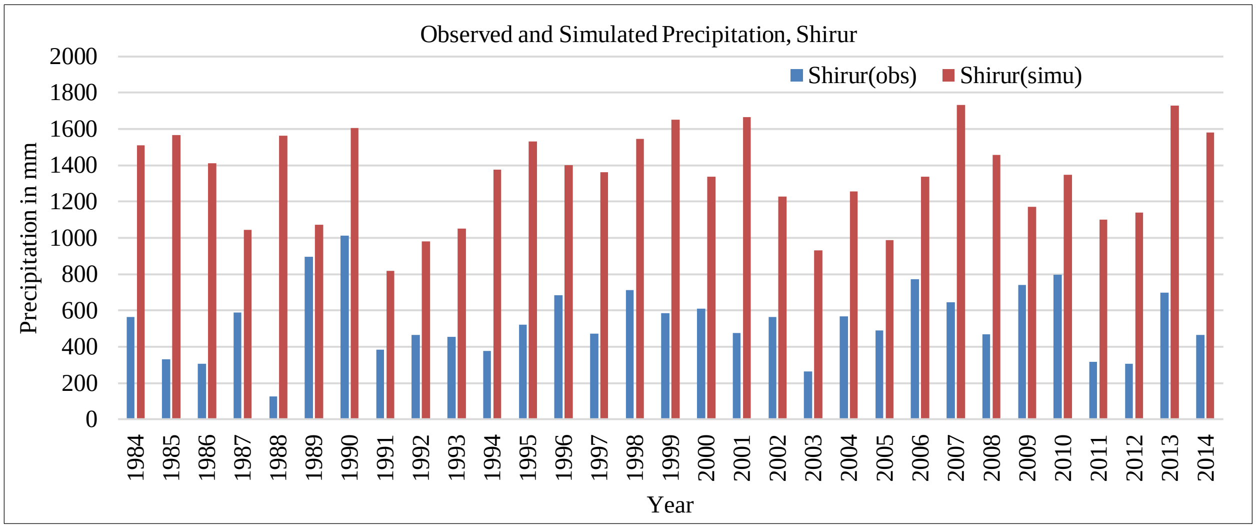

Fig. 20 The observed and simulated precipitation for Shirur station

6. Downscaling of Rainfall

In this analysis, future data is downscaled for the future period from 2021 to 2099. Shared Socioeconomic Pathways (SSPs) are scenarios that describe different future pathways of global societal development and their potential impacts on climate. SSPs are used in conjunction with climate projections, like those from the Coupled Model Intercomparison Project (CMIP6), to explore the effects of socioeconomic changes on greenhouse gas emissions, adaptation, and mitigation efforts.

The SSPs are categorized as SSP1 (Sustainability), where the world is making good progress toward sustainability, with a strong emphasis on environmental stewardship and reduced inequality. SSP2 (Middle of the Road) is where world where trends broadly follow historical patterns with moderate challenges to both mitigation and adaptation. SSP3 (Regional Rivalry) where a fragmented world with a focus on regional issues, leading to high challenges for mitigation and adaptation. SSP4 (Inequality) where a highly unequal world, with elites in some regions adapting well while others face great difficulty. SSP5 (Fossil-fueled Development) where a world driven by rapid economic growth and fossil fuel reliance, leading to high emissions but low challenges for adaptation due to increased wealth. This study considered only SSP245 and SSP585 emission scenarios. The SSP245 scenario involves a net change in the energy balance of the climate system that is radiative forcing of 4.5 w/m^2 up to 2100, representing a moderate pathway for forthcoming greenhouse gas exhaust. This situation assumes the implementation of a Climate change mitigation strategy. Consequently, the downscaled future precipitation data shows an overall increase in average precipitation. On the other hand, SSP585 entails an additional radiative forcing of 8.5w/m^2 by 2100, depicting the upper limit of scenarios where climate protection measures are inadequately implemented. As illustrated in Figures 21 and 24, downscaled precipitation remains relatively constant until 2057, followed by an increasing trend after that.

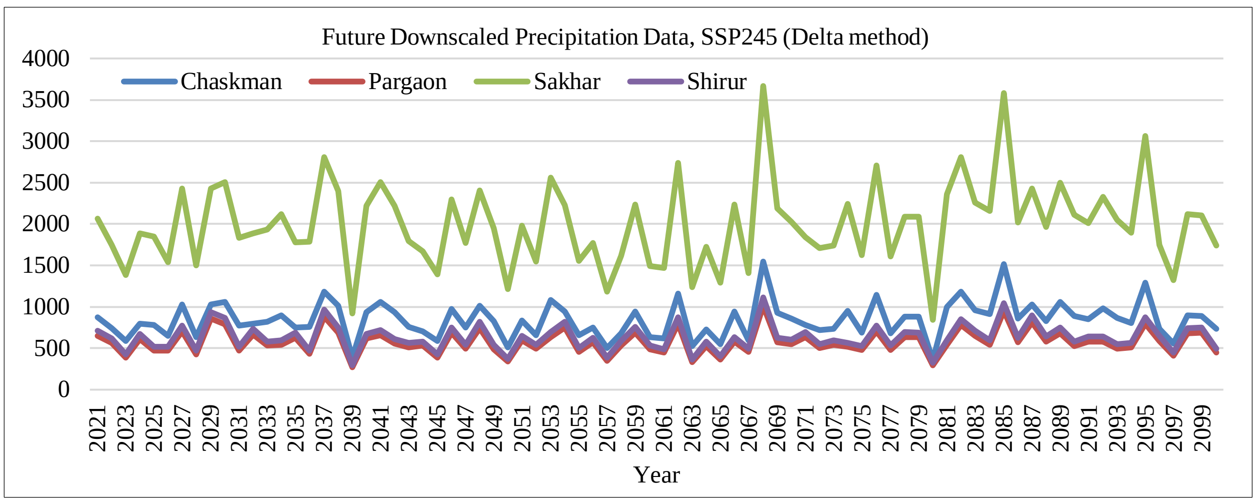

Fig. 21 Future downscaled data by delta method for all stations for the SSP245 scenario

6.1. Downscaling of Rainfall for SSP 245 (Empirical Quantile Mapping Method)

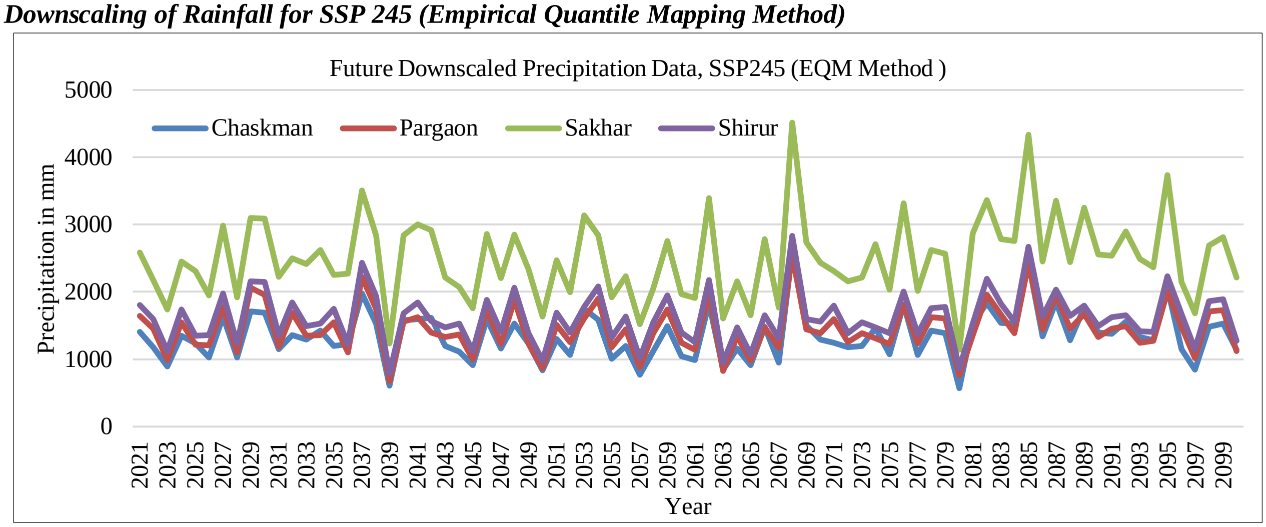

Fig. 22 Future downscaled data by EQM method for all stations for the SSP245 scenario

6.2. Downscaling of Rainfall for SSP 245 (Quantile Mapping Method)

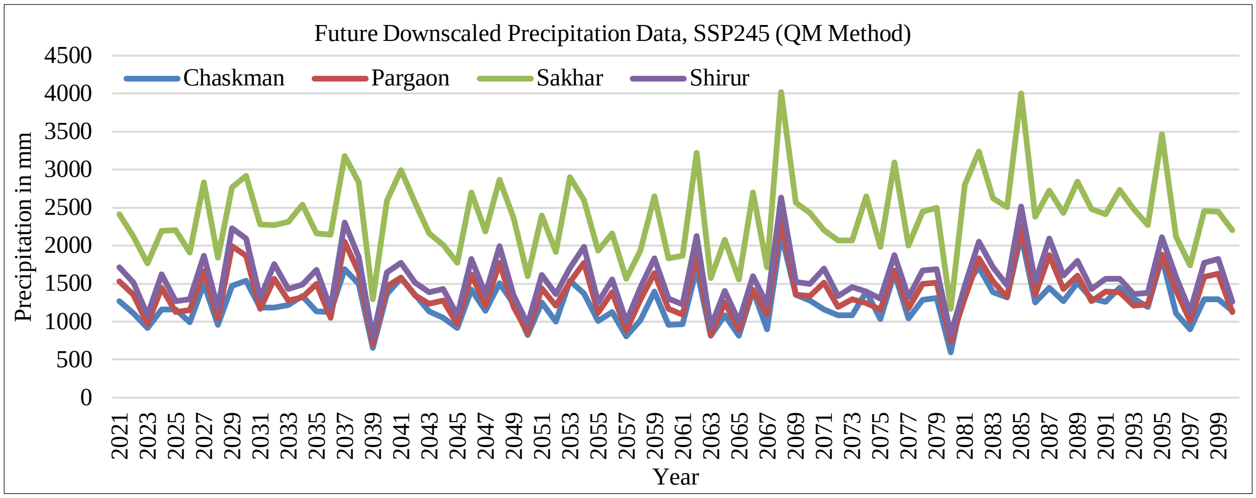

Fig. 23 Future downscaled data by QM method for all stations for the SSP245 scenario

6.3. Downscaling of Rainfall SSP 585 (Delta Method)

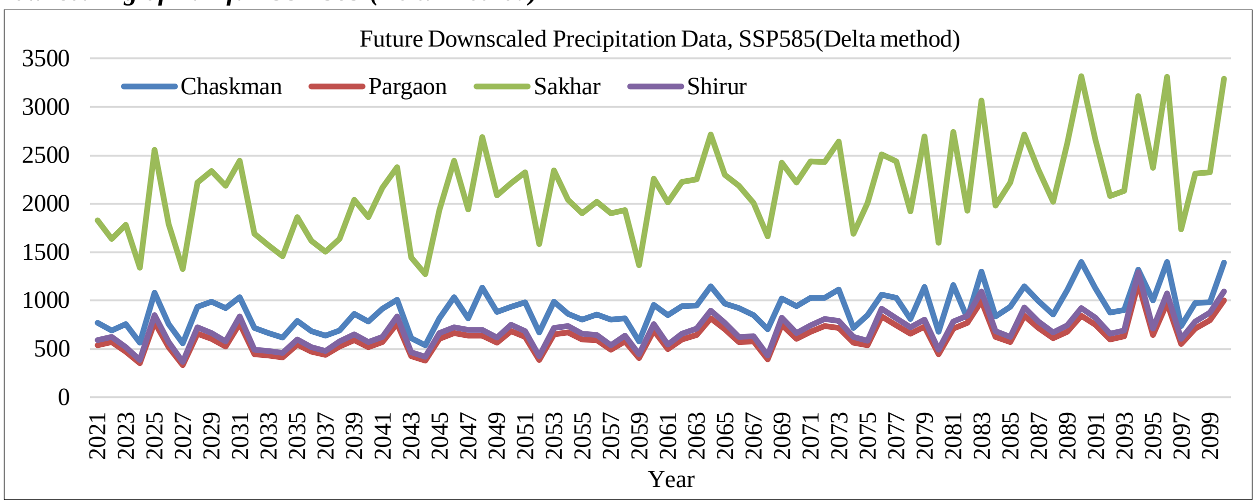

Fig. 24 Future downscaled data by delta method for all stations for the SSP585 scenario

6.4. Downscaling of Rainfall SSP 585 (Empirical Quantile Mapping Method)

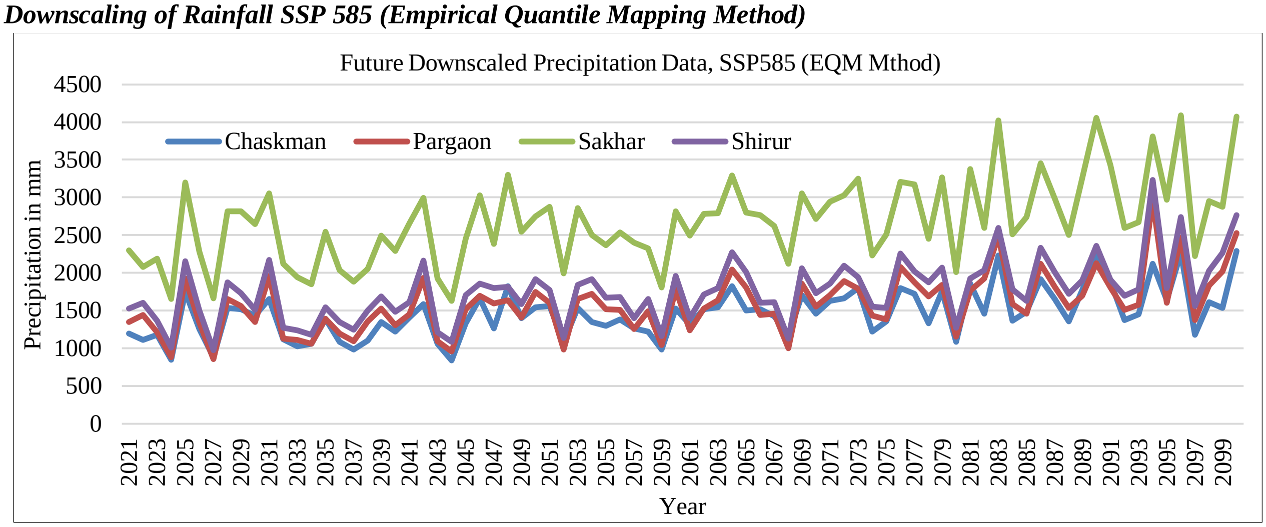

Fig. 25 Future downscaled data by EQM method for all stations for the SSP585 scenario

6.5. Downscaling of Rainfall SSP 585 (QM Method)

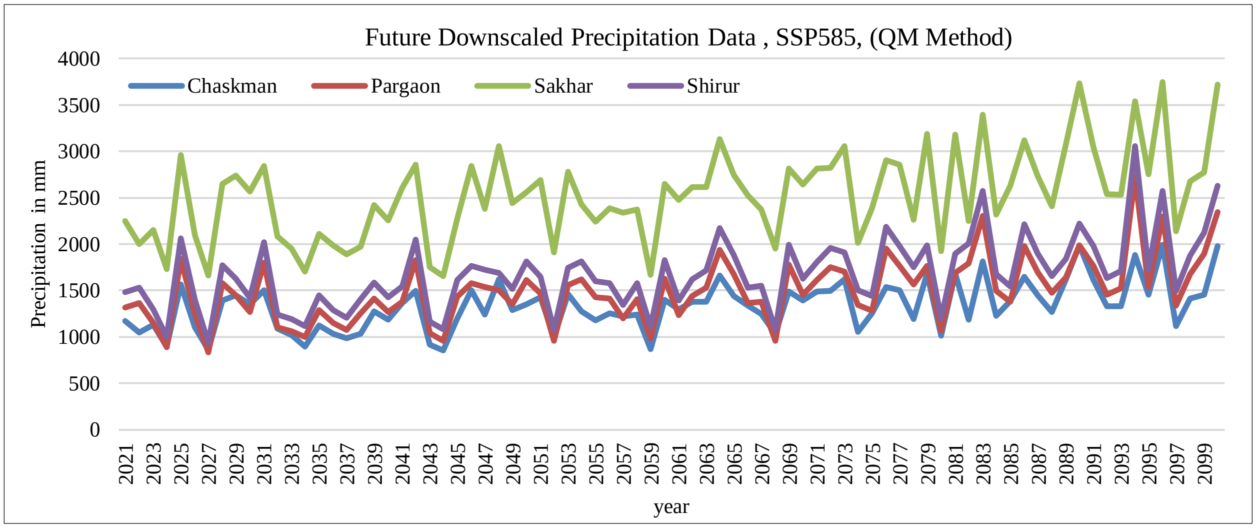

Fig. 26 shows future downscaled data by the QM method for all stations for the SSP585 scenario

7. Conclusion

Future climate projections for the Bhīma river basin utilize data from the CNRM-CM6-1 model developed by the CNRM/CERFACS group for CMIP6, succeeding the CNRM-CM5-1 model from CMIP5. Statistical downscaling involved three approaches, namely the delta approach, the quantile mapping approach, and the empirical quantile mapping approach. The delta method proves most suitable as per the evaluation criteria. This analysis employed a set of eight indices to summarize key features necessary for climate change effect studies. In the SSP245 scenario, precipitation remains relatively stable until 2099 with minimal changes, whereas in SSP585, there is a noticeable year-on-year increase in precipitation. Notably, precipitation at Paragon and Shirur stations shows greater increases compared to Chaskaman and Sakhar.

Peak rainfall is projected to occur in 2069 across all four stations under the SSP245 scenario, while in SSP585, it is expected to peak in 2096 at all stations. The increase in the projected annual average precipitation for the Bhīma river basin is 26 to 55% for SSP245 and 24 to 126% for SSP585. If the result is compared with Krishna River Basin (KRB) in Maharashtra, the results give a notable increase in the annual average rainfall, in the future, considering all SSP scenarios. The rise in the projected annual average rainfall reached 12% to 54% for all SSP scenarios compared to the past ensemble average. Future periods presented a switch in the periodic peak flows compared to the baseline period more readiness for water in the future in the Krishna River Basin (KRB).

7.1. Hydrological and Socioeconomic Impact Assessment

The downscaling of CMIP6 models indicates that the average annual precipitation over the Bhima River Basin is expected to increase, which might have substantial hydrological and socioeconomic ramifications for the area. It is anticipated that these effects will take several forms, including local livelihoods, agricultural output, flood risks, and water availability.

7.1.1. Hydrological Impact

The hydrological cycle of the Bhima River Basin will be directly impacted by an increase in yearly precipitation, which could result in higher river discharge and modifications to the seasonal flow patterns. Although more rainfall might make water more accessible, particularly during the monsoon season, it also makes extreme hydrological events like floods more frequent and intense. Higher peak discharges could overwhelm current flood control systems, resulting in more frequent inundations, given the basin's historical sensitivity to flooding, especially in low-lying areas.

The rates of groundwater recharge, which are essential for maintaining domestic water supply and agriculture throughout the dry season, may also be impacted by the changed precipitation regime. However, because of increased surface runoff, excessive rainfall may impair the efficiency of natural recharge processes. Particularly in areas where groundwater is the main supply for irrigation, this imbalance between the availability of surface water and groundwater could make problems with water management worse.

7.1.2. Socioeconomic Impact

The expected changes in precipitation are likely to have major socioeconomic effects, notably on agriculture, which is the dominant economic activity in the Bhima River Basin. By reducing water stress, an increase in rainfall may boost crop yields in rain-fed agricultural systems. The potential increases the likelihood of crop damage, soil erosion, and nutrient loss for more extreme rainfall events, which could have a detrimental effect on agricultural productivity as a whole. The bulk of the agricultural labor force in the area consists of smallholder farmers, who may be especially susceptible to these disruptions since they have fewer means to adjust to changing weather patterns.

A direct hazard to housing, infrastructure, and public health could result from the increasing likelihood of floods in addition to its effects on agriculture. Communities in flood-prone areas may experience recurring financial losses as a result of destruction to real estate, public utilities, and transportation infrastructure. The cumulative impact of these occurrences may put pressure on regional economies, raise the rate of poverty, and call for more expenditures on resilient infrastructure and disaster preparedness. Furthermore, changes in patterns of water availability may affect the demand for water resources in a variety of sectors, including household and industrial use. Maintaining the region's socioeconomic stability depends on controlling the balance between water supply and consumption as the population expands.

7.1.3. Adaptation and Policy Implications

Integrated Water Resource Management (IWRM) techniques that take into account both surface and groundwater resources are desperately needed to lessen the possible detrimental effects of these hydrological changes. The main objectives of the policy should be to increase the capacity of water storage, upgrade the infrastructure for managing floods, and support climate-variable agriculture. To support the livelihoods of vulnerable populations, socioeconomic adaptation techniques like crop diversification, enhanced irrigation systems, and infrastructure resistant to flooding are crucial.

7.2. Scope for Research

The results of this study underscore the significance of ongoing, multidisciplinary research on the vulnerability of river basins like the Bhima to climate change, especially with regard to precipitation patterns. Future research in this field can expand upon the current work in various directions, substantially enhancing the accuracy and application of climate projections and risk assessments.

7.2.1. Exploration of Additional Climate Models

Although CMIP6 models were the main tool used in this work, investigating alternative global and regional climate models can yield a more thorough and reliable picture of potential future climatic scenarios. Using ensembles of many GCMs or the outputs of Regional Climate Models (RCMs) like CORDEX can help reduce the uncertainty associated with individual models and better represent the range of probable outcomes. Improved predictions of precipitation extremes and variability which are essential for managing water resources and reducing the danger of flooding, can be achieved through the use of multiple models. In addition, incorporating new generations of climate models as they become accessible will guarantee that projections are grounded in the most recent climate science, taking into account improvements in modeling methodologies, parameterizations, and the addition of novel variables like land-use change and atmospheric dynamics.

7.2.2. Application of Advanced Downscaling Techniques

The downscaling techniques used in this work, such as Delta, Empirical Quantile Mapping (EQM), and Quantile Mapping (QM), are commonly used for enhancing the spatial resolution and correcting bias in climate model outputs. Future studies, however, would profit from investigating more sophisticated downscaling strategies, such as those based on machine learning or dynamic downscaling using RCMs. Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) are two examples of machine learning techniques that have demonstrated promise in capturing the intricate links between large-scale climatic variables and local-scale climate variability. This could lead to more accurate downscaling estimates. Furthermore, by including both physical processes and statistical corrections, hybrid techniques that integrate statistical and dynamical downscaling may further improve precipitation estimates. These techniques could enhance the depiction of extreme weather occurrences, which is important for comprehending vulnerability in areas susceptible to monsoonal flooding, such as the Bhima River Basin.

7.2.3. Extending the Study to Other River Basins

Future studies should apply the risk assessment approach created for the Bhima River Basin to other river basins in order to get a more comprehensive understanding of how climate change affects various hydrological regions. This would make it possible to compare distinct geographic, meteorological, and socioeconomic circumstances, providing insights into how different places may be affected differently by climate change with regard to water resources. Policymakers and water managers could benefit from the collection of useful data that could come from doing similar studies for basins with different levels of water stress, such as desert regions or regions with highly seasonal water supply. Academics can create a more comprehensive framework for climate change vulnerability assessments by expanding the scope to encompass several river basins. This would make it easier to identify adaptation methods and vulnerabilities unique to a given region, resulting in basin-level water resource management plans that are more focused and efficient.

7.2.4. Incorporating Additional Climate and Socioeconomic Variables

In order to conduct thorough risk assessments, future research should also take into account the integration of additional climate variables beyond precipitation, such as temperature, evapotranspiration, and extreme weather occurrences (such as heat waves and droughts). These factors have an impact on agricultural output and water availability, two important factors for the socioeconomic stability of areas where people rely on river basins for their livelihoods.

Furthermore, socioeconomic variables, including urbanization, population growth, and changes in land use, will be included to provide a more comprehensive understanding of vulnerability. Researchers will be able to evaluate the ability of local populations to adjust to future climatic circumstances and create more successful adaption strategies by modeling the interaction between climate and socioeconomic variables.

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References

[1] A.K. Srivastava, M. Rajeevan, and S.R. Kshirsagar, “Development of a High Resolution Daily Gridded Temperature Data Set (1969–2005) for the Indian Region,” *Atmospheric Science Letters*, vol. 10, no. 4, pp. 249-254, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[2] Cunrui Huang et al., “Projecting Future Heat-Related Mortality under Climate Change Scenarios: A Systematic Review,” *Environmental Health Perspectives*, vol. 119, no. 12, pp. 1681-1690, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[3] H.J. Fowler, S. Blenkinsop, and C. Tebaldi, “Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological Modelling,” *International Journal of Climatology*, vol. 27, no. 12, pp. 1547-1578, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[4] W.W. Immerzeel, and P. Droogers, “Calibration of a Distributed Hydrological Model Based on Satellite Evapotranspiration,” *Journal of Hydrology*, vol. 349, no. 3-4, pp. 411-424, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[5] Shimelis Behailu Dessu, and Assefa M. Melesse, *Evaluation and Comparison of Satellite and GCM Rainfall Estimates for the Mara River Basin, Kenya/Tanzania*, Climate Change and Water Resources, pp. 29-45, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[6] P. Eric, and J. Salathe, “Comparison of Various Precipitation Downscaling Methods for the Simulation of Streamflow in a Rainshadow River Basin,” *International Journal of Climatology*, vol. 23, no. 8, pp. 887-901, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[7] R.L. Wilby, C.W. Dawson, and E.M. Barrow, “SDSM - A Decision Support Tool for the Assessment of Regional Climate Change Impacts,” *Environmental Modelling & Software*, vol. 17, no. 2, pp. 145-157, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[8] R.L. Wilby, and T.M.L. Wigley, “Downscaling General Circulation Model Output: A Review of Methods and Limitations,” *Progress in Physical Geography: Earth and Environment*, vol. 21, no. 4, pp. 530-548, 1997. [CrossRef] [Google Scholar] [Publisher Link]

[9] M.Z. Hashmi, A.Y. Shamseldin, and B.W. Melville, “Statistical Downscaling of Precipitation: State-of-the-Art and Application of Bayesian Multi-Model Approach for Uncertainty Assessment,” *Hydrology and Earth System Sciences Discussions*, vol. 6, no. 5, pp. 6535-6579, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[10] V.T.V. Nguyen, T.D. Nguyen, and P. Gachon, “Statistical Downscaling Methods for Climate Change Impact Studies,” *Conference on Adapting to Climate Change in Canada*, 2005. [Google Scholar]

[11] SD-GCM Tool, Agrimetsoft, 2023. [Online]. Available: https://agrimetsoft.com/SD-GCM.aspx

[12] Hyun-Suk Kang, Fredolin Tangang, and R. Krishnan, “Regional Climate Downscaling Over Asia-Pacific Region,” *Asia-Pacific Journal of Atmospheric Sciences*, vol. 52, no. 2, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[13] Yura Kim et al., “Spatial Analysis of Future East Asian Seasonal Temperature Using Two Regional Climate Model Simulations,” *Asia-Pacific Journal of Atmospheric Sciences*, vol. 52, pp. 237-249, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[14] F. Wetterhall et al., “Conditioning Model Output Statistics of Regional Climate Model Precipitation on Circulation Patterns,” *Nonlinear Processes in Geophysics*, vol. 19, no. 6, pp. 623-633, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[15] K. Eckhardt and U. Ulbrich, “Potential Impacts of Climate Change on Groundwater Recharge and Streamflow in a Central European Low Mountain Range,” *Journal of Hydrology*, vol. 284, no. 1-4, pp. 244-252, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[16] Subimal Ghosh, and P.P. Mujumdar, “Climate Change Impact Assessment: Uncertainty Modeling with Imprecise Probability,” *Journal of Geophysical Research: Atmospheres*, vol. 114, no. D18, pp. 1-17, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[17] Lauren E. Hay, Robert L. Wilby, and George H. Leavesley, “A Comparison of Delta Change and Downscaled Gcm Scenarios for Three Mountainous Basins in the United States,” *Journal of the American Water Resources Association*, vol. 36, no. 2, pp. 387-397, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[18] Dipak R. Samal, and Shirish S. Gedam, “Assessing the Impact of Land Use Change on Stream Flow in a Semi-Urban River Basin, Maharashtra, India,” *International Journal of Hydrology Science and Technology*, vol. 3, no. 4, pp. 351-363, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[19] A.W. Wood et al., "Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs," *Climatic Change*, vol. 62, pp. 189-216, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[20] S. Kannan, and Subimal Ghosh, "A Nonparametric Kernel Regression Model for Downscaling Multisite Daily Precipitation in the Mahanadi Basin," *Water Resources Research*, vol. 49, no. 3, pp. 1360-1385, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[21] D. Maraun et al., "Precipitation Downscaling Under Climate Change: Recent Developments to Bridge the Gap between Dynamical Models and the End User," *Reviews of Geophysics*, vol. 48, no. 3, pp. 1-34, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[22] D.A. Sachindra et al., "Statistical Downscaling of General Circulation Model Outputs to Precipitation Part 2: Bias-Correction and Future Projections," *International Journal of Climatology*, vol. 34, no. 11, pp. 3282-3303, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[23] R.L. Wilby et al., "Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods," *Supporting Material of the Intergovernmental Panel on Climate Change*, vol. 27, pp. 1-27, 2004. [Google Scholar] [Publisher Link]

[24] Akiyo Yatagai et al., "APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges," *Bulletin of the American Meteorological Society*, vol. 93, no. 9, pp. 1401-1415, 2012. [CrossRef] [Google Scholar] [Publisher Link]