Statistical Downscaling for Evaluating Precipitation and Extremes for Bhima River Basin

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Abstract: The hydrological implications of global climate change on regional levels are often studied by scaling down large-scale climatic variables modelled by General Circulation Models (GCMs). Hydro meteorological variables refers to the use of statistical downscaling methods (SDSM) for minimising precipitation. In this paper, we recommend a statistical downscaling model that relies on three different methods namely delta, quantile mapping, empirical quantile mapping. In order to explore statistical downscaling method, the station Chaskaman, Paragon, Shirur, Sakhar have been chosen for a study area to test the precipitation methodology. All stations are located in Bhima river basin. To find the pattern from the historical base on observation (training period) and then apply the pattern to historical and SSPs periods. The forecasted future based on climate predictions which is CMIP6 model namely CNRM-CM6-1 is used. The downscaling findings suggest that the SDSM model could be effectively accepted in terms of daily precipitation downscaling throughout the calibration as well as evaluation stages. SDGCM model predicts that overall average annual rainfall will increase at all chosen stations in the future (2021-2100) in river basins for SSP245 scenarios and also increased total average rainfall for all the selected station for SSP585 scenarios. The downscaling results reveal how the statistical downscaling model performs effectively in the downscaling of daily precipitation.

Keywords*: SDSM, GCMs, Climate change, rainfall, downscaling;*

1. Introduction

Climate change may have a substantial effect on water resources owing to changes in the hydrological process. Rainfall as well as temperature are the key variables that have a direct impact on the climate. To forecast and assess future changes in climate caused by the current rise of greenhouse gas concentrations in the environment, Global climate models (GCMs) are being used. Since GCM results cannot be utilized directly for any hydrological simulation given its coarse resolution, downscaling is employed to convert the coarse spatial resolution of GCM output to a fine resolution that can generate data from stations or point-based information of a particular region (Nguyen et al, 2005, Wilby & Wigley 1997, Dauson & Wilson 2007, Hashmi et al 2009). Downscaling methods are classified into two types: statistical downscaling (SD) as well as dynamical downscaling (DD).

Statistical downscaling was applied in this investigation. It describes a strategy that uses random or predictable functions to infer local data based on longer scale interpretations from a cross scale association (Salathe, 2003). Statistical downscaling is a technique for obtaining fine-resolution climate change data by developing an apparent statistical relationship connecting large-scale atmospheric circulation with local variables. 2011 (Huang et al.)

It is described as the establishment of an empirical connection between a broad scale atmospheric values (predictor) with a local scale variable (predicted). Software SDGCM V2.0, developed by agrimet soft, is used (Wilby et al. 2004). The main objective of the present study is to investigate the versatility of SDGCM for downscaling precipitation. SDGCM can be used to offer regional data on climate change under projected emission scenarios (SSP245, SSP585) for present studies on impact of climate change assessment in hydrology (Wilby et al 2004). Flow chart of Methodology.

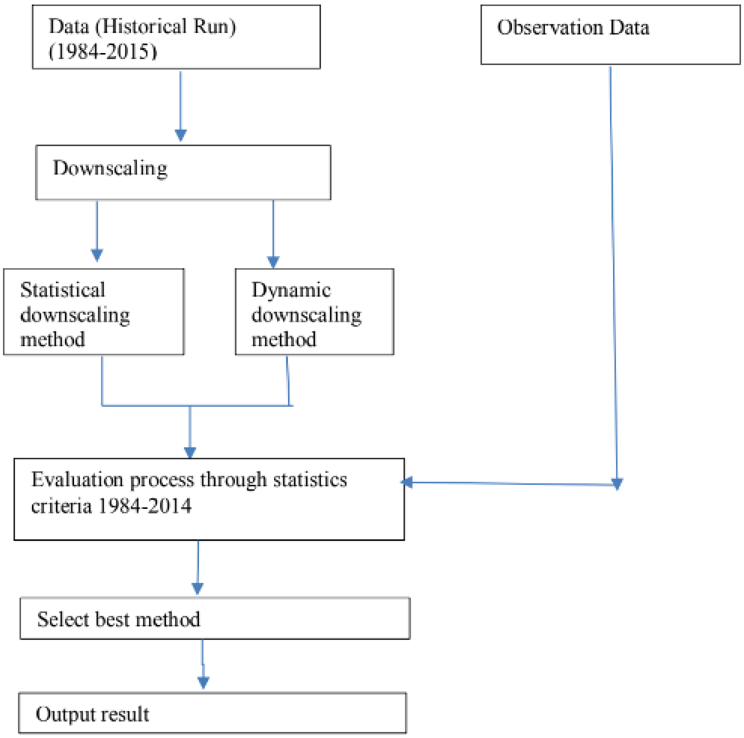

Fig No 1.1

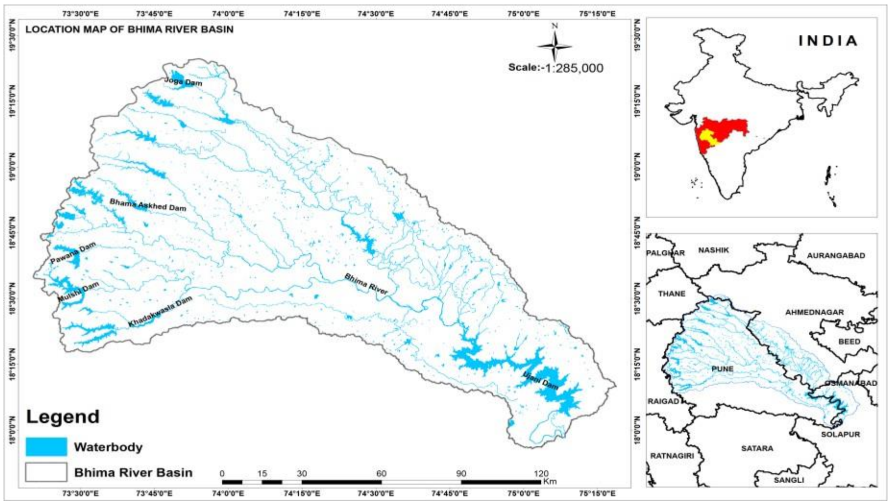

Fig 1.2 Study Area

1.1 Study Area

Bhima River originates in India's rain shadow area located in the Western Ghats. The Upper Bhīma basin extends geographically from 73°30’0’’-75°15’0” E and 18°0’00”-19°30’00”N, encompassing a total area around 70614 km2 (Fig. 1.1). The basin's geography is undulating, with elevations ranging from 499 to 1298 meters above the sea level. The basin's western edge is highly rugged. The center region is characterized by small hills, whereas the eastern region is marked by gently sloping terrain and declining hills (Central Ground Water Board, Department of Water Resources). The climate in the basin is tropical monsoon, with maximum and minimum temperatures of roughly 38°C to 11°C in April and the month of January, respectively. The basin receives an average annual rainfall of 1233 mm, which is controlled mainly by south-west monsoon. The existence of the Western Ghats range of mountains results in over 3000 millimeters of rainfall in the western section of the basin, which gradually drops to 600 mm at the basin discharge (Samal and Gedam, 2015). Considering its close proximity to Western Ghats, the Bhīma River, one of the main tributaries of the river Krishna, discharges a substantial amount of flow. A large portion of the basin is encompassed by wastelands, including open and dense scrub, degraded terrain, barren rocky waste, and stony waste, deemed useless for cultivation because of their thin soil coverage and susceptibility to erosion. Four stations namely Chaskaman, Shirur, Sakhar and Paragon are selected in this river basin. Thus, understanding the effect of climatic changes will help determine the best and most appropriate course of action for the future improvement of water resources. Precipitation data is one kind of metrological information that is used for research. Data on the precipitation is collected through HDUG (Hydrological Data User Group) Nasik. Owing to the extension of Pune metropolitan area, the topography of the basin is swiftly urbanizing in the past few years, attracting the interest of researchers to evaluate the effects on water resources as well as climate change (Immerzeel and Droogers, 2008; Wagner et al., 2013, Wagneret al., 2019).

1.2 Methodology

There are several steps which is used to downscale GCM. The input is predictor (GCM Value) and predict and (observed value). The data set used are precipitation variable. The predict and is HDUG Data and predictor is GCM data. Utilizing correlation and partial correlation analysis, along with scatter plot, the data set is selected. When statistical downscaling is performed, a multi linear regression model is used (Kannan et.al.(2011). The model typically predicts the daily rainfall at each location for the present and the future. The everyday rainfall and temperature records are used to compute the monthly and annual temperatures (Srivastava et al, 2008).

The flow chart of different step in this study as above. Fig no 1

1.3 Statistical downscaling

Here, we used the delta method for statistical downscaling, the most popular GCM output, which depends on the link between local climate surface variables as well as large scale atmospheric variables. (Marun et al 2010, Kang et al 2016,Kim et al 2016). It is a straightforward process that is simple to use. (Dessu and Melesse 2013), Wetterhall et al (2012) referred this as being a direct method. According to Marun et al. (2010), the delta technique solely uses the model's reaction to climate change in order to modify observations because it serves as a reasonable benchmark in bias correction. Several studies on the impacts of climate change have utilized the bias correction downscaling technique that is also known by the delta change technique (Eckhardt and Ulbrich 2003). The delta approach just includes the GCM's signal for climate change in the observation (Hay et al 2000). The advantages of delta algorithms are their simplicity and low data requirements. The calculation of downscale precipitation in this investigation is carried out as follows.

P^{delta} = $P_{mod,\ daily}$ x (P_{obs}/P_{mod}) monthly

P^{delta} is a downscaled precipitation data value. P_{mod} represents the mean precipitation data throughout the controlled period, while P_{obs} indicates the mean observed precipitation. (Historical GCM run). Applying the future period to the equation will allow us to employ future data. The developed software programme (Agrimet soft SD-GCM 2017) is utilized in this investigation to execute the delta approach. A practical technique for downscaling the CMIP6 model for SSPs scenarios is the SD-GCM (statistical downscaling GCM) tool. The observation data as well as output data in this tool would be in an excel file. One can use this tool for verification metrics. Three statistical downscaling methods are included in the SD-GCM tool: delta, empirical quantile mapping (EQM), (Boe et al. 2007), and quantile mapping (QM) (Panofsky and Briiar, 1968).

With the use of this software, a user can create a database that can be used to apply each CMIP6 model to any SSP245 or SSP 545 scenario. A separate file must be provided for the SD GCM with manually entered values and other information. The names of all CMIP6 models follow a unique format. The SD GCM tool includes a feature for model data evaluation. In this stage, the user can evaluate the CMIP6 model's capability with observational data from a recent era. The observational data would be stored in an excel file. During the evaluation phase, there are six efficiency criteria: Pearson Correlation, Spearman Correlation, d (Index of Agreement), Nash-Sutcliffe Efficiency, RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error).

1.4 Concept of Downscaling

The results of hydrological, agricultural, as well as other studies cannot be evaluated using the General Circulation Model (GCM) simulations raw data. Downscaling techniques have been developed because the geographic scale of GCM outputs, which is typically 250 km, is insufficient and too coarse. The difference between crude and fine-scale climate data is filled via downscaling. According to Fowler et al. (2007), spatial downscaling relates to techniques used to convert coarser resolution GCM outputs into finer-resolution geographic climatic information, such as reducing a 500-kilometer grid cell's output to a 20-kilometer resolution.

Statistical downscaling (SD) and dynamic downscaling (DD) are the two main categories of downscaling. (Christensen et al., 2007). By layering a fine-scale climatic model inside a coarse-scale framework, DD creates domains of climate-related parameters that are spatially comprehensive. Due to its high computational requirements, DD is only really useful for single-decade simulations and has a very limited application in impact studies. Due to their complexity, DD models demand a lot of computing power, frequently on par with that needed for GCM simulations. These models can be implemented incorrectly. A regional climate model (RCM), restricted by broader GCM nodes, is employed in DD for modelling the target area at finer levels (Ghosh et.al, 2009).

SD techniques have a high chance of choosing from related users as they are simple to implement and don't require a lot of computational power. They can also be executed quickly by a computer with basic capabilities using only simple regression analyses. The development of a huge array of SD approaches is based on the identification of statistical relationships between regional data from ground-based stations with large-scale synoptic predictions. Since DD is computationally constrained to a spatial resolution of 20–50 km, it is unable to create site-specific projections of climate. The ability to downscale various GCM (or RCM) climatic projections using SD approaches is one of their advantages given that they require less processing. The SD approach also offers station-scale climatic data using GCM-scale outputs and is comparatively simple to apply in comparison to DD approaches. (Yatagai et al, 2012).

Regression (transfer function) approaches (e.g. Kang et al. 2007), stochastic weather generators (Richardson 1981) along with weather pattern strategies, generally, are three groups into which statistical methods can be differentiated. There are several different statistical downscaling techniques. Bias Correction (BC), which has been widely used for impact assessments and used in studies on climate change around the world, is one among the most well-known and prevalent of them (Wood et al., 2002; Payne et al. 2004). (Theme ßl et al. 2012) is one of the greatest resources for assessing the efficacy of various BC techniques.

These methods involve numerous statistical techniques that are applied with multiple applications across the globe, but practically all such applications utilising CMIP6 outputs are challenging for end users to comprehend and neither of them have an executable file that is simple to run. Due to this limitation, user-friendly software modules are essential for facilitating downscaling for end users. The SD GCM programme supports four distinct SD techniques.

SD-GCM V1.0 just requires the GCM and daily station (observation) data to function.

The CMIP5 / CMIP6 / CORDEX data can be used monthly and daily with the SD-GCM V2.0.

1.5 Methods for statistical downscaling utilised in the SD GCM V1.0 Software

In the SD GCM tool, statistical downscaling can be accomplished by employing one of three methods: the EQM (Empirical Quantile Mapping) approach, the QM (Quantile Mapping), or the Delta method. The following provides explanations for each of them.

1.5.1 Statistical downscaling using the delta technique (Dessu and Melesse, 2013):

The temperature and precipitation from the GCM data have been downscaled as shown in Eqs. 1 and 2.

1. $_{SD}P^{Delta} = P_{GCM\ SSP}$ X Pobs/PGCM HIST

2. $T^{Delta}_{SD} = T_{GCM\ SSP}$ + (Tobs – TGCM HIST)

where the downscaled values for precipitation and temperature, are P(SD, Delta) and T(SD, Delta), respectively. The terms P(Obs) and P(GCMhist) refer to the average observed and historical precipitation data, respectively. GCM's ssp values for the upcoming period are represented by subscript GCM ssp, while the observation values are indicated by subscript Obs.

1.5.2 Quantile Mapping (QM) statistical downscaling technique

According to Panofsky and Brier (1968), QM represents a statistical downscaling technique which has been applied in various fields of research. Calculating the modelled probabilistic distribution in relation to the observed probabilistic distribution using the quantum mechanical equation. Data on precipitation is used to compute this idea. Equation 3 is used by SD GCM for evaluation, while Equation 4 is applied for future downscaling.

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

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

Cumulative distribution function (CDF) of observation and GCM data for the period under consideration is depicted in equation (Eq. 3) which is currently being used.

1.5.3 Statistical downscaling approach using Empirical Quantile Mapping (EQM)

A comprehensive study for statistical downscaling techniques, known as EQM, has been published by Wetterhall and his co-workers in 2012. Empirical cumulative distribution function (ECDF) is used by the EQM as in Eq. 4, and each of its elements are the same as those used by the SD GCM in Eqs. 5 and 6, respectively, for evaluation and future downscaling.

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

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

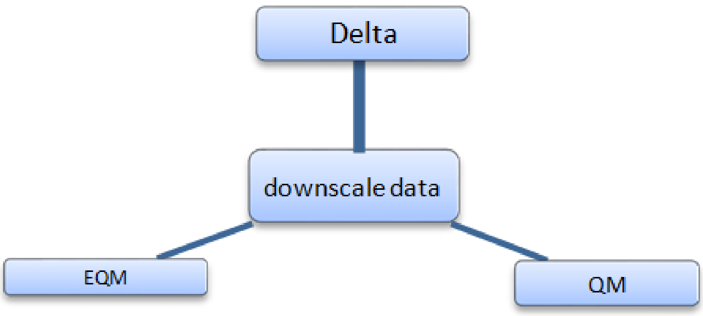

Fig. 1.2 Three methods of statistical downscaling in the SD GCM tool

1.6 Input Station and GCM Data downscaling

Three different types of data are employed and loaded: observational data, historical GCM data, and prediction GCM data for hypothetical scenarios. Uploading is done using an input file 'excel file'. By choosing Browse file, the user can choose the station's weather information. The user may browse and choose the desired file (observation data/in-situ) in the visible window. Daily scale should be used for the station data.

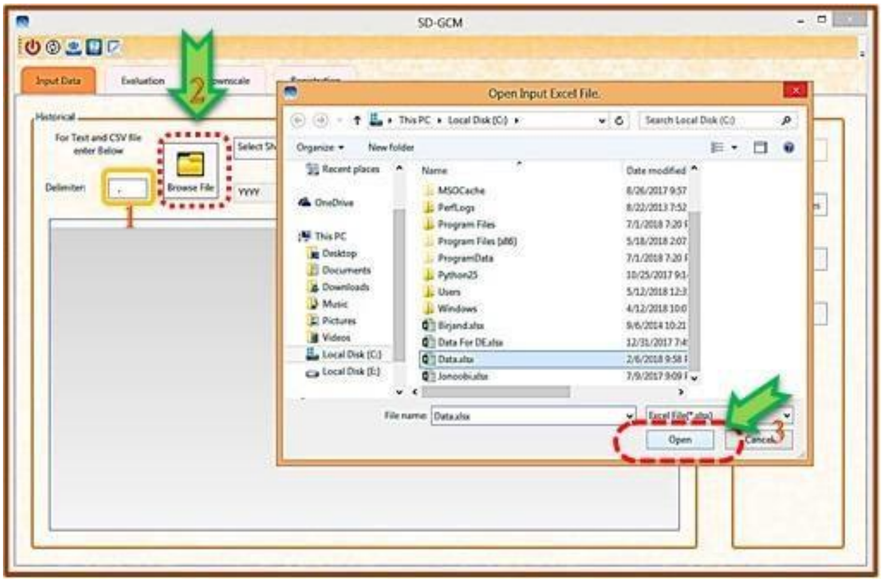

Fig. 1.3 Select as well as browse station (observation) data file

The user must then set various station data properties after choosing the input file. The user should enter the "StationName, Latitude and Longitude, Unit" by choosing the desired input sheet.

1.7 Statistical Downscaling in SD-GCM

Under the chosen SSPs scenarios, the user must begin using the downscaling approach for future data. In this instance, the user must choose between three time periods: station, historical, and anticipated data. While downscaling future information, the user can explicitly choose the desired year. The user has a choice of statistical downscaling techniques. It makes sense to choose the Delta approach in this stage since it was chosen throughout its evaluation period.

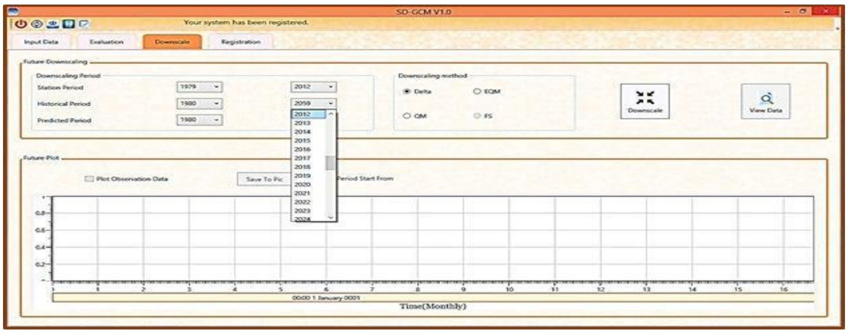

Fig. 1.4 Statistical downscaling across a future term and the Downscale tab

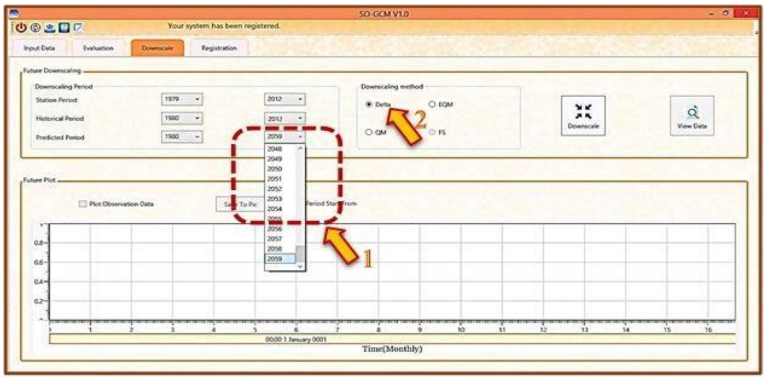

Fig. 1.5 choosing the prediction data for specific SSP scenarios

The Downscale button indicated that the procedure of downscaling had been completed. By selecting "Plot Observation Data" checkbox within the "Future plot" screen, the user can view the time sequence of observation data on the graph. the final graph representing the anticipated data.

1.8 Selection of GCM Model

Sr.No	Name of GCMModels	Climate model description	Resolution
1	CNRM-CM6-1	The CNRM/CERFACS simulation group of CMIP6's climate model	AOGCM high resolution 0.25 degreein ocean and 0.5 degree in the atmosphere

1.9 Statistical Analysis for Model Implementation

1. Root Mean Square Error (RMSE):- The average discrepancy among a statistical model's anticipated value and its true value is measured by root mean square error (RMSE). It refers to standard deviation of residual mathematically. The residual shows the gap between the data points and regression line.

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

2. NRMSE: -The NRMSE function enables users to compute the normalised root mean square (NRMSE) absolute values between expected and observed values using various normalisation techniques.

NRMSE= RMSE/ X_0

3. Pearson Correlation Coefficient: - A specific kind of correlation coefficient known as the Pearson coefficient shows the association between two variables that are assessed over the same range of values. The strength of the link among two continuous variables is measured by the Pearson coefficient.

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

4. M.A.E. - MAE can be calculated by adding all residuals (differential between the observed and anticipated value) and dividing the result by the overall number of data points in the set. Without taking into account the direction of the errors, Mean Absolute Error calculates average magnitude of errors in a group of forecasts. MAE is the weighted average of all individual deviations between the actual observation and the forecast across the test sample. The average model prediction error is expressed in terms of the relevant variable by both mean absolute as well as root mean square errors. Both the errors are unaffected by the direction of mistakes and have a range of 0 to infinity. Given their negative orientation, lower values are preferable. Using this equation, the mean absolute error is calculated.

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

5. M.B.E.:- The mean bias error deviation between two data set. It has a unit of variable. The value near zero arethe best.

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

6. Index of Agreement: - The ratio between mean square errors to potential error is represented by the agreement index. A perfect match is indicated by a score of 1 for agreement, whereas a value of 0 indicates total disagreement.

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

7. NSE: - One value below the proportion of error variance for the simulated time series divided with the variance for observed time series is used to compute Nash-Sutcliffe efficiency. Nash-Sutcliffe Efficiency is equal to 1 (NSE=1) in the case of a perfect model having estimate error variance equivalent to zero.

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

1.10 Result and Discussion

1.10.1 GCM Model CNRM-CM6-1Village- Shirur

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe model Efficiency
Delta	2.688	1.829	0.362	0.683	1.49	-0.01	0.587	-0.45
QM	5.994	4.078	0.372	0.686	3.05	2.16	0.396	-6.212
EQM	6.198	4.216	0.361	0.682	3.15	2.3	0.378	-6.712

GCM Model CNRM-CM6-1
Village- Sakhar

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe model Efficiency
Delta	6.706	1.465	0.647	0.772	3.55	-0.02	0.787	0.175
QM	7.338	1.603	0.666	0.78	3.87	1.01	0.784	0.012
EQM	7.696	1.681	0.652	0.774	4.04	1.19	0.769	-0.087

GCM Model CNRM-CM6-1
Village- Pargaon

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index Of Agreement	Nash Sutcliffe model Efficiency
Delta	2.5	1.867	0.332	0.646	1.42	-0.01	0.557	-0.525
QM	5.398	4.03	0.342	0.65	2.8	1.89	0.375	-6.11
EQM	5.645	4.215	0.328	0.651	2.9	2.03	0.353	-6.776

GCM Model CNRM-CM6-1
Village- Chaskaman

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index of Agreement	Nash Sutcliffe model Efficiency
Delta	3.183	1.642	0.513	0.754	1.74	0.01	0.688	-0.357
QM	4.45	2.295	0.531	0.762	2.33	0.98	0.617	-1.653
EQM	4.768	2.459	0.507	0.749	2.44	1.13	0.585	-2.045

1.10.2 Evaluation criteria:-

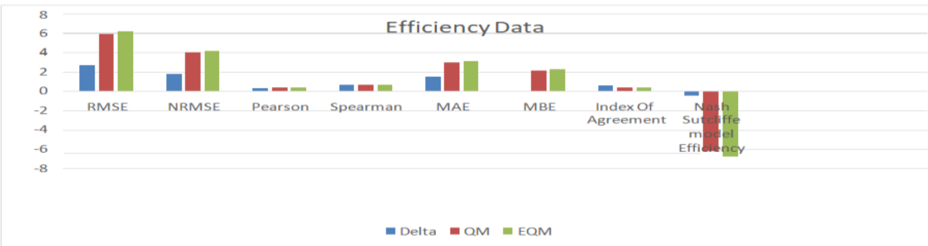

Figure 1.6

1.10.2 Evaluation Criteria: - The effectiveness of statistical downscaling techniques within the common period may be evaluated using this criterion. In the evaluation downscaling there are three different time periods: station, historical, and predicted period. The historical period refers GCM historical data. SDGCM is able to choose a common base based on historical data and station data from the same time period. The user will select 3 periods in "Evaluation"tab: Station period, Historical period, and Predicted period (based on GCM). SD-GCM will calculate calibration period and evaluation period based on these triple periods. The calibration period is determined based on the overlap of Station period and Historical period (It is better the user determine the same period for station and historical) and the evaluation period is determined based on Predicted period.

There are four statistical downscaling methods in the downscaling approach, and three of those are in use at the moment. These methods are Delta, QM, EQM methods. After data was downscaled correctly then observe the result of efficiency criteria. In the comparison of evaluation the user can use five methods of efficiency criteria between observation and historical data of GCM Model. The efficiency criteria are once the data has been properly downscaled, the user can compare it to historical data from the GCM model using five different efficiency criteria: RMSE, MAE,Spearman, and Pearson, Index of Agreement, and Nash Sutcliffe model. Taking into account the efficiency criteria'sresults, the user will be able to come to a decision.

In this instance, an RMSE value of 0 denotes a perfect fit for the model. The model as well as its predictions are better the smaller the RMSE. A greater RMSE denotes a significant departure from the ground truth with the residual. In thiscase delta method is having lower value so delta method is selected.

The normalised root mean square value (NRMSE), typically connects the RMSE with the variable's observed range. As a result, NRMSE can be understood as fraction of the total range that the model typically resolves. In this case the value of NRMSE is lower as compared to other so delta method is selected.

The good Pearson value is near + or – 1then It is believed to be an ideal correlation; when one variable rises, the other one usually follows suit. Strong correlation is defined as the coefficient value falling between + - 0.50 to + 1. In this case all the values are near about 0.35 but less at delta method Pearson value.

Non-parametric test called Spearman rho is used to assess the degree of correlation between two variables. A value of r = 1 indicates a perfect positive correlation, while a value of r = -1 implies a perfect negative correlation. In this case all the values are near about therefore delta method is selected. There is no set formula for what constitutes a good score because mean absolute error, or MAE, appears on the same scales as the target being predicted for. The closer MAE gets to zero, more accurate is the model. The good score is evaluated within dataset as in this case the delta method is having value close to zero so delta method is more accurate method.

The MBE (mean bias error) occurs when prediction are smaller in value than observation. Unsystematic error RME should be close to the RMSE with RMSEs close to 0, as has been observed.

The ratio of mean square error to potential error is represented by the index of agreement. A perfect match is represented by agreement value 1, and total disagreement is represented by zero.

Nash Sutcliffe efficiency (NSE), a normalised statistic, assesses the extent to which the graph of observed against simulated data matches the 1:1 line by estimating the relative amount of residual variance in comparison with measured data. From one to -infinity, the NSE has a range. A score of one denotes a perfect fit, whereas a value of zero denotes that the accuracy would have been the same with a mean value.

1.11 **Observed and Simulated precipitation**: - The evaluation result of SDGCM Model downscaling of precipitationis as follows.

(Delta method of downscaling)

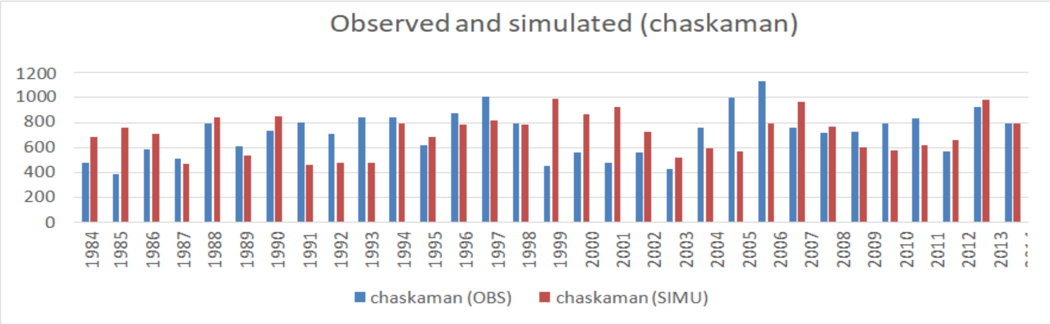

Fig. 1.7

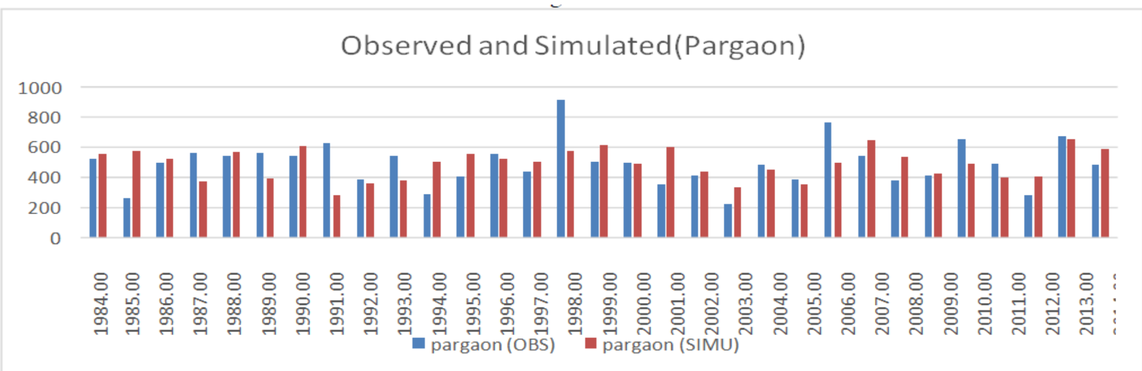

Fig 1.8

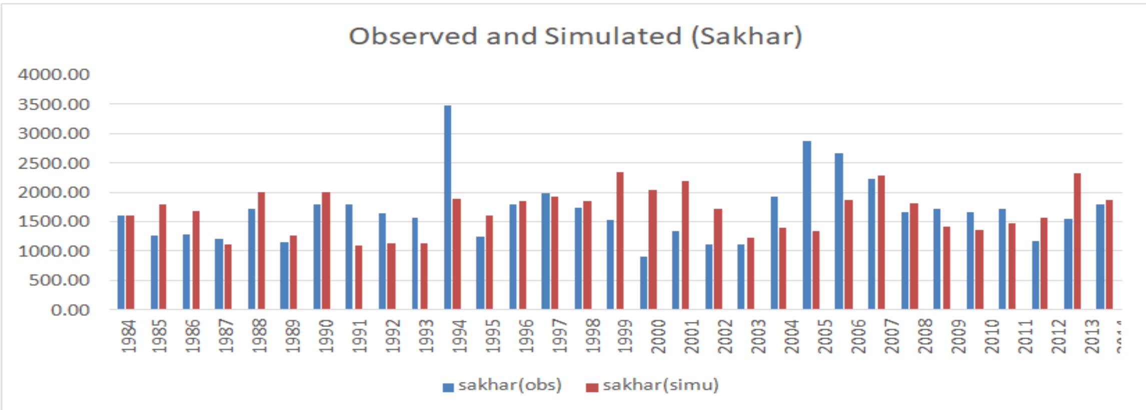

Fig 1.9

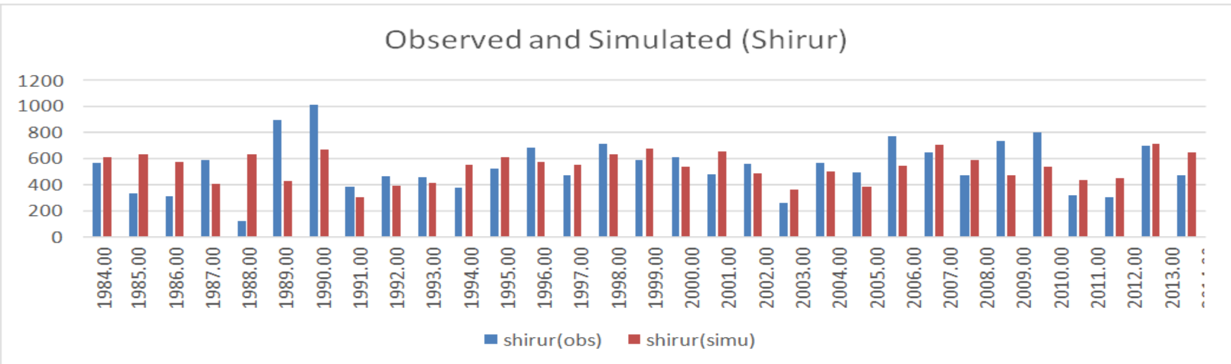

Fig 1.10

1.12 **Downscaling of Rainfall (SSP 245) (delta method):-** In this analysis the data is downscaled for future for the period 2021 to 2099. SSP245 scenario around the year 2100, will have an increased radiative force of 4.5 W/m2, which represents the middle pathway for projected greenhouse gas emissions. This scenario implies that steps are being taken to protect the environment. So in this connection the future precipitation downscaled data demonstrates that precipitation has been increasing on an average.

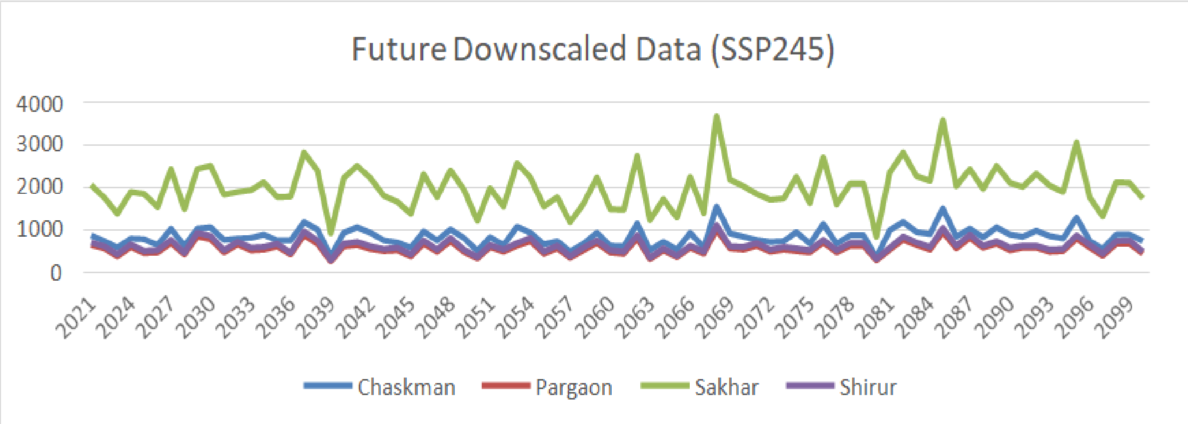

Fig 1.11

1.13 **Downscaling of Rainfall (SSP 585) (delta method):-** The SSP585 scenario around the year 2100, would result in an increased radiative force of 8.5 w/m2, indicating the upper limit of the possible set of scenarios. Where climate protection measures are not taken properly. Therefore it is observed that in Fig 1.12 the downscaled precipitation is constant up to 2057 and then there is a projected tendency of rising precipitation.

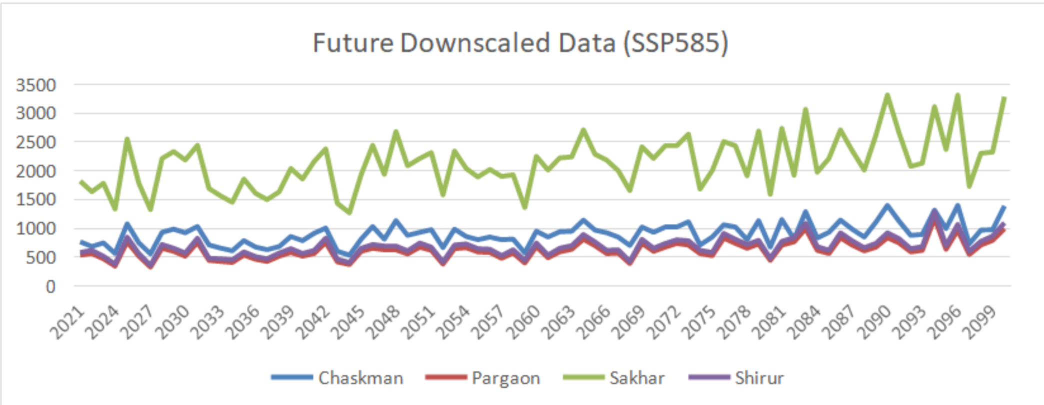

Fig 1.12

1.16 Conclusion

Output of model CNRM-CM6-1, created by CNRM/CERFACS modelling unit for CMIP6, was used to estimate the future climate for the Bhima river basin. It is the CMIP5 climate model that replaces the CNRM-CM5-1 model. Three techniques—delta, quantile mapping, empirical quantile mapping have been proven to be effective in statistical downscaling. This analysis was carried out using a set of eight indexes with the goal of consolidating certainkey features useful for studying the impacts of climate change. The study shows that in SSP245 the precipitation is constant up to 2099 with a very minor changes but there is a sudden increase in precipitation in SSP585 scenario that the precipitation is increasing every year. The paragon and shirur station precipitation is increasing as compare to chaskaman and sakhar.

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