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STATISTICAL DOWNSCALING AND FUTURE PROJECTION OF MAXIMUM TEMPERATURE ACROSS SEMI ARID REGION AT BHIMA RIVER BASIN, INDIA

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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 maximum and minimum temperature. In this paper, we propose a statistical downscaling model that works on three different methods namely delta method, quantile mapping method, empirical quantile mapping. In order to examine statistical downscaling method, the station Chaskaman, Paragon, Shirur, Sakhar have been selected for a study area to test the temperature downscaling methodology. All the 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 is used. The downscaling findings suggest that the SDSM model could be effectively accepted in terms of daily maximum and minimum temperature downscaling throughout the calibration as well as evaluation stages. SDGCM model predicts that overall average annual temperature will increase at all selected stations in the future (2021-2100) in river basins for SSP245 scenarios and also increased total average temperature for all the selected station for SSP585 scenarios. The downscaling results shows that how the statistical downscaling model works effectively in the downscaling of daily maximum and minimum temperature.
Keywords: SDSM, GCMs, Climate change, maximum temperature, minimum temperature, 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).

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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 (predictand). Software SDGCM V2.0, developed by agrimetsoft, is used (Wilby et al. 2004). The main objective of the present study is to investigate the versatility of SDGCM for downscaling maximum and minimum temperature. 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.

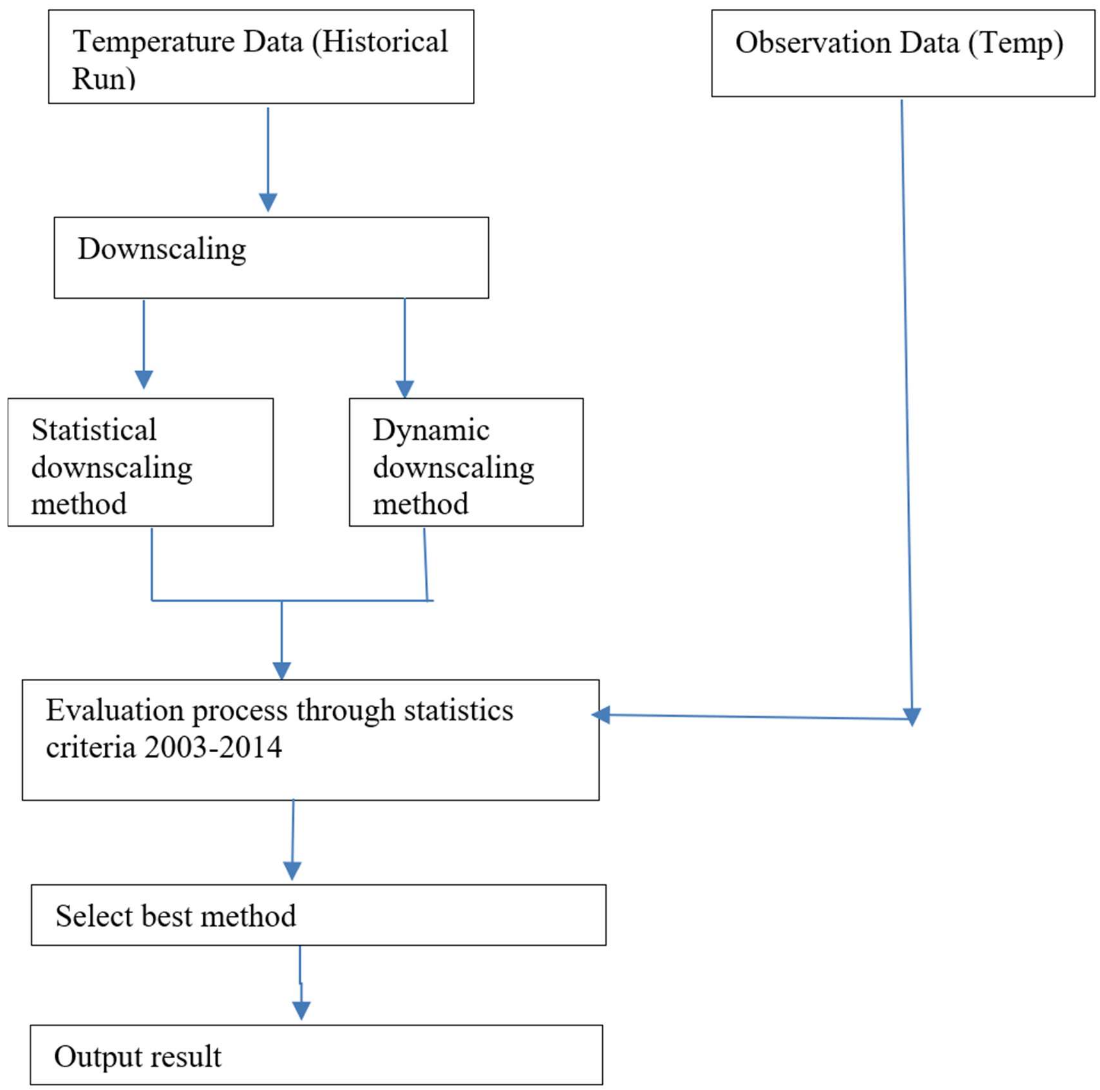

Fig 1.1

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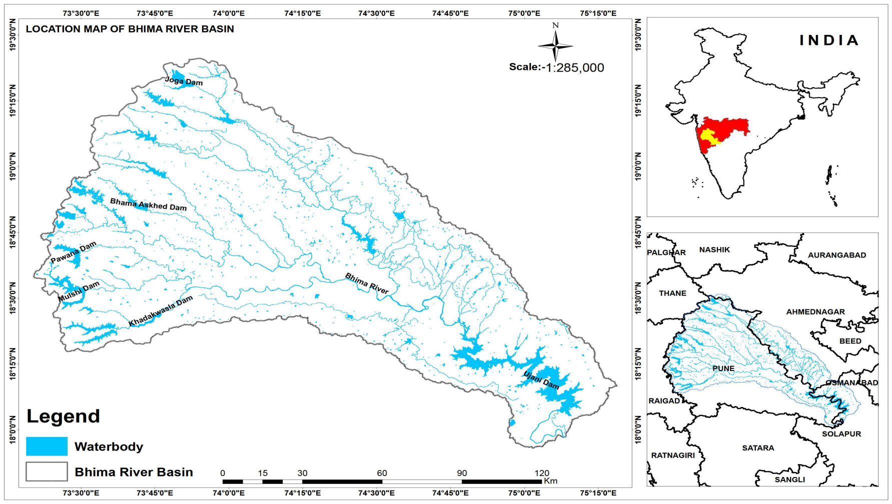

Fig 1.2 Study Area of Bhima river basin

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. Maximum and minimum temperature data is one kind of metrological information that is used for research. Data of maximum and minimum temperature 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, Wagner et al., 2019).

1.2 Methodology

There are several steps which is used to downscale GCM. The input is predictor (GCM Value) and predictand (observed value). The data set used are max.and min. temperature variable. The predictand 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 max.and min.temperature at each location for the present and the future. The everyday 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

1.3 Statistical downscaling

The delta method is used for statistical downscaling, the most important GCM output, which depends on the relation between local climate surface variables (predictand) as well as large scale atmospheric variables (predictor). (Marun et al 2010, Kang et al 2016,Kim et al 2016). It is a 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 only uses the model's reaction to climate change in order to modify observations because it serves as a fair and sensible benchmark in bias correction. Many studies on the impacts of climate change have used 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 and action for climate change in the observation (Hay et al 2000). The advantages of delta algorithms are their simplicity and minimum data requirements. The calculation of downscale temperature in this investigation is carried out as follows.

$$T_{SD}^{delta} = T_{GCMSSP} + (T_{obs} - T_{GCMHIST})$$

T_{SD}^{delta} is a downscaled temperature data value. The terms T(Obs) and T(GCMhist) refer to the average observed and historical temperature 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. The developed software programme (Agrimetsoft SD-GCM 2017) is used in this systematic study to accomplish the delta approach. A practical technique is used for downscaling the CMIP6 model for SSPs (SSP245/SSP585) scenarios is the SD-GCM (statistical downscaling GCM) tool. The observation data as well as output data in this tool would be shown in excel file. This tool can use for verification metrics. Three statistical downscaling methods are available in the SD-GCM tool. These methods are delta, Empirical Quantile Mapping (EQM), (Boe et al. 2007), and Quantile Mapping (QM) (Panofsky and Briiar, 1968).

By using this software, a user can create a database that can be used to apply each CMIP6 model to 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 distinctive format. The SD GCM tool incorporate a feature for model data evaluation. In this stage, the user can assess the CMIP6 model's capability with observational data from a recent era. The observational data would be stored in an excel file. In the the evaluation phase, six efficiency criteria is tested. These criteria are as 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 assessed using the General Circulation Model (GCM) simulations raw data. The Downscaling techniques have been grow because the geographic scale of GCM outputs, which is typically 250 km to 300 km, which is insufficient and too coarse. The difference between coarse-scale and fine-scale climate data is filled by using downscaling technique. According to Fowler et al. (2007), spatial downscaling techniques used to convert coarser resolution of GCM outputs into finer-resolution geographic climatic information, like reducing a 500- 600 kilometre grid cell's output to a 20-30 kilometre resolution.

Statistical downscaling (SD) and dynamic downscaling (DD) are the two main types of downscaling. (Christensen et al., 2007). By layering a fine-scale climate model inside a coarse-scale framework, dynamic downscaling (DD) creates domains of climate-related variable that are spatially comprehensive and extensive. Due to its high computational requirements, Dynamic Downscaling (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, and is employed in Dynamical Downscaling (DD) for modelling the target area at finer levels (Ghosh et.al, 2009).

Statistical downscaling (SD) techniques have a high chance of selecting from related users as they are simple to implement and does not require a lot of computational power. They can also be perform quickly by a computer with basic capabilities using only simple “regression analyses”. The development of a huge array of Statistical downscaling (SD) approaches is based on the identification of statistical relationships between regional data from ground-based stations with large-scale synoptic and comprehensive predictions. Dynamic Downscling (DD) is computationally constrained to a spatial resolution of 20–50 km, it is not able 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 it require less processing. The Statistical Downscaling approach also offers station-scale climatic data using GCM-scale outputs and is comparatively simple to apply in comparison with Dynamical Downscaling 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, there are three groups into which statistical or mathematical methods can be differentiated. There are various different statistical downscaling techniques. Bias Correction (BC), which has been widely used for climate change 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). (Themeßl et al. 2012) is one of the greatest resources for assessing the efficacy of various Bias Correction (BC) techniques.

These methods involve numerous statistical techniques that are applied with multiple applications across the world, but practically all such applications utilising CMIP6 outputs are challenging and testing 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 from the GCM data have been downscaled as shown in Equation

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

where the downscaled values for temperature, are T(SD,Delta) . The terms T(Obs) and T(GCMhist) refer to the average observed and historical temperature 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), Quantile Mapping 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 1 is used by SD GCM for evaluation, while Equation 2 is applied for future downscaling.

1. $T_t^{Eval} = \text{Inv CDF}\frac{Stat}{Tt-}(\text{CDF}\frac{HIST}{Tt-Cal}(T_{t-Eva}^{GCM}))$
2. $T_t^{Predict} = \text{Inv CDF}\frac{Stat}{Tt-Hi}(\text{CDF}\frac{HIST}{Tt-H}(T_{t-SSP}^{GCM}))$

Cumulative distribution function (CDF) of observation and GCM data for the period under consideration is depicted in equation (Eq. 1) 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 Emperical Quantile Mapping (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. 3 and 4, respectively, for evaluation and future downscaling.

3. $T_t^{Eval} = \text{InvECDF}\frac{Stat}{Tt-}(\text{ECDF}\frac{HIST}{Tt-}(T_{t-Eval}^{GCM}))$
4. $T_t^{Predict} = \text{InvECDF}\frac{Stat}{Tt-H}(\text{ECDF}\frac{HIST}{Tt-Hi}(T_{t-SSP}^{GCM}))$

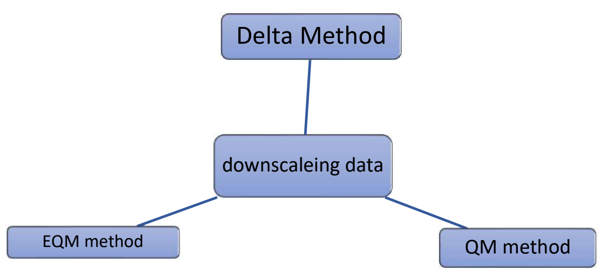

Fig. 1.3 Three methods of statistical downscaling

1.6 Input Station and GCM Data downscaling

Three different types of data are loaded namely observation data, historical GCM data, and prediction GCM data for hypothetical scenarios. The said data is uploaded using an input 'excel file'. The Browse file is used to choose the station's information. The browse and choose option is used to select the desired file in the window. Daily scale is used for the station data.Fig 1.4 shows selection of station and input data.

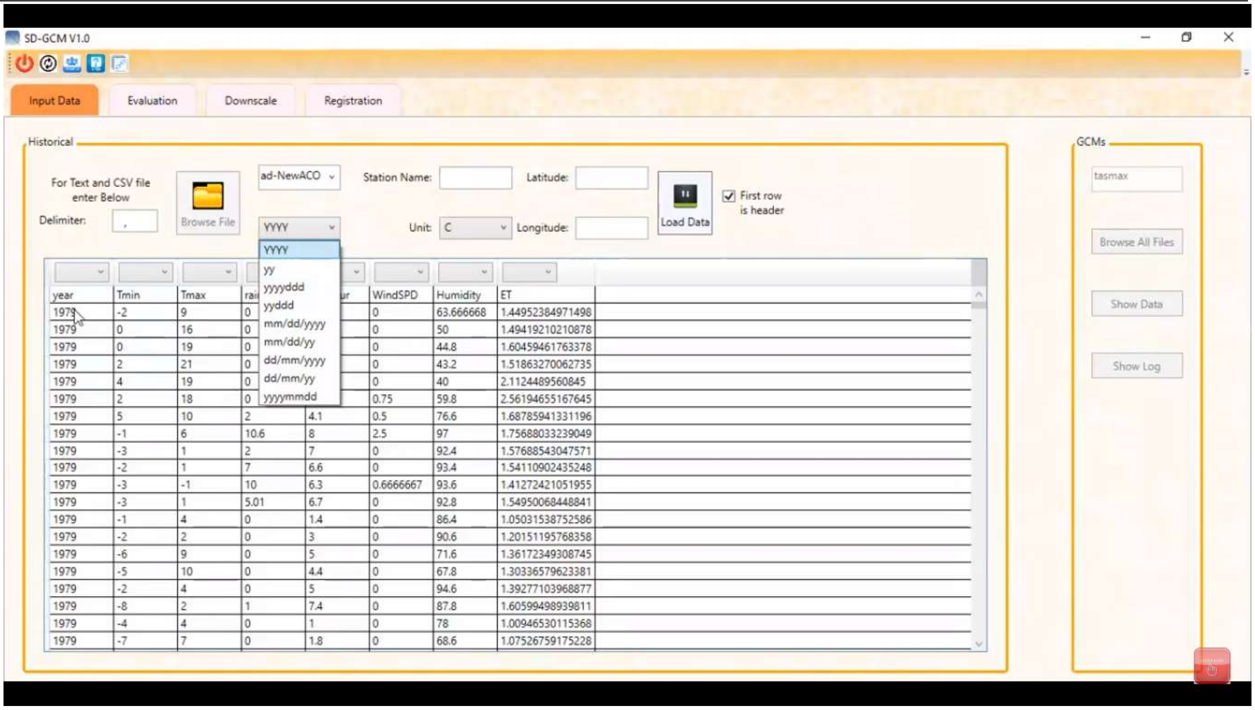

Fig. 1.4 Select as well as browse station (observation) data file

The user must then set various station data properties After choosing the input file the station data properties setting is done. . The "Station Name, Latitude and Longitude, Unit" can choose the desired input sheet.

1.7 Statistical Downscaling in SD-GCM

The chosen SSPs scenarios are using for the downscaling approach for future data. Three time periods are using namely station data, historical data, and anticipated data. At the time of downscaling future information, one can choose the desired year. The user can use statistical downscaling techniques. It makes sense to choose the Delta approach in this stage because it was selected throughout its evaluation period.Fig 1.5 shows statistical downscaling methods in window.

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Fig. 1.5 Statistical downscaling across a future term and the Downscale tab

Fig. 1.6 choosing the prediction data for specific SSP scenarios

The Downscale button is used to downscale data. The tab "Plot Observation Data" and "Future plot" are used, to view the time sequence of observation data on the graph. The final graph representing the anticipated data.Fig 1.6 shows evaluation and prediction.

1.8 Selecion of GCM Model

Sr. No	Name of GCM Models	Climate Model description	Resolution in Degree
1	CNRM-CM6-1	The CNRM simulation group of CMIP6's climate model	AOGCM high resolution 0.25 degree in ocean area and 0.5 degree in the atmosphere area.

1.9 Statistical Analysis for Model Implementation

1. Root Mean Square Error (RMSE):- The average discrepancy among a statistical model's expected value and its actual 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 normalized RMSE (NRMSE) is relates the RMSE to the observed range of the variable.The NRMSE function enables users to compute the normalized root mean square (NRMSE) absolute values between predicted and observed values using various normalization techniques.

$$NRMSE = RMSE / X_0$$

3. Pearson Correlation Coefficient: - The pearson correlation coefficient is a correlation coefficient between two set of data.A specific type of correlation coefficient known as the Pearson coefficient shows the relation 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 is a measure of errors between paired observations expressing the same phenomenon.MAE can be calculated by adding all residuals (differential between the observed and predicted value) and dividing the result by the total data points in the set. Mean Absolute Error calculates average magnitude of errors in a group of predict. 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

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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 are the 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 given 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: - The 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-CM6-1

Village- CHASKAMAN

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index Of Agreement	Nash Sutcliffe model Efficiency
Delta	1.69	0.056	0.868	0.865	1.31	0.01	0.931	0.733
QM	1.671	0.055	0.868	0.865	1.29	0.01	0.931	0.739
EQM	1.666	0.055	0.868	0.865	1.28	0.01	0.931	0.741

GCM Model CNRM-CM6-1
Village- PARGAON

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index Of Agreement	Nash Sutcliffe model Efficiency
Delta	2.304	0.072	0.857	0.822	1.88	0.02	0.906	0.518
QM	1.783	0.056	0.857	0.822	1.4	0.01	0.925	0.711
EQM	1.704	0.054	0.869	0.82	1.3	0	0.931	0.736

GCM Model CNRM-CM6-1
Village- SAKHAR

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index Of Agreement	Nash Sutcliffe model Efficiency
Delta	1.852	0.063	0.855	0.852	1.47	0.01	0.923	0.723
QM	1.854	0.063	0.855	0.852	1.47	0.01	0.923	0.723
EQM	1.796	0.061	0.863	0.852	1.37	0	0.927	0.739

GCM Model CNRM-CM6-1
Village- SHIRUR

Method	RMSE	NRMSE	Pearson	Spearman	MAE	MBE	Index Of Agreement	Nash Sutcliffe model Efficiency
Delta	2.142	0.068	0.877	0.845	1.75	0.02	0.923	0.626
QM	1.74	0.055	0.877	0.845	1.38	0.01	0.935	0.753
EQM	1.652	0.053	0.888	0.845	1.25	0	0.942	0.778

1.10.2 Evaluation criteria:-

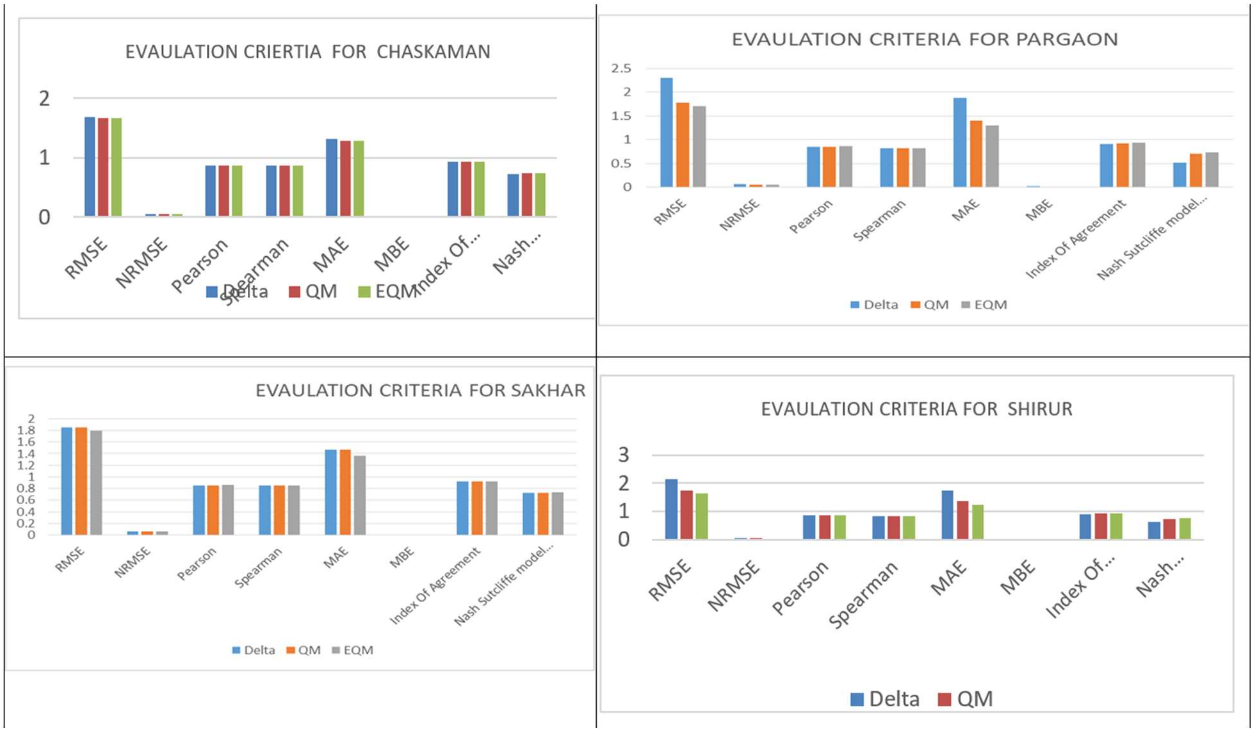


Fig 1.7

1.10.2 Evaluation Criteria: - The effectiveness of statistical downscaling techniques within the common period is evaluated using this criterion. In this method of evaluation downscaling there are three different time periods namely station data period, historical period, and predicted period. The historical period refers GCM historical data. SDGCM software is able to choose a common base on historical data and station data from the same time period. The user would select three periods in "Evaluation tab" that is Station period, Historical period, and Predicted period (based on GCM). SD-GCM software would calculate calibration period and evaluation period which is based on these three periods. The calibration period is decided 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 calculated based on Predicted period.

There are various statistical downscaling methods in the downscaling technique, and three of those are in used here. These methods are Delta method, Quantile Mapping (QM) and Emperical Quantile Mapping (EQM) methods. Observe the result of efficiency criteria after data get downscaled. To make comparison of evaluation the user would use five types methods of efficiency criteria between observation data and historical data of GCM Model. The user can compare it to historical data and predicted data from the GCM model by five different efficiency criteria namely RMSE, MAE, Spearman, and Pearson, Index of Agreement, and Nash Sutcliffe model. With the help of efficiency criteria's results, the user would be able to take a decision about the feasibility of downscaling method..

In this case, RMSE value of zero indicates a perfect fitting of the model. The model as well as its predictions are better if the value is smaller the RMSE. A greater RMSE shows a significant departure from the ground truth with the residual. In this case Emperical Quantile Mapping (EQM) method is having lower value so this method is selected for future downscaling for study region.

The normalised root mean square value (NRMSE), typically links the RMSE with the variable's observed range. As a result, NRMSE can be recognize 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 EQM method is chosen.

The good Pearson value is near +1 or – 1 then it is convinced 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 0.87 but less at EQM 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 EQM method is considered. The closer MAE gets to zero, more accurate is the model. The good score is evaluated within dataset as in this case the EQM method is having value close to zero so EQM method is more accurate method for this case.

The MBE (mean bias error) takes into consideration when prediction are smaller in value than observation.In thos case the EQM mean bias error is smaller.

The ratio of mean square error (MSE) to potential error (PE) is constituted by the index of agreement. A perfect match is when agreement value 1, and total disagreement when it is zero.

Nash Sutcliffe efficiency (NSE), a normalized statistic, evaulates the extent to which the graph of observed against simulated data matches the 1:1 line by appraising the relative amount of residual variance in differentiation with measured data. The NSE has a range from one to infinity. A score of one represent a perfect fit, whereas a value of zero indicates that the accuracy would have been the same with a mean value.

1.11 Observed and Simulated Temperature: - The evaluation result of SDGCM Model downscaling of temperature is as follows.

(Delta method of downscaling)

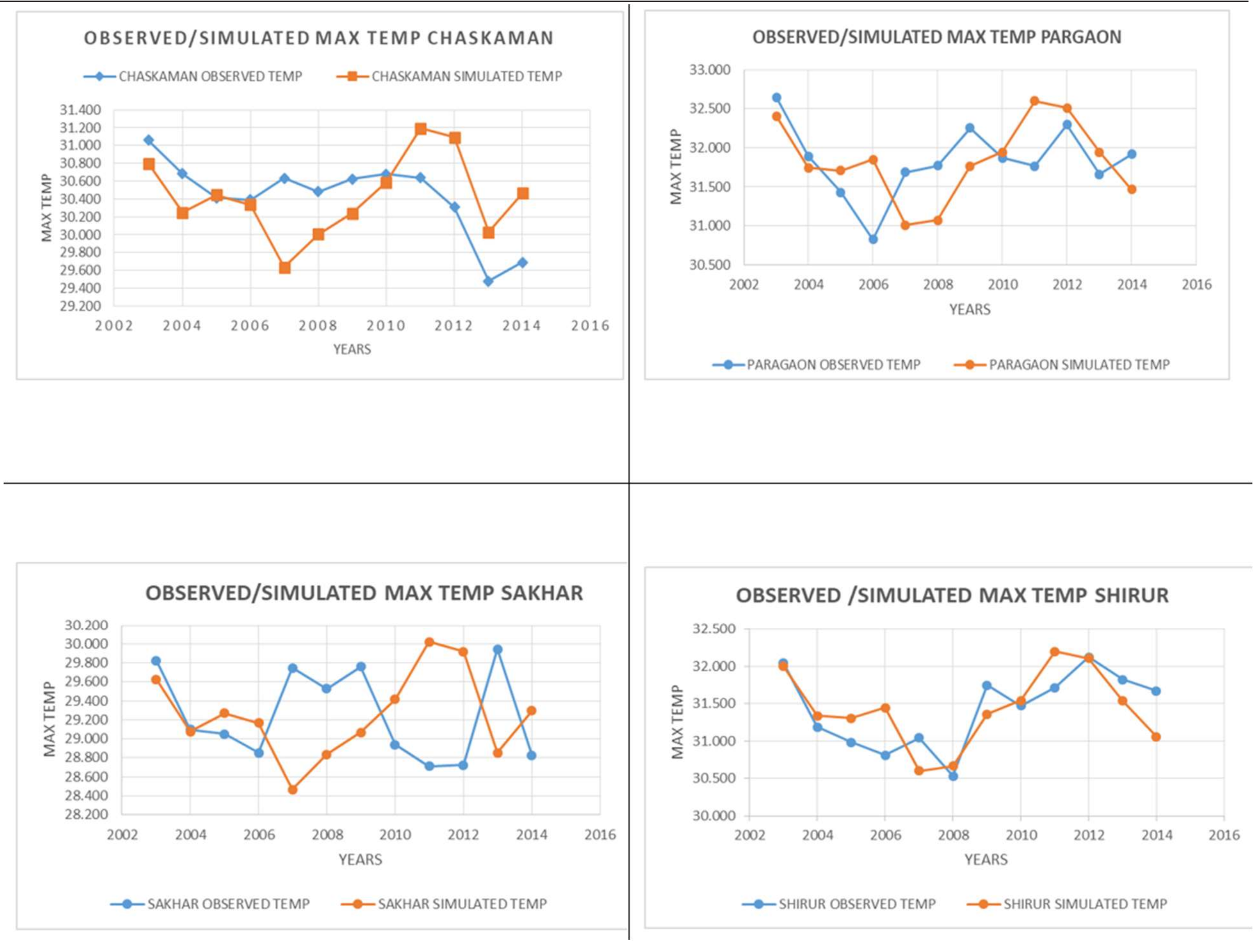
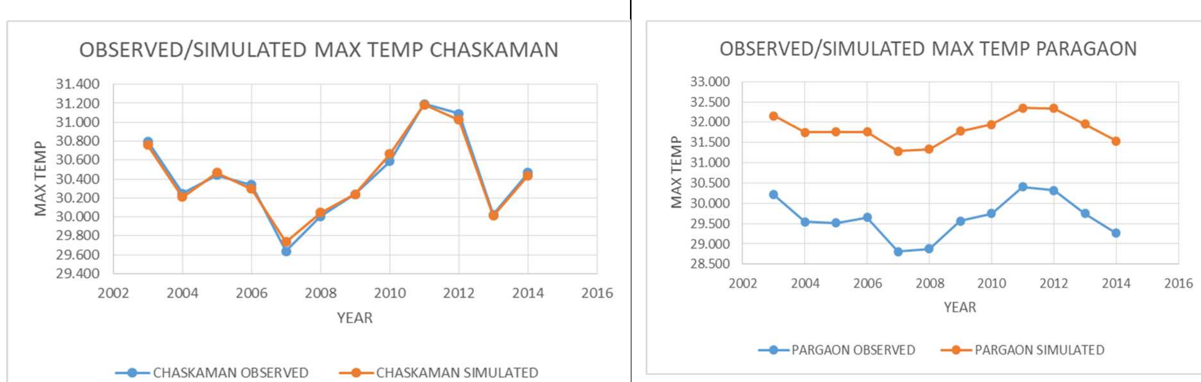


Fig. 1.8

1.12 Observed and Simulated Temperature: - The evaluation result of SDGCM Model downscaling of temperature is as follows.
(EQM method of downscaling)



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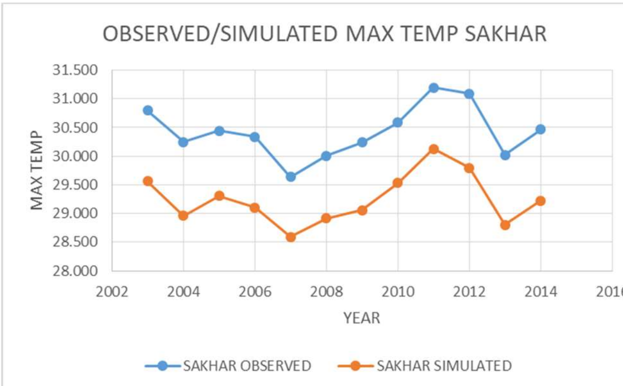


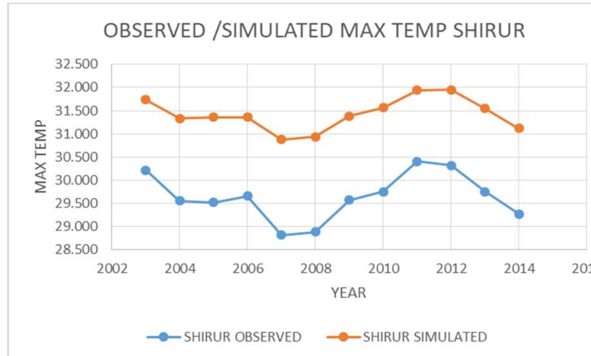
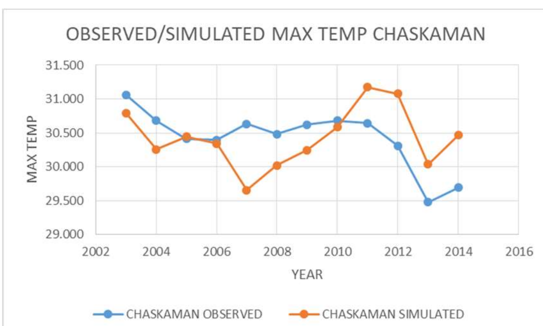
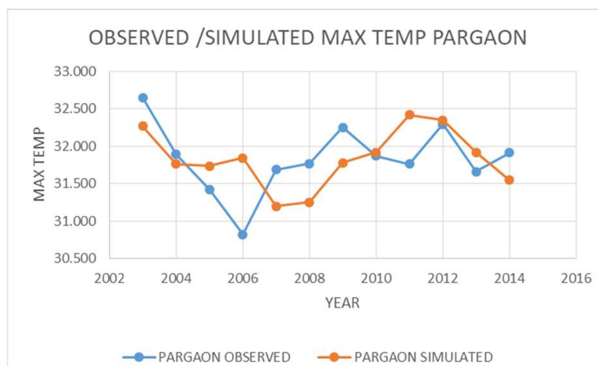


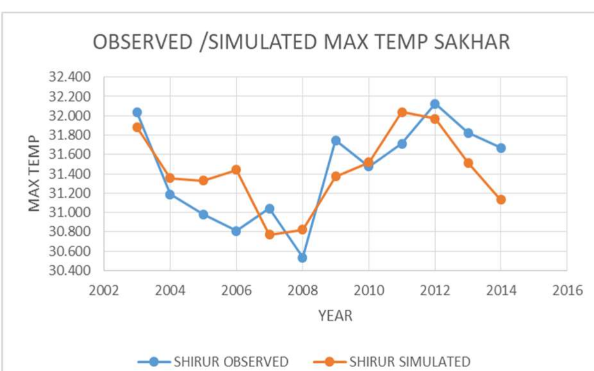
Fig 1.9

1.13 Observed and Simulated Temperature: - The evaluation result of SDGCM Model downscaling of temperature is as follows.

(QM method of downscaling)







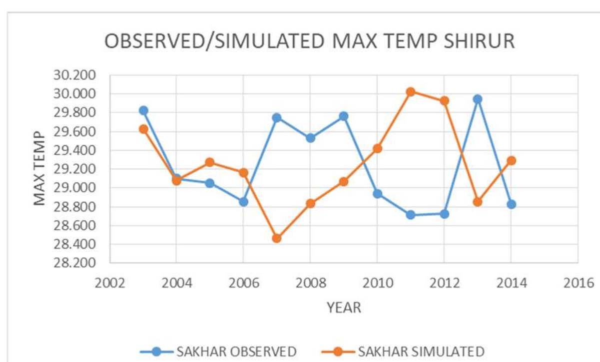


Fig 1.10

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

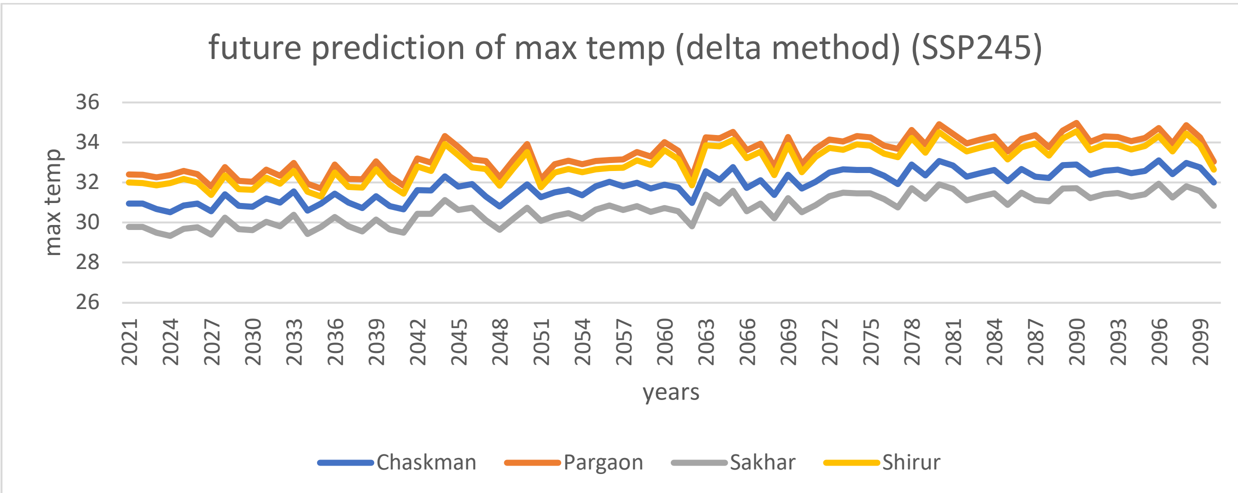


Fig 1.11

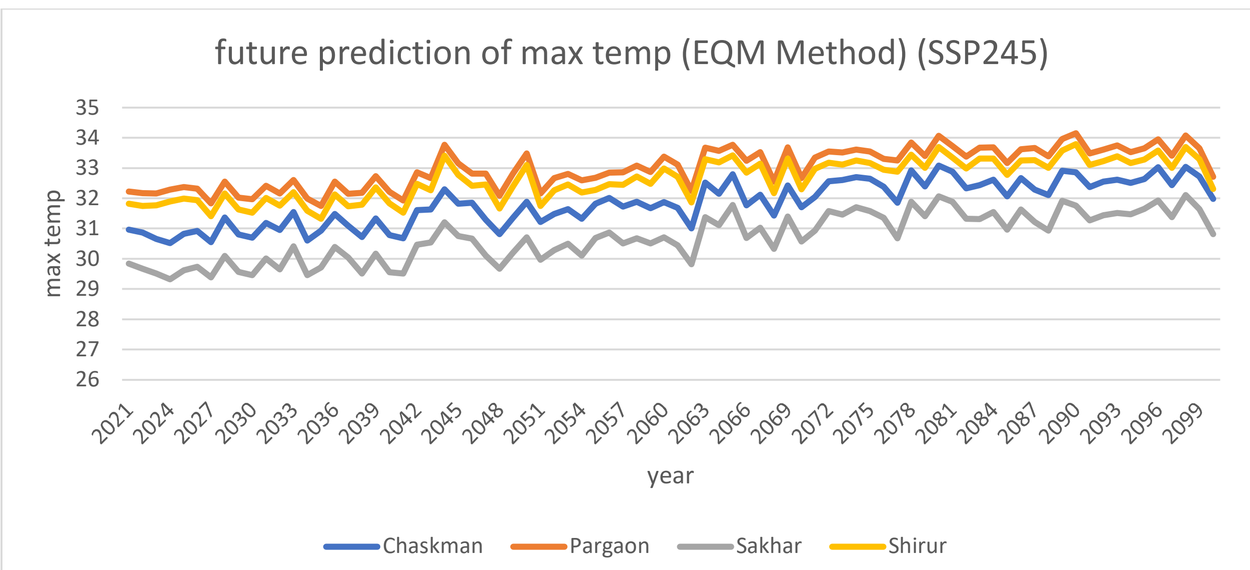


Fig 1.12

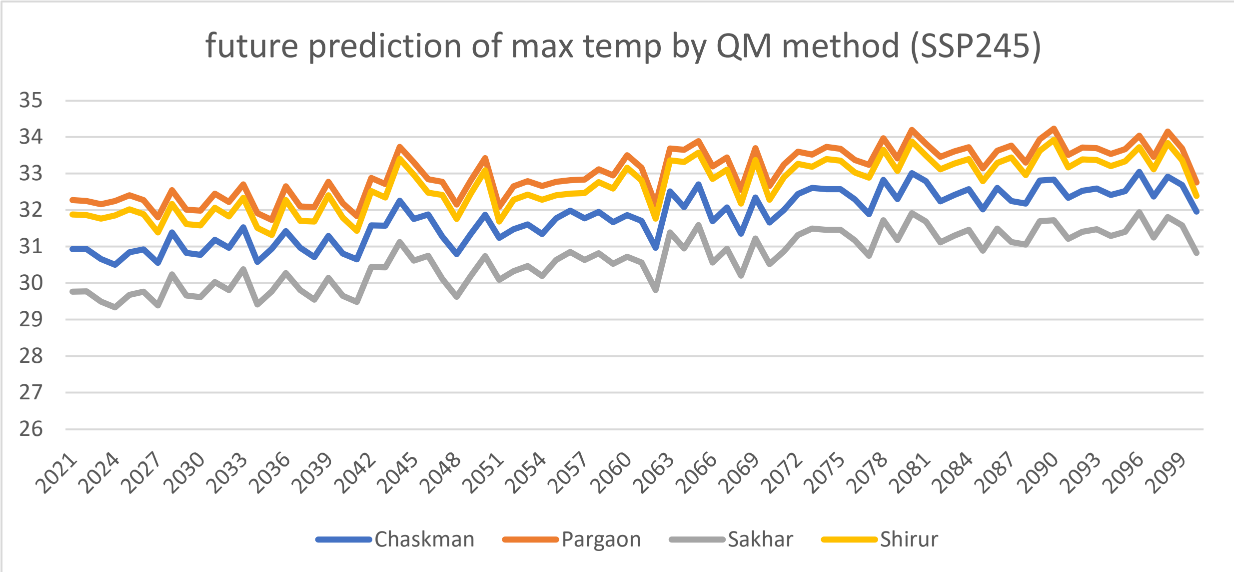


Fig 1.13

1.13 Downscaling of Max.Temperature (SSP 585) (Delta method):- The SSP585 scenario around the year 2100, would result in an increased radiative force of 8.5 w/m2, shows the upper limit of the possible set of scenarios. Where climate protection precautions are not followed properly. Therefore it is observed that in Fig 1.14 the downscaled max.temperature is constant up to 2054 and then there is a projected tendency of rising max.temperature.

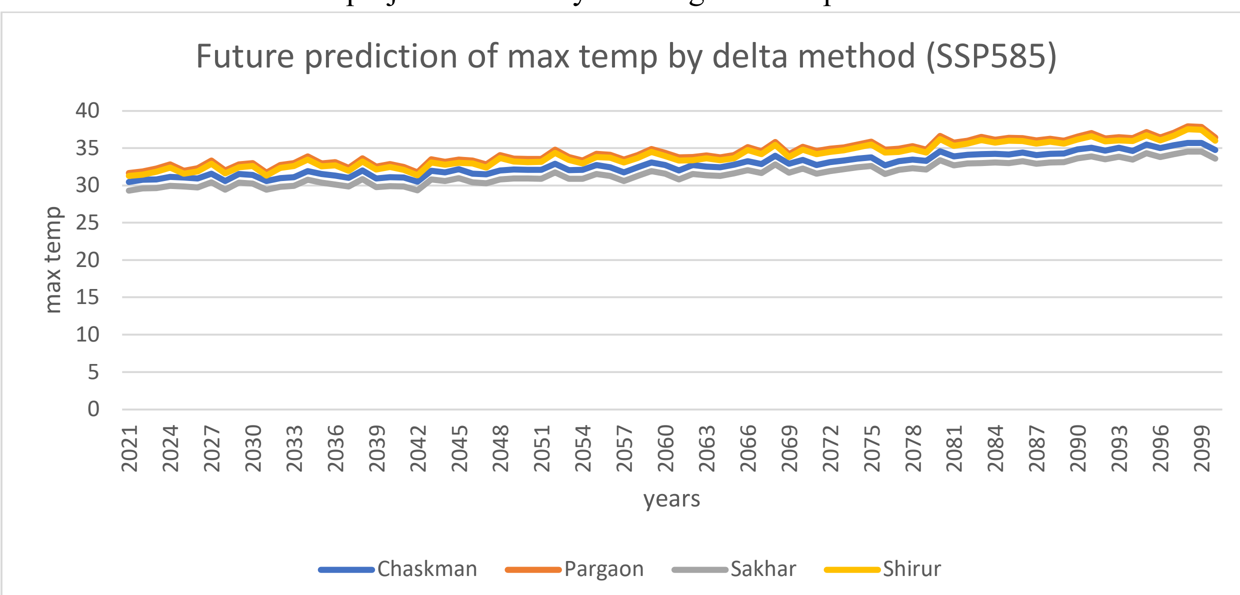


Fig 1.14

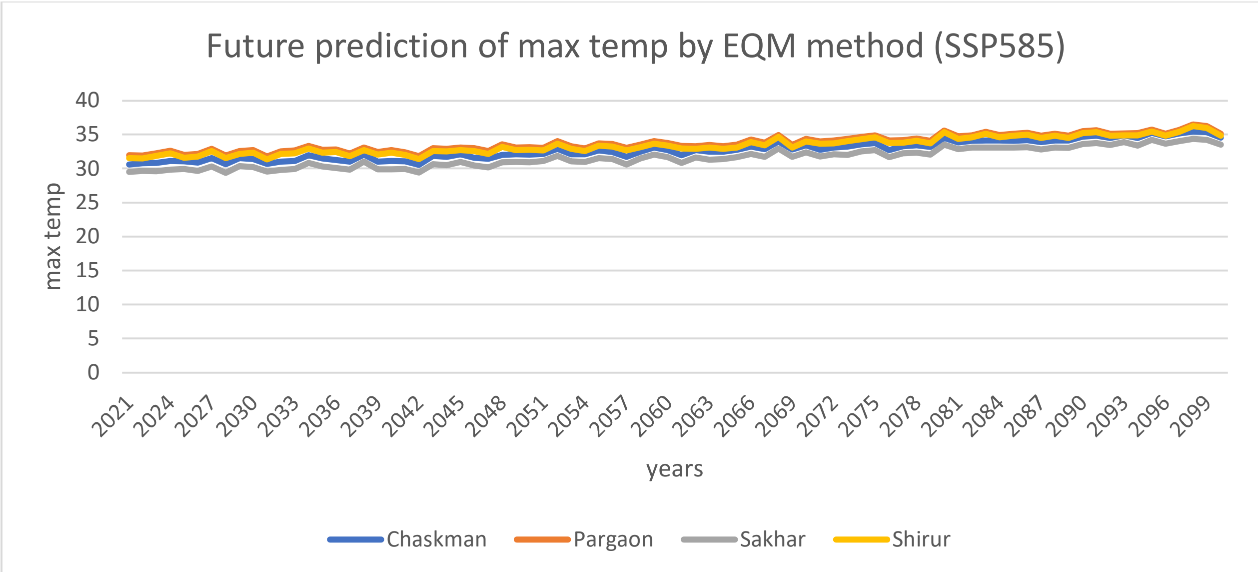


Fig 1.15

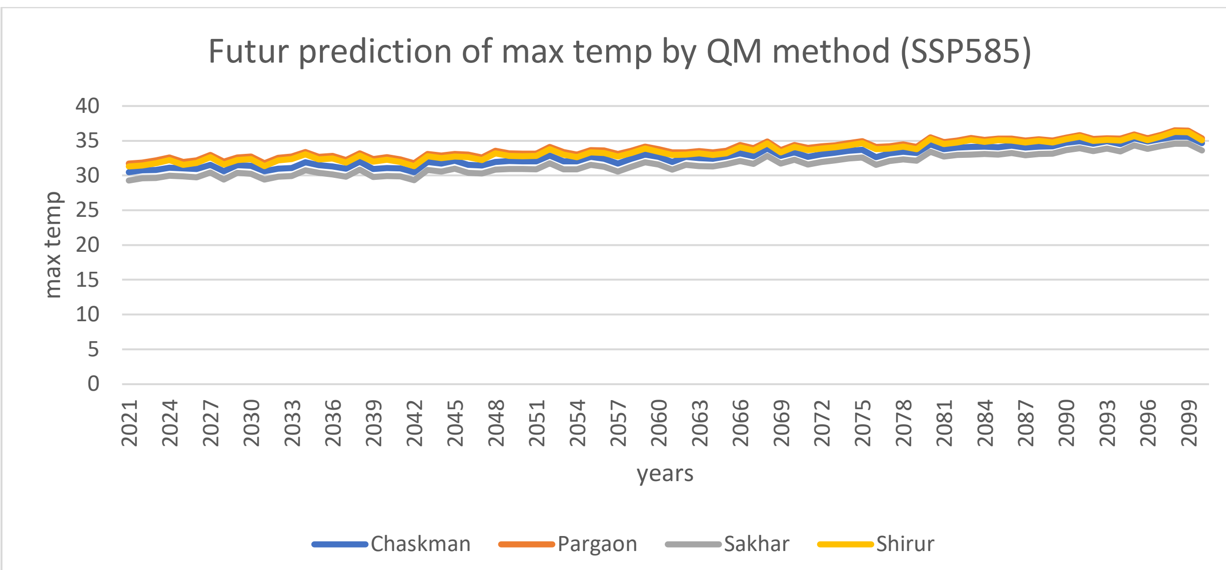


Fig 1.16

1.16 Conclusion

The output of model CNRM-CM6-1, produced by CNRM/CERFACS modelling unit for CMIP6, is used to estimate the future climate for the Bhima river basin semi arid region. It is the CMIP6 climate model that replaces the CNRM-CM5-1 model. Three different technique namely delta method, quantile mapping method, empirical quantile mapping method have been proved to be effective in statistical downscaling. This analysis was conducted using a set of eight indexes with the goal of consolidating certain key features useful for studying the impacts of climate change. The study shows that in SSP245 the maximum temperature is constant up to 2057 with a very minor changes but there is a sudden increase in max. temperature. In SSP585 scenario that the maximum temperature is increasing every year. The pargaon and shirur station max. temperature is increasing as compare to chaskaman and sakhar.

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References

[1] Srivastava AK, Rajeevan M, Kshirsagar SR (2008) Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian Region

[2] Huang C, Barnett AG, Wang X, Vaneckova P, FitzGerald G, Tong S (2011) Projecting future heat-related mortality under climate change scenarios: a systematic review. Environ Health Perspect 119:1681–1690.

[3] Fowler HJ, Blenkinsop S, Tebaldi C (2007) Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. Int J Climatol 27:1547–1578.

[4] Immerzeel, W., Droogers, P., 2008. Calibration of a distributed hydrological model based on satellite evapotranspiration. J. Hydrol. 349, 411–424. doi:10.1016/j.jhydrol.2007.11.017. Immerzeel, W., Gaur, A., Zwart, S.J., 20

[5] Dessu, S.B., Melesse, A.M.: Evaluation and comparison of satellite and GCM rainfall estimates for the Mara River Basin, Kenya/Tanzania. Chapter Climate Change and Water Resources Volume 25 of the series The Handbook of Environmental Chemistry 29–45 (2013).

[6] XuewelFan,Li Jiang,Jiaojiao Gou (2021),Statistical downscaling and projection of future temperature across the Loess Plateau, China

[7] Dawson, R. L. Wilson C. W. (2007). SDSM 4.2 — A Decision Support Tool for the Assessment of Regional Climate Change Impacts.

[8] Wilby, R.L., Wigley, T.M.L. (1997). ―Downscaling general circulation model output: a review of methods and limitations‖. Progress in Physical Geography 21, 530–548.

[9] A.H.Baghanam et al (2020), Statistical downscaling and projection of future temperature change for Tariz city,Iran,IOP conference Earth Environ Sci.491012009

[10] Nguyen, V. T. V., Nguyen, T. D., and Gachon, P. (2005). ―Statistical downscaling methods for climate change impact studies‖. Conference on Adapting to Climate Change in Canada 2005: Understanding Risks and Building Capacity. Le Centre Sheraton Montréal Hotel, Montréal, Québec, May 4-7, 2005

[11] AgriMetSoftn.d.: SD-GCM Tool [Computer software]. Available at: https://agrimetsoft.com/SD-GCM.aspx. (2017).

[12] Kang, H.S., Tangang, F., Krishnan, R.: Regional climate downscaling over Asia-Pacific region. Asia-Pacific J Atmos Sci. 52, 77 (2016).

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4086-4106
[13] Kim, Y., Jun, M., Min, S.K., Suh, M.S., Kang, H.S.: Spatial analysis of future east Asian seasonal temperature using two regional climate model simulations. Asia-Pacific J Atmos Sci. 52, 237 (2016a)
[14] Wetterhall, F., Pappenberger, F., He, Y., Freer, J., Cloke, H.L.: Conditioning model output statistics of regional climate model precipitation on circulation patterns. Nonlin. Processes Geophys. 19, 623–633 (2012. www.nonlin-processes-geophys.net/19/623/2012/).
[15] Eckhardt, K., Ulbrich, U.: Potential impacts of climate change on groundwater recharge and streamflow in a central European low mountain range. J. Hydrol. 284, 244–252 (2003)
[16] Ghosh, S., Mujumdar, P.P., 2009. Climate change impact assessment- uncertainty modeling with imprecise probability. J. Geophys. Res. Atmos. 114, D18113
[17] Hay, L.E., Wilby, R.L., Leavesley, G.H.: A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. J. Am. Water Resour. Assoc. 36(2), 387–397 (2000).
[18] Samal, D.R, Gedam, S.S., 2015. Assessing the impact of land use change on streamflow in a semi-urban river basin, Maharashtra, India. Int. J. Hydrol. Sci. Technol. 3, 351–363.
[19] Wood, A.W., Leung, L.R., Sridhar, V. et al.: Climatic Change 62–189 (2004).
[20] Kannan, S., Ghosh, S., 2013. A nonparametric kernel regression model for downscaling multisite daily precipitation in the Mahanadi basin. Water Resource. Res. 49.
[21] Maraun, D. et al., 2010. Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user.
[22] Sachindra, D.A., Huang, F., Barton, A., Perera, B.J.C.: Statistical downscaling of general circulation model outputs to precipitation – part 2: bias-correction and future projections. Int. J. Climatol.
[23] Wilby, R., et al., 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods.
[24] Yatagai, A. et al., 2012. APHRODITE: constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. Bull. Am. Meteor. Soc. 939 (1401–1415), 727
[25] Wilby RL, Dawson CW. Using SDSM version 3.1 A decision support tool for the assessment of regional climate change impacts, User Manual; 2004.
[26] Rowan Fealy and John Sweeeney (2008),Statistical downscaling of temperature , radiation and potential evapotranspiration to produce a multiple GCM ensemble mean for a selection of sites in Ireland