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Climate Change Effects on Spatiotemporal Distribution of Precipitation over West Central India: A Statistical Downscaling Approach

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The long-term shifts in temperatures and weather patterns are referred to as climate change. Climate change not only leads to long-term shifts in average temperatures but also changes in the spatial and temporal distribution of rainfall over continents. This study aims to predict likely changes in the rainfall pattern induced by climate change over the West Central (WC) region of India. The approach uses a statistical downscaling technique that converts coarse-scale outputs of the global climate model (GCM) to high-resolution future precipitation projections giving refined distribution. The decision support tool that uses a robust statistical downscaling technique viz. statistical downscaling model (SDSM) is used for assessing local climate change impacts.

The research includes the study of likely regional climate variability, by integrating historical observational data and empirical relationships between large-scale climate variables and local weather patterns. Historical data and the SDSM, version 4.2, are employed to forecast future rainfall trends. Rainfall data from the India Meteorological Department and the National Centre for Environmental Prediction (NCEP) from 1961 to 2001 are used along with outputs from general circulation models (GCMs), viz. Hadley Centre coupled model, version 3 (HadCM3), and coupled global climate model, version 3 (CGCM3), for the period 1961–2099. Rainfall scenarios are presented for three future time periods (2011–2040, 2041–2070, and 2071–2099). The study indicates a significant increase in the mean annual precipitation across the West Central India region, particularly in the 2050s and 2080s.

Mean annual rainfall is projected to rise by 10–19.4% under HadCM3 A2 and B2 scenarios. The HadCM3 indicates the month of September as the month of the highest precipitation in later time periods, whereas it is the month of August, according to CGCM3 simulations. When comparing the results of the two models, HadCM3 gives better results, as indicated by better R^2 value in validation. Thus, the analysis gives climate change-induced likely changes in the spatiotemporal distribution of precipitation over the West Central India region. The insight given by the work will be useful for decision making in many sectors like agriculture, water management, disaster risk reduction, and infrastructure planning.

Keywords: climate change, downscaling, NCEP, HadCM3, CGCM3, statistical downscaling, SDSM.

Introduction

The term *climate change* refers to long-term variations in temperature and weather patterns. These fluctuations could be caused by natural events such as large-scale volcanic eruptions, variations in solar activity as well as burning fossil fuels, deforestation, and some agricultural and industrial practices by human beings. Climate change-related hydrological studies give emphasis on rainfall as a critical variable. Climate change imposes a remarkable impact on the hydrological cycle, the world's water supplies in the form of surface water and groundwater.

Climate change affects global temperature changes (IPCC, 2013; Feng et al., 2014). Climate change influences rainfall patterns, which in turn influences agriculture and water supply. Changes in the spatiotemporal distribution of rainfall over time may make things worse. Since precipitation is the main factor influencing the availability and distribution of water on the Earth's surface, it is undeniably an essential component of the hydrological cycle. Precipitation is essential for maintaining ecosystems, replenishing freshwater supplies, and sculpting the topography through weathering and erosion (Changnon et al., 1988; Jakeman and Hornberger, 1993).

The summer monsoon in India provides a significant portion of the country's yearly precipitation in most regions, particularly in the central, northern, and western regions of the country. In these areas, it often makes up 70–90% of the yearly rainfall total. The perception of an increase in daily rainfall amount and occurrence due to climate change is not found correct for some of the regions in India. The possible reason may be the spatial variability of local changes such as rapid urbanization, industrialization, and deforestation (Srivastava et al., 2015). The hydrological variables, such as runoff and soil moisture, are influenced by the frequency of precipitation. Upcoming occurrences of heavy rainfall and the decreasing trend of moderate rainfall are observed across Central India. However, the different regions of India are responding to global warming in different ways to the frequency and volume of rainfall (Goswami et al., 2006). Similarly, heavy rainfall with increasing trends and moderate rainfall with decreasing trends are studied over Central India (Ghosh et al., 2009).

The adaptability of the statistical downscaling model (SDSM) for downscaling temperature and precipitation in the Upper Godavari basin, India, is examined by regression analysis that constructs connections between predictands and predictors based on empirical statistical relationships, presenting simplicity and minimal computational requirements (Saraf and Regulwar, 2016). The study discusses future precipitation and temperature projections for the region under inquiry.

Munawar et al. (2021) used the SDSM approach for RCPs in the Jhelum River basin to study climate change by adding GCM (CCSM4). Using SRM, the Jhelum River Basin discharge was simulated using de-biased downscaled data and MODIS data. This approach allows for a detailed examination of how variations in greenhouse gas emissions and socio-economic factors may influence temperature trends in the region. The daily rainfall behavior in the four homogeneous regions of India is studied by Zheng et al. (2016). They indicate that it has a relation with the strength of monsoon. The strength of the monsoon (strong/weak) and corresponding Indian summer monsoon rainfall (ISMR) play a significant role in climate change studies. Rainfall rates are primarily stronger (weaker) over NWI (North West India), CI (Central India), and SPIN (South Peninsular India) during intense (weak) monsoons. In contrast, rainfall rates over NEI (North East India) show no significant changes between solid and weak monsoons. The daily time estimates with a 25-kilometer spatial precision for the Indian summer monsoon rainfall (ISMR) by projecting future ISMR values using the A2 scenario emphasize an expected increase in rainfall in India's west coast, northeast, and western areas (Shashikanth and Ghosh 2013). Informed adaptation and mitigation plans for the many climatic zones of the Indian subcontinent may be formulated with the help of this thorough research, which provides insightful information about the possible geographical distribution of rainfall patterns under various climate scenarios.

The global climate models are used in this study. The Hadley climate model, version 3 (HadCM3), is a climate model developed by the Hadley Centre for Climate Prediction and Research in the United Kingdom. It is a coupled atmosphere-ocean model that includes components for simulating the atmosphere, ocean, sea ice, and land surface. HadCM3 has been used in various climate studies and assessments to understand past and future climate changes. The number 3 refers to the third version of a coupled climate model. No specific coupled global climate model, version 3 (CGCM3), stands out universally, as different research institutions may develop their own coupled models using a similar nomenclature. However, models with the coupled global climate model generally incorporate atmosphere, ocean, land surface, and sea ice components, allowing for a comprehensive simulation of the Earth's climate system.

This study in particular uses historical data to forecast the spatiotemporal variability of future rainfall in the West Central area of India. The downscaling method used in this work shows the relationship between local and regional climate variables, which are derived from atmospheric variables at a larger scale. Like other climate models, HadCM3 and CGCM3 are helpful tools researchers may use to study and forecast the complex interactions that make up the Earth's climate system. This research aims to provide essential insights into the region's vulnerability to changing climate conditions and improve adaptation strategies for sustainable development by understanding the influence of climate change on rainfall distribution over time and location. It helps researchers to predict future weather patterns and understand the potential impacts of various factors, including greenhouse gas emissions.

Climate change impact assessment studies are carried out by downscaling. Global climate model (GCM) output is available at coarse resolution. The downscaling technique shows the relation between local and regional scale climate variables derived from large F-scale atmospheric variables (Hewitson and Crane, 1996). The GCMs are unable to resolve important sub-grid-scale features, such as clouds and topography, for local-scale hydrologic impacts of climate change in the Tunga–Bhadra River basin, India, and its consequences for the management of water resources and agriculture in the study area. This may be because the output of the GCMs is unreliable at individual grids (Meenu et al., 2013).

The spatial and temporal resolution of GCM projections using SDSM 4.2 enables a more localized and detailed analysis of precipitation variability in water-stressed regions like the Upper Mahanadi basin (Subbarao and Maity, 2017). Because of their coarse (grid) resolution and the local variety of terrain and climate, basin-level water resource planners are unable to fully comprehend the impact of climate change on the hydrological cycle on a worldwide scale (Minville et al., 2008).

The maximum temperature of the Ganga basin is predicted to fluctuate in the future owing to climate change using a statistical downscaling model (SDSM) under the RCPs 2.6, 4.5, and 8.5 scenarios of the CanESM2 model outputs (Gupta et al., 2023).

Downscaling is of two types: (1) dynamical downscaling and (2) statistical downscaling. Dynamic downscaling dynamically extrapolates the impacts of large-scale climatic phenomena to regional or local scales using high-resolution regional climate models. Instead of statistically portraying important meteorological phenomena, it models their physics. Dynamic downscaling uses regional climatic models (RCMs). Statistics-based methods are used in statistical downscaling to establish relations between observed local climate responses and large-scale climate trends. It establishes a statistical relationship between the local and global climate using observed data.

This research includes a statistical downscaling method. The GCM outputs frequently possess a coarse spatial resolution. The statistical downscaling method enhances the outputs to fine resolution and enables them to represent local and regional climate characteristics in a better fashion. Statistical downscaling provides correlations between GCM outputs (predictors) and local climatic variables (predictands).

A technique for converting general circulation model (GCM) predictors into surface and local variables through downscaling methods has been developed (Wilby and Wigley, 2000). It examines the climate variables at regional or local scales and enhances the understanding of climate change impacts on specific areas. Nonparametric methods for modelling GCM and biases were individually corrected for each GCM in the study using observed data from the baseline (1961–1990) to verify scenario uncertainty in drought assessment in the Mahanadi River basin in India, assuming that all scenarios have the same probability and that all models' bias-free GCM simulations are equally accurate (Ghosh and Mujumdar, 2007). The present work therefore aims to determine the dry and wet spell lengths over the study area for various time scales and to comprehend the spatiotemporal variation in future rainfall over the West Central region of India utilizing a statistical downscaling approach employing SDSM.

Global climate models (GCMs) are vital resources for researching and forecasting global climate trends and shifts. They are fundamental components of climate research that advance our knowledge of the intricate relationships that make up the Earth's climate system. GCM outputs with GHG concentration in the atmosphere are the best tool for generating future scenarios. With a resolution of 150–300 km by 150–300 km, researchers display GCM data for the entire world in a three-dimensional grid format (Mujumdar and Ghosh, 2008). However, for hydrological impact assessment studies at the regional scale, GCM outputs are not used directly due to spatial resolution. Hence, downscaling is necessary to derive the local scale variables from atmospheric GCM output.

The SDSM utilizes multiple linear regression approaches to create statistical correlations between local climate variables, predictands, and larger-scale climate predictors. SDSM is a promising and performing downscaling model that combines unpredictable weather generation (SWG) with multiple linear regression (MLR) (Wilby et al., 2002). SDSM progresses on a daily time series of NCEP predictors and observed precipitation or temperature daily time series (Huang et al., 2011). Model reliability is determined by examining the downscaling of precipitation in the Indian monsoon area and using an appropriate set of predictor variables.

The research on the statistical downscaling of rainfall to investigate climate change, presents a study on the likely variation of precipitation patterns in the European Alps under various climate change scenarios, projecting the potential changes in local climates and their effects on the region's ecosystems, water resources, and communities (Schmidli et al., 2007). The impact of climate change on the overturning circulation of the South Asian monsoon was explored using SDSM to downscale rainfall estimates over the Western Ghats of India (Krishnan et al., 2013). The study highlights the monsoon circulation that stabilizes even in uncertain future projections. India's West Central region includes Gujarat, Maharashtra, Madhya Pradesh, and parts of Rajasthan. Potential effects of rising temperatures in the recent decade and shifting weather patterns include longer dry periods and more frequent and severe downpour events.

This research presents a novel way to examine future rainfall trends over the West Central region of India by assessing the effects of climate change on spatiotemporal variation in precipitation distribution using the daily fine-gridded rainfall dataset (0.25°X0.25°) and the SDSM. The study thoroughly analyzes future rainfall scenarios filling a notable gap in regional climate change understanding. This innovative methodology enables the creation of accurate future scenarios, offering crucial insights into the potential evolution of precipitation dynamics in response to shifting climatic conditions in this specific geographic location. It is challenging to identify the potential predictors that significantly affect the rainfall patterns in West Central India, which makes this study more interesting. Ultimately, the significance of statistical downscaling for rainfall scenarios in West Central India lies in its ability to provide precise, localized projections with high resolution. These projections equip stakeholders with essential insights, enabling informed decision-making and the implementation of effective adaptation strategies by accurately capturing the complex climate dynamics of the region.

The current research employs the following objectives:

1 to study the climate change effects on the spatiotemporal variation in future rainfall over the West Central region of India, by a statistical downscaling approach;

2 to analyze the performance of the model at different spatial and temporal scales and anticipate the hydrological challenges over the study area in the upcoming decades;

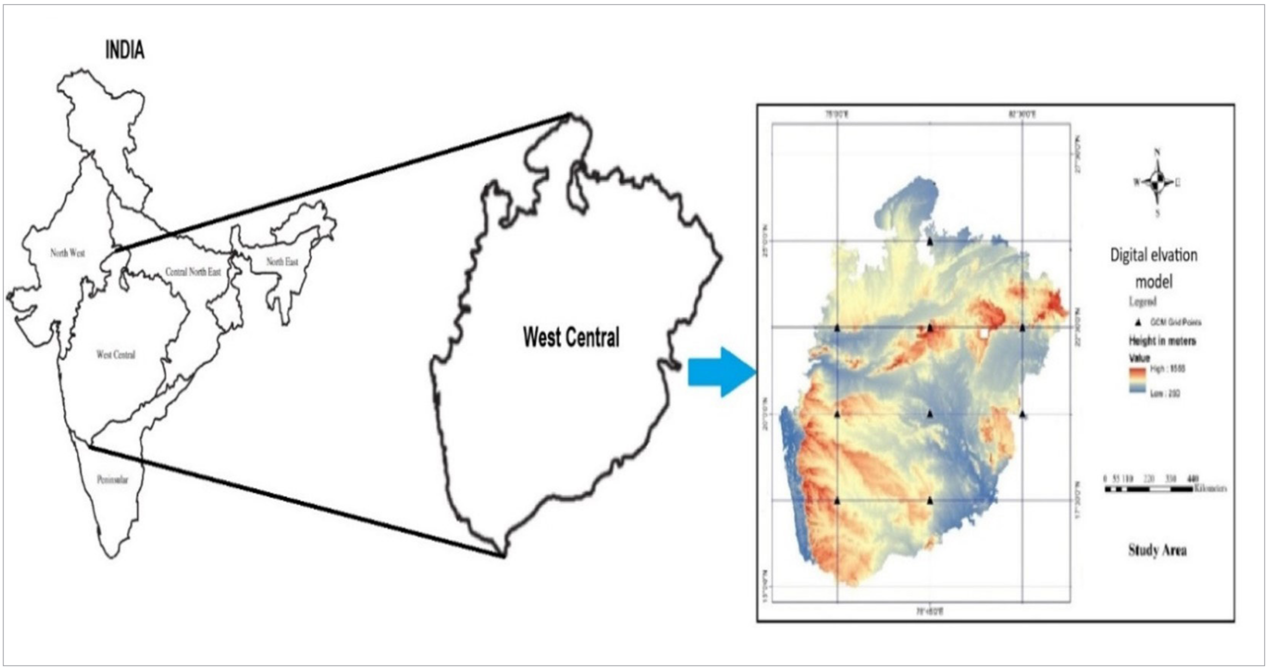
3 to study the dry spell and wet spell lengths over the study area at different time scales.

Methods

Study area

West Central (WC) is a region with a spatial domain spanning 16.5°N to 26.5°N and 74.5°E to 86.5°E. The West Central region encompasses an area of 962 694 km^2, or around 33.42% of India. The average annual rainfall over the West Central region is 1158.19 mm based on observed rainfall values of IMD for 1961–2001. The study area covers a total of eight meteorological subdivisions of India (as defined by the Indian Institute of Tropical Meteorology), namely West Madhya Pradesh, East Madhya Pradesh, Madhya Maharashtra, Marathwada, Vidarbha, Chhattisgarh, Telangana, Konkan and Goa and North Interior Karnataka. The topography of the WC region does not have much

Fig. 1. *Map of India highlighting study area, West Central (WC)*



influence on extreme events. As per the studies carried out by the National Climate Centre (NCC Research Report, September 2013, R.R.No.1) on the IMD4 data set for the temporal domain from 1901 to 2013, over homogenous regions of India, there were clear upward trends in the occurrence of both very heavy rainfall (VHR > 150 mm) and heavy rainfall (HR > 100 mm). To examine the extreme rainfall trends across the region in the future, the study attempts to anticipate future rainfall trends over the West Central India region, which includes drought-prone subdivisions viz. Marathwada, Vidarbha, and Madhya Maharashtra. *Fig. 1* shows the map of India highlighting the study area.

Data used

Observed data at local scale (predictand). The daily precipitation data at all grid points with a resolution of 0.25° x 0.25° (latitude x longitude) are obtained from the India Meteorological Department (IMD) (Pai et al., 2014). The dataset includes real-time rainfall for 1961–2001 on a temporal scale.

Large scale atmospheric variables (predictors). The reanalysis dataset (NCEP/NCAR) with a horizontal resolution of 2.5° x 2.5° and 17 constant pressure levels from 1961 to 2003, together with monthly mean atmospheric variables, are obtained from the National Centre for Environmental Prediction (https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.html)

The analysis includes the 40-year GCM output from CGCM3 (3.750 latitude x 3.750 longitude) and HadCM3 (2.5° latitude x 3.75° longitude) from our analysis. The Canadian Climate Impacts Scenarios Group collects these standardized predictor variables of NCEP/NCAR, HadCM3 and CGCM3 (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi) and the website of Data Access Integration (DAI) (http://loki.qc.ec.gc.ca/DAI/predictors-e.html). The period of the years 1961 through 1990 is considered as the baseline for assessing future climate change over a period 2001 through 2099 for HadCM3 with scenarios A2 and B2, and for CGCM3 with scenarios A1B and A2).

Statistical downscaling model (SDSM)

The SDSM employs multiple linear regression approaches to construct statistical correlations between local-scale climate variables (predictands) and large-scale climate predictors (Wilby et al., 2002). These connections, which are established using historical data, are thought to be relevant in the future. The SDSM uses the general circulation model (GCM) predictions to downscale local data for future periods. For a thorough explanation of SDSM, see (Wilby and Dawson, 2013;

Wilby et al., 2002). The SDSM is widely used in studies related to climate change and is used to downscale a variety of hydroclimatic variables, such as temperature (Yang et al., 2012), seasonal or monthly precipitation (Meenu et al., 2013; Pervez and Henebry, 2014). HadCM3 data with a year length of 360 days and CGCM3 data with 365 days is used to run the model for scenario generation.

The basic idea behind regression models in downscaling is to establish a statistical relationship between large-scale predictors (such as temperature, humidity, and atmospheric pressure) and local-scale predictors (like rainfall) based on historical observations. Regression model is selected as the method of precipitation prediction based on the characteristics of the data. The stepwise regression is followed in the variable selection process, and the present study employs the method of multiple linear regression.

Model development. The regression model is constructed using historical climate data, including large-scale predictors and local-scale observations. The model aims to establish a statistical link between large-scale predictors and observed local-scale rainfall.

The detailed methodology of SDSM is as follows:

a *Preprocessing of the da*ta: The quality of observed data (predictand) is checked by the 'quality control' command in SDSM. It involves cleaning, transforming, and organizing raw data to prepare it for further analysis or modelling.

b *Statistical relationship and variable transformation:* After the quality control check, data 'transformation' and variable 'screening' are carried out. The set of predictors strongly influencing the rainfall is obtained by performing separate monthly, seasonal, and annual analyses. The predictors with the best statistical connection to the predictors are selected in this step.

c *Downscaling:* Downscaling the predictand presents a significant issue when choosing the predictors based on partial correlation *P* value and *R* value or examining the relationship between each predictor in scatter plots. After screening the variables, the model is calibrated using the first 20 years of daily data (1961–1980). The 'conditional' process is chosen to downscale precipitation and the 'unconditional' process is chosen to downscale temperature (Wilby and Dawson, 2013).

d *Evaluating model performance:* The quality of the downscaled forecasts is evaluated by comparing them with observed fine-scale rainfall data from the past or with other reference points to analyze how well the model captures the patterns and variances in rainfall.

e *Uncertainty analysis:* The level of uncertainty of the downscaled projections is analyzed to investigate the sources of uncertainty, including those related to predictor choice, variability, and model structure. When using ensemble methods, one needs to consider multiple climate models or examine different emission scenarios.

f *Generate future scenario:* Synthetic daily precipitation time series generated by the "Scenario generator" window are downscaled using HadCM3 and CGCM3 predictors. The predicted daily precipitation time series occurrences for HadCM3 and CGCM3 with A1B and A2 scenarios were downscaled using the A2 and B2 scenario predictors. The flow chart below illustrates the approach used in the current investigation. The observed IMD data (for the historical period of 1961–2001) are compared to the outcomes of model simulations. Model calibration and validation findings were satisfactory. *Fig. 2* shows a schematic diagram of the downscaling methodology using SDSM.

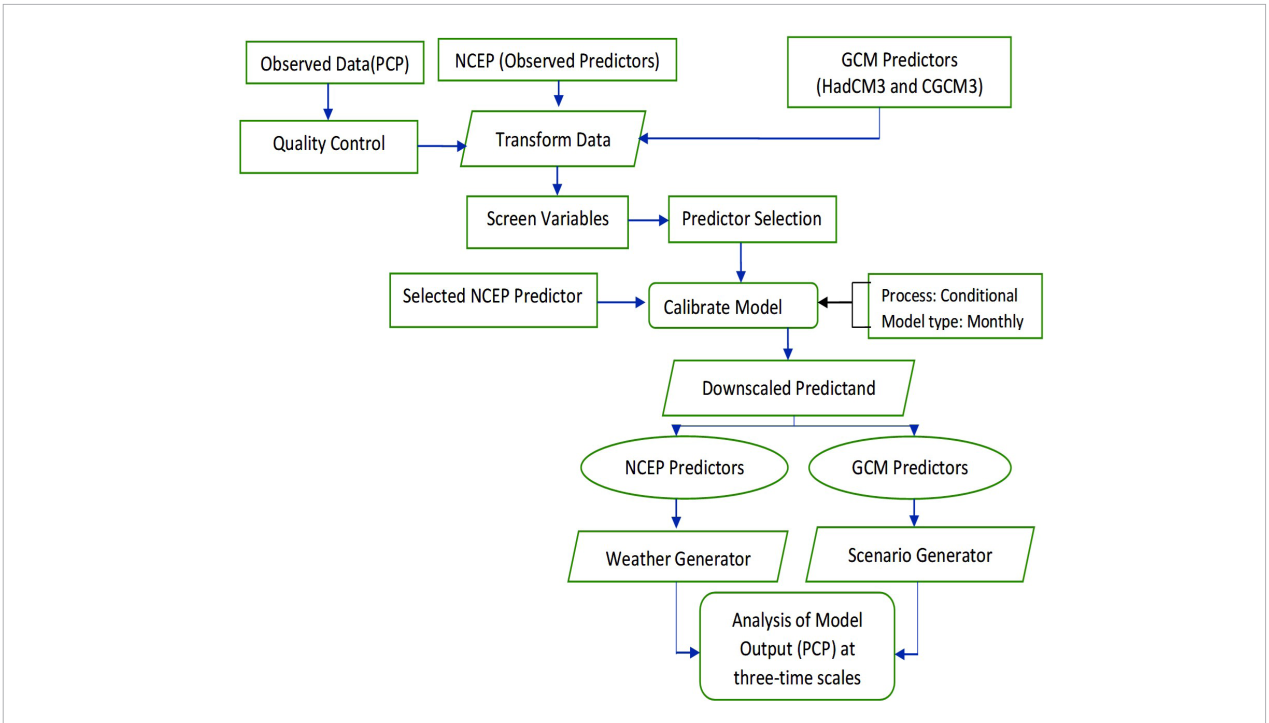
Equation (1) describes the linear relationship between the predictor variables (*j = 1, 2, ..., n*) and the occurrence of a wet day on day W_i. This equation draws a link between the occurrence of wet days and large-scale atmospheric predictors. To summarize, SDSM uses linear conditioning with observed large-scale predictors to generate station-scale weather characteristics. For conditional downscaled processes like daily precipitation, the occurrence of a wet day is governed by a linear relationship with predictor variables X_{ij}.

$$W_i = \propto_0 \sum_{j=1}^{n} \propto jX_{ij} \quad (1)$$

The predictor variables show the current large-scale weather conditions, and under a specific constraint $0 \leq W_i \leq 1$, precipitation occurrence depends on uniform random number $r \leq W_i$. The value of W_i varies within the range of 0 to 1; notably, this variable is continuous, ranging from 0 to 1, rather than a binary (0 or 1) value. For example, W_i is equal to 0.2, which might be used to represent a day with high pressure. Next, if and only if *R* is less than or equal to 0.2, the variable *R* determines the probability that a wet day will occur.

Equation (2) defines the equation for the total downscaled precipitation (*Pi*) on i^{th} day, assuming the return

Fig. 2. *Schematic diagram of downscaling methodology using SDSM*



of a rainy day. The occurrence of rainy days is evaluated using the *R* parameter. Depending on the amount of rain or the precision of the measurement, different places may have different wet-day thresholds (mm). Wet day return (*Pi*), which is a downscaled measure of total precipitation, is provided by:

$$P_i^k = \beta_0 \quad + \sum_{j=1}^{n} \beta_j \, X_{ij} + \varepsilon_i \qquad (2)$$

where *K* is the transformation (e.g., logarithmic, inverse standard, fourth root, none if not applicable); X_{ij} is selected predictor sand; and ε_i model error.

This study uses the SDSM to examine the effects of climate change on precipitation distribution across India's West Central region, presenting a novel method for assessing future rainfall patterns in the area. By means of a comprehensive examination of spatiotemporal fluctuations in future rainfall scenarios, this study substantially advances our comprehension of local climate change.

Calibration and validation

Calibrating a statistical downscaling model involves modifying its parameters to suit the specific region and climate variables under examination. This step helps to adjust for biases and discrepancies between the outputs of the downscaled model and observed historical climate data. By calibrating the model, it becomes more accurate in reproducing the statistical relationships between local climate variables (temperature and precipitation at a specific location) and global climate models. Validation is the process of assessing the performance of the downscaled model. To evaluate the model's reliability in predicting future events, validation provides an objective assessment of its ability to generalize to new data. Validation helps identify the uncertainties associated with downscaled forecasts.

In the present study, the model is calibrated over a period of 1961 to 1980 and validated over the period 1981–2000 by observed precipitation data and observed predictors selected through the screening process (NCEP variables). A monthly model is chosen, and 12 distinct regression equations are conducted independently for each month. A total of 26 NCEP predictors were downloaded for the selected grid box. The methodology discusses the selection criteria for predictors given in *Table 1*.

Model results for the calibration and validation period were statistically tested by root mean square error (RMSE), coefficient of determination (R^2), standard deviation (SD), standard error (SE), and mean (μ).

Table 1. *Selected NCEP predictors through the screening process of SDSM*

Sr. No	Predictor (variable) description	Symbol	Unit
1	The mean temperature at 2 m	nceptempas	°C
2	500 hpa airflow strength	ncepp5_fas	m/s
3	850 hpa zonal velocity	ncepp8_uas	m/s
4	Surface divergence	ncepp_zhas	s^{-1}
5	500 hpa geopotential height	ncepp500as	M
6	Surface specific humidity	ncepshumas	g/kg

However, R^2 gives a correlation between observed data and model-simulated results that will ultimately test the reliability and accuracy of the model.

Future rainfall scenarios are generated using HadCM3 and CGCM3 data for each scenario output. A daily synthetic rainfall of twenty ensembles from 1961 to 2099 is calculated and then averaged to separate for three investigated time periods (each of 30 years), such as 2011–2040, 2041–2070 and 2071–2099.

Results and Discussion

The success of a predictive model is discussed in this section. Researchers have identified a group of variables called predictors, which can be used to predict a specific outcome referred to as the predictand. The present study attempts to use several measures to judge the accuracy of the model:

RMSE: It stands for root mean square error. It shows how far off the predicted values were from the real values. For this model, the RMSE numbers for the calibration phase are between 11.26 and 11.58, and for the validation phase, they are between 16.38 and 16.56. In general, lower RMSE numbers mean that the model works better. The results show that the model works better in the calibration than in the validation phase.

Standard error: The number shows the uncertainty of the model's forecasts. In this case, it is between 7.32 and 8.64 during calibration and 8.42 and 9.46 during validation. The accuracy of the model increases when the standard error is low.

Coefficient of determination (R^2): The R^2 coefficient of determination shows how well the model's forecasts match the actual data. A value of 1 means the fit is perfect, and a value of 0 means no fit. The range for R^2 is between 0.75 and 0.82 during the testing phase. The range for the validity phase is between 0.77 and 0.80. These numbers show that the model explains a lot of the variation in the data, which is usually a good sign.

Table 2 for calibration and *Table 3* for validation highlight the results. These tables explain the model's performance, including predictor variable contributions and other statistics.

Table 2. *Mean monthly precipitation of observed and downscaled data for the calibration period 1961–1980*

GCM	Description	SD (mm)	μ (mm)	SE (mm)	R^2	RMSE
HadCM3	Observed	30.25	28.34	8.23	-	-
	NCEP	26.32	24.76	7.59	0.75	11.58
CGCM3	Observed	30.82	28.27	8.64	-	-
	NCEP	26.57	24.13	7.32	0.82	11.26

Table 3. *Mean monthly precipitation of observed and downscaled for validation period 1981–2000*

GCM	Description	SD (mm)	μ (mm)	SE (mm)	R^2	RMSE
HadCM3	Observed	28.25	30.74	9.13	-	-
	NCEP	23.36	28.36	8.39	0.77	16.38
CGCM3	Observed	28.69	30.24	9.16	-	-
	NCEP	22.87	28.53	8.42	0.80	16.56

In predictive modelling, the choice of predictor variables is critical to the model's ability to predict the predictor successfully. Earlier researchers have extensively studied the significance of predictor variables and their impact on predictive model performance.

Evaluation of precipitation changes on a monthly basis

According to the findings of the spatial mapping of rainfall variation by downscaling studies carried out on homogeneous monsoon regions of India, the precipitation fluctuated more in the meteorological sub-divisions of Western India.

Increasing trends in monthly precipitation changes (mm) for both the GCMs in the respective scenarios were shown in SDSM, HadCM3 A2 and B2 scenarios. *Fig. 3* shows the highest monthly precipitation changes in September over the time period 2071–2099. Similarly, CGCM3 shows the monthly precipitation variation for A1B and A2 scenarios over different time periods (*Fig. 4*). The results show a notable change in the month of August for both the scenarios of CGCM3. From the investigated time period 1 to time period 3, there is a notable increase in monthly precipitation.

The mean monthly precipitation for both the HadCM3 and CGCM3 models is presented in *Fig. 5* and *Fig. 6*, respectively. Both models showed seasonal precipitation changes over three investigated time periods. During the monsoon months of time periods 2 and 3, the increases in monthly precipitation are 6.7% and 12.4% (HadCM3, A2 scenario) and 11.5% and 14.2% (HadCM3, B2 scenario), respectively (see *Fig. 5*). However, *Fig. 6* shows that the results of CGCM3 highlighting the increase in the monthly precipitation for time periods 2 and 3 during non-monsoon months are 3.84% and 10.3% (CGCM3, A1B scenario) and 5.76% and 12.27%, (CGCM3, A2 scenario) respectively, as shown in *Fig. 6*.

According to the A2 and B2 scenarios in the HadCM3 model, there will be a notable rise in precipitation in August (7.63–22.38 mm), September (13.84–28.54 mm), and October (8.39–19.03 mm) with various amounts predicted. The A2 and B2 scenarios exhibit a reduction of 3.6–6.4 mm and 4.3–7.9 mm, respectively, in the months of May and June. Similar increases in the mean monthly precipitation were noted in CGCM3 under A2 and A1B scenarios in the 2020s, 2050s, and 2080s for the months of June (9.23–26.00 mm), July (5.52–19.81 mm), August (10–16.8 mm), and September (6.29–17.2 mm). In April (3.52–6.64 mm) and May (2.72–7.64 mm), the CGCM3 model predicts lower mean monthly precipitation in the A1 and A1B scenarios. Under both models, there is a rise in the anticipated precipitation throughout the monsoon season (June, July, August, and September).

Fig. 3. *Mean monthly change in projected precipitation under A2 and B2 scenarios of the HadCM3 model*

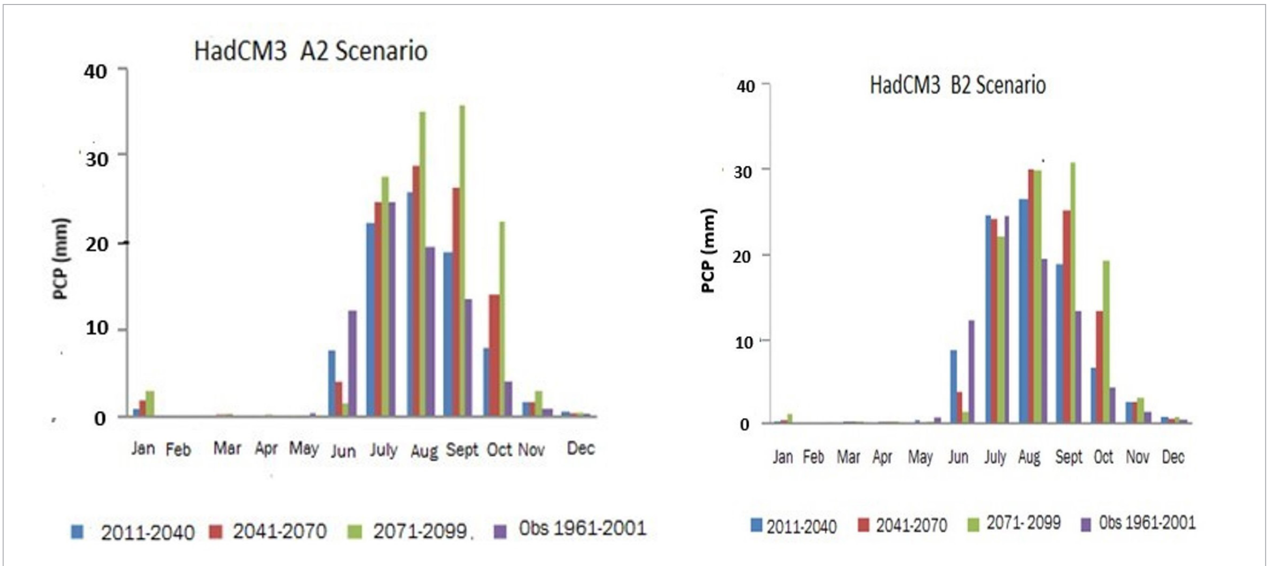


Fig. 4. *Mean monthly change in projected precipitation under A1B and A2 scenario of the CGCM3 model*

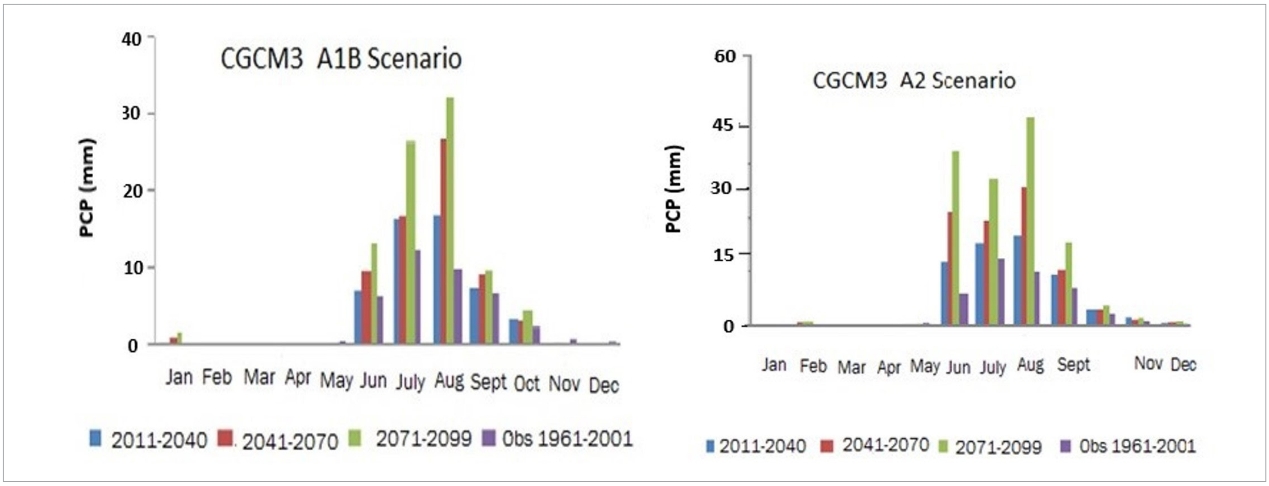


Fig. 5. *Observed monthly mean precipitation compared to a downscaled precipitation of the HadCM3 model for A2 and B2 scenarios over three investigated time periods*

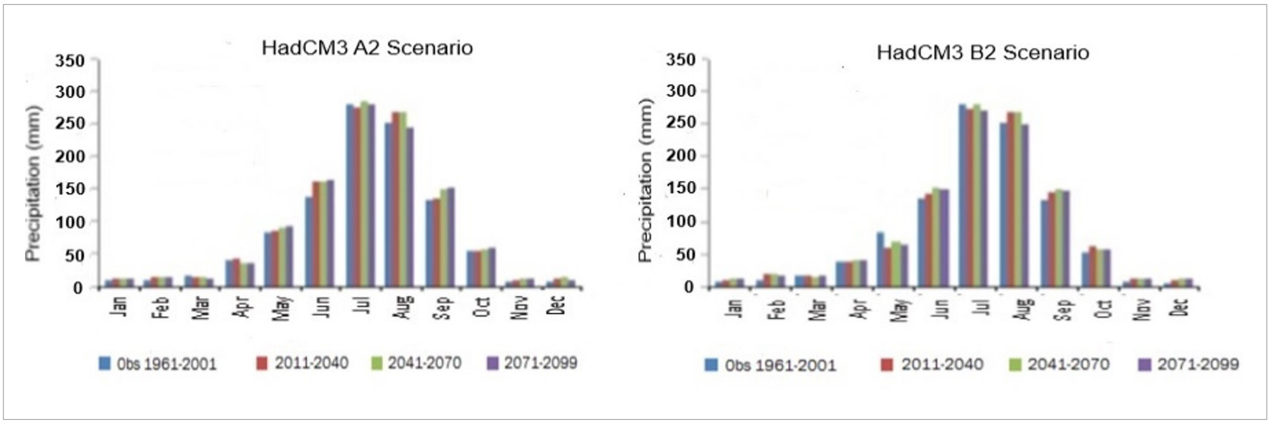
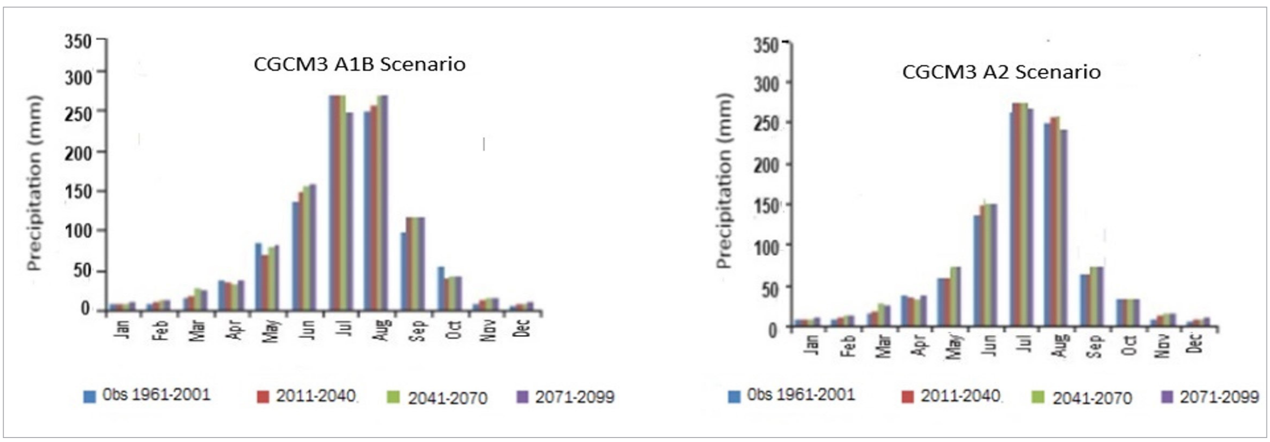


Fig. 6. *Observed monthly mean precipitation compared to a downscaled precipitation of the CGCM3 model for A1B and A2 scenarios over three investigated time periods*



Evaluation of precipitation changes on a yearly basis

The downscaled study results show an overall increase in the mean annual rainfall under the CGCM3 A1B and A2 scenarios of 12.0%, 14.6%, 17.1%, and 13.2%, 15.0%, and 18.0%, respectively, during the 2020s, 2050s, and 2080s compared to the base period; corresponding increases under the HadCM3 A2 and B2 scenarios were 10.0%, 12.3%, 18.6%, and 11.2%, 14.0%, 19.4%, respectively, during the 2020s, 2050s, and 2080s about the base period. The A2 scenario reports a notable rise in the mean annual precipitation under both models over the 2020s, 2050s, and 2080s.

Observed changes in dry and wet spells

Maximum dry and wet spell lengths of HadCM3 for the A2 and B2 scenarios were calculated and are represented graphically in *Fig. 7*. The yearly mean length of the maximum dry spell length in the HadCM3 model grows in the first period under the A2 scenario and decreases in the second and third under the B2 scenario. Time period 3 (2071–2099) shows an increase in the wet spell length in A2 and B2 scenarios, whereas dry spell length shows a decrease in the third time period (*Fig. 7*). In both cases, the month of July or August shows the most extended wet spells. The maximum dry spell length is the most prolonged dry spell with amounts below the wet-day threshold. The HadCM3 model shows comparatively less impact in dry spell length forecast than the CGCM3 model. Maximum wet spell length is the longest, with amounts more significant than or equal to the wet-day threshold. *Fig. 7* explains the mean maximum monthly dry spell length in October and November in the A2 scenario and from October to December in the B2 scenario.

Mean monthly dry and wet spells in CGCM3 for A2 and A1B scenarios were obtained, as discussed in *Fig. 8*. The maximum dry spell showed a decrease in A2 and A1B scenarios in almost all months except February in time period 3, with almost increasing trends in time period 1 (2011–2040). The CGCM3 model exhibits a higher rise in dry spell length forecast than the HadCM3 model. In the CGCM3 A2 scenario, wet spell length

Fig. 7. *Monthly projected maximum dry and wet spells of HadCM3 for A2 and B2 scenarios in number of days*

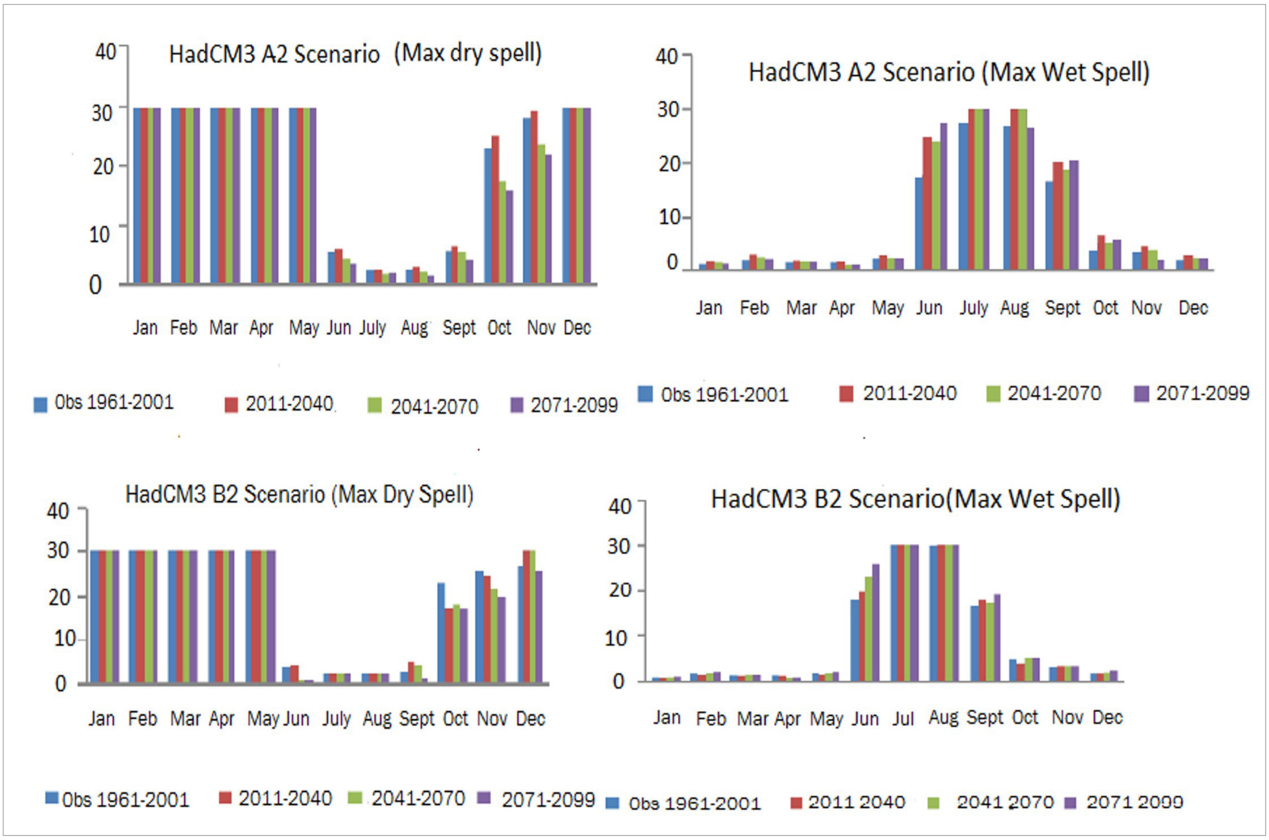
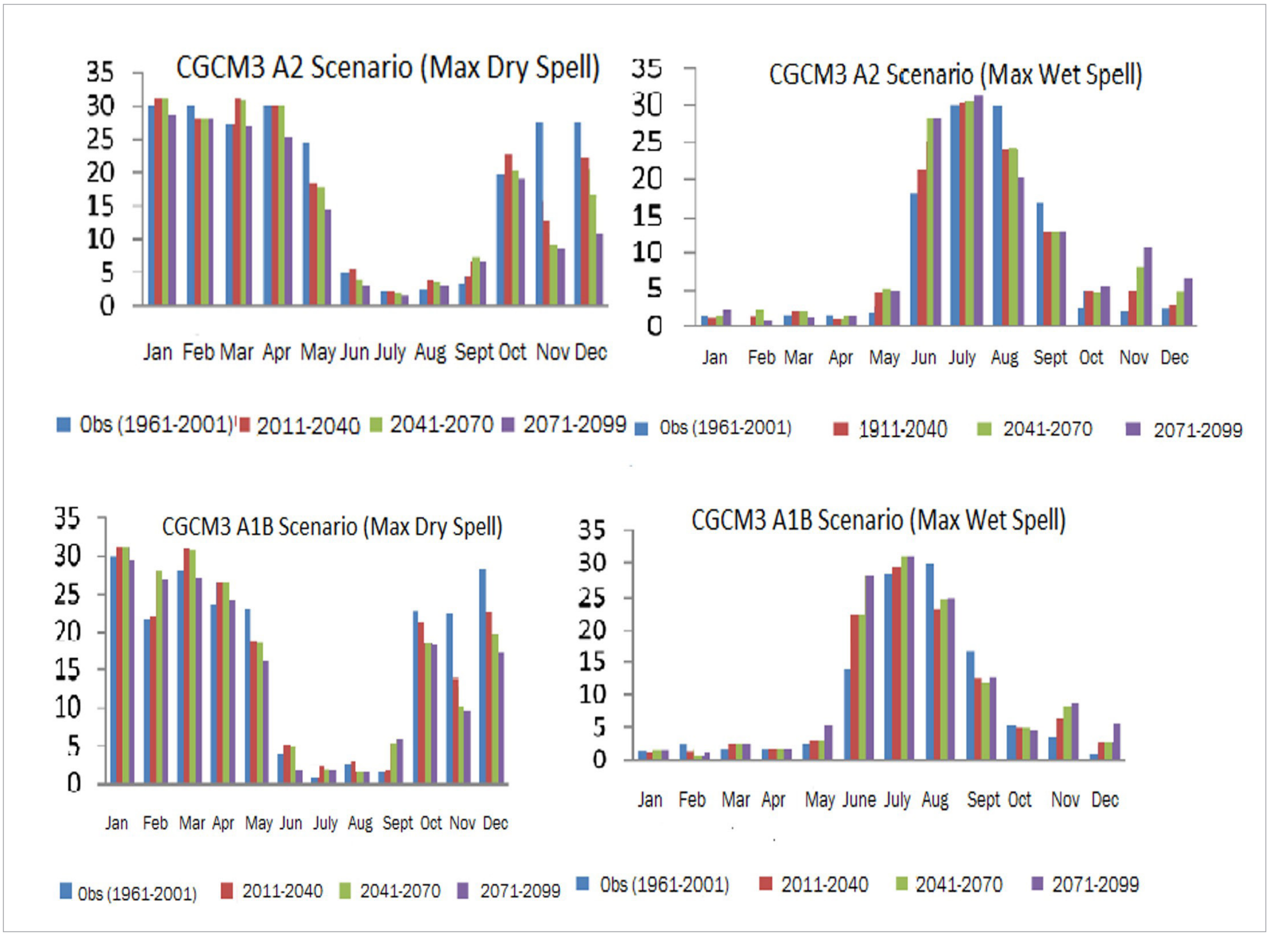


Fig. 8. *Monthly projected max dry and wet spells of CGCM3 for A2 and A1B scenario in number of days*



increased from June to September except for August in time period 1, 2 and 3. Also, in the A1B scenario, similar trends in the monsoon period were observed.

Fig. 8 highlights the CGCM3 model predictions that the rainy spell will get shorter in the 2020s and 2050s before getting longer in the 2080s.

Conclusions

A stochastic weather generator and multilinear regression algorithm are combined to create the SDSM tool. The results indicate that the monthly sub-model is more effective for predicting precipitation. Time period 3 (2071–2099) showed an increasing trend of monsoon rainfall. Both models showed increasing rainfall trends for all the scenarios. The mean annual rainfall trends are likely to increase by 10.0% to 18.6% as per the A2 scenario and about 11.2% to 19.4% as per the B2 scenario of HadCM3, respectively, over 2011–2099. However, the CGCM3 shows an increasing trend in annual precipitation from 12.0% to 17.1% under A1B and 13.0% to 18.0% under A2 scenarios, respectively. As shown by model results, *Fig. 3* and *Fig. 4* show rainfall variations over each investigated time period for two GCMs.

The study uses the SDSM, a hybrid downscaling strategy that combines MLR and SWG approaches, to estimate long-term precipitation scenarios (2011–2040, 2041–2070, and 2071–2099) in West Central India. The monthly SDSM sub-model shows efficiency in downscaling precipitation using predictors from the CGCM3 and HadCM3 models under the A2, A1B, and B2 emission scenarios. The results show a constant increase in the mean monthly precipitation across both models and all emission scenarios for the future (2020s, 2050s, and 2080s). Notably, the CGCM3 model demonstrates a faster rate of rise than HadCM3. While in HadCM3, the augmentation is more noticeable in August, September, and October under the A2 and B2 scenarios. Recognizing the uncertainties associated with the CGCM3 and HadCM3 models, as well as the limits of SDSM in downscaling, the study emphasizes the higher reliability of results, as seen by a higher R^2 during validation. A1B and B2 show the greatest and lowest predicted increments, respectively, with carbon dioxide (CO_2) concentrations of 720 ppm and 450 ppm. Despite the fact that the A2 scenario in this study had the highest CO_2 levels (850 ppm), the A1B scenario shows the highest rise.

Analysis of precipitation patterns indicated significant differences among the models. In CGCM3, June, July, and August depict a considerable rise under the A1 and A1B scenarios. A notable increase is seen in the HadCM3 model in August, September, and October for both the A2 and B2 scenarios. The CGCM3 model exhibits a higher rise in dry spell length forecast than the HadCM3 model. The two models have different outcomes in wet spell length. Wet spell length decreases in the 2020s and 2050s but increases in the 2080s, according to CGCM3. However, the HadCM3 model predicts a rise in the wet spell length throughout the three time periods. Different patterns are shown in the predicted future by both models.

Dry spell length projection significantly increases CGCM3 than HadCM3; however, wet spell duration shows distinct trends. CGCM3 shows that wet spell length decreases in the 2020s and 2050s but increases in the 2080s, whereas HadCM3 shows that it increases over all three time periods.

Future climate change may be uncertain, reflecting on rainfall scenarios, but significant changes in the future scenarios, as per model simulations, may show an impact on future water issues. These types of studies are helpful in adopting appropriate water management strategies for the future. It is assumed that the relation between predictor (large-scale atmospheric variables) and predictand for generating future scenarios remains the same over time. However, significant climatic changes may cause future results to decline. Thus, the predicted rainfall scenarios for the West Central region will be helpful in water management processes. The evaluation of future climate scenarios along with the application of a multilinear regression technique and a stochastic weather generator within the SDSM tool suggest potential increases in annual precipitation and monsoon rainfall for the West Central region of India. This research will be useful for development planners, decision-makers, and stakeholders, as it provides vital insights for developing region-wise water management policies to adapt to climate change in the West Central India region.

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References

Changnon S., Huff F., and Hsu C. (1988) Relations between Precipitation and Shallow Groundwater in Illinois. Journal of Climate 1(12):1239-1250. https://doi.org/10.1175/1520-0442(1988)001<1239:RBPASG>2.0.CO;2

Feng S., Hu Q., Huang W., Ho C. H., Li R., and Tang Z. (2014) Projected climate regime shift under future global warming from multi-model, multi-scenario CMIP5 simulations. Global and Planetary Change 112:41-52. https://doi.org/10.1016/j.gloplacha.2013.11.002

Ghosh S., Mujumdar P. (2007) Nonparametric methods for modeling GCM and scenario uncertainty in drought assessment. Water Resources Res. 43:W07405. https://doi.org/10.1029/2006WR005351

Ghosh S., Luniya V. and Gupta A. (2009) Trend analysis of Indian summer monsoon rainfall at different spatial scales. Atmos. Sci. Lett. 10:285-290. https://doi.org/10.1002/asl.235

Goswami B., Venugopal V., Sengupta M., Madhusoodanan S., Prince K. Xavier (2006) Increasing Trend of Extreme Rain Events Over India in a Warming Environment. Science 314:1442-1445. https://doi.org/10.1126/science.1132027

Gupta N., Patel J., Gond S., Tripathi R., Omar P., Dikshit P. (2023) Projecting Future Maximum Temperature Changes in River Ganges Basin Using Observations and Statistical Downscaling Model (SDSM). In: Pandey, M., Azamathulla, H., Pu, J.H. (eds) River Dynamics and Flood Hazards. Disaster Resilience and Green Growth. Springer, Singapore. https://doi.org/10.1007/978-981-19-7100-6_31

Hewitson B. and Crane R., (1996) Climate downscaling: techniques and application. Climate Research 7:85-95. https://doi.org/10.3354/cr007085

Huang J., Zhang J., Zhang Z., Xu C., Wang B., Yao J. (2011) Estimating future precipitation change in the Yangtze River basin using statistical downscaling method. Stoch. Environ. Res. Risk Assess 25:781-792, https://doi.org/10.1007/s00477-010-0441-9

IPCC, Climate Change (2013) The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, Cambridge. Available at: https://www.ipcc.ch/report/ar5/wg1/

Jakeman A. and Hornberger G. (1993) How much complexity is warranted in a Rainfall-Runoff model? Water Resources Research 29:2637-2649. https://doi.org/10.1029/93WR00877

Krishnan R., Sabin T., Ayantika D., Kitoh A., Sugi M., and Murakami H. (2013) Will the South Asian monsoon overturning circulation stabilize any further? Climate dynamics 40:187-211. https://doi.org/10.1007/s00382-012-1317-0

Meenu R., Rehana S., and Mujumdar P. (2013) Assessment of hydrologic impacts of climate change in Tunga - Bhadra river basin, India with HEC-HMS and SDSM. Hydrological Processes 27:1572-1589. https://doi.org/10.1002/hyp.9220

Minville M., Brissette F. and Leconte R. (2008) Uncertainty of the Impact of Climate Change on the Hydrology of a Nordic Watershed. Journal of Hydrology 358(1-2):70-83. https://doi.org/10.1016/j.jhydrol.2008.05.033

Mujumdar P.P. and Ghosh S. (2008) Modeling GCM and Scenario Uncertainty Using a Possibilistic Approach: Application to Mahanadi River Basin. Water Resources Research 44:W06407. https://doi.org/10.1029/2007WR006137

Munawar S., Tahir M., Baig M., (2021) Future climate change impacts on runoff of scarcely gauged Jhelum river basin using SDSM and RCPs. Journal of Water and Climate Change 12(7):2993-3004. https://doi.org/10.2166/wcc.2021.283

NCC Research Report (2013) National Climate Centre Office of the Additional Director General of Meteorology (Research) India Meteorological Department, Pune. Available at: https://imdpune.gov.in/Reports/NCCResearchReports.

Pai D., Sridhar L., Rajeevan M., Sreejith O., Satbhai N. and Mukhopadhyay B. (2014) Development and analysis of anew high spatial resolution (0.25o x 0.25o) long period (1901-2010) daily gridded rainfall data set over India. NCC Research Report No. 1. https://doi.org/10.54302/mausam.v65i1.851

Pervez M. and Henebry G. (2014) Projections of the Ganges-Brahmaputra precipitation downscaled from GCM predictors. Journal of Hydrology 517:120-134. https://doi.org/10.1016/j.jhydrol.2014.05.016

Saraf V. and Regulwar D. (2016) Assessment of Climate Change for Precipitation and Temperature Using Statistical Downscaling Methods in Upper Godavari River Basin, India. Journal of Water Resource and Protection 8:31-45. https://doi.org/10.4236/jwarp.2016.81004

Schmidli J., Goodes G., Frei C., Haylock M. (2007) Statistical and dynamical downscaling of precipitation: An evaluation and comparison of scenarios for the European Alps. Journal of Geophysical Research Atmosphere 112:1-20. https://doi.org/10.1029/2005JD007026

Shashikanth K. and Ghosh S. (2013) Fine Resolution Indian Summer Monsoon Rainfall Projection with Statistical Downscaling. International Journal of Chemical, Environmental and Biological Sciences (IJCEBS) 1(4): ISSN 2320-4079. https://www.researchgate.net/publication/287654326

Subbarao P. and Maity R., (2017) Spatio-temporal downscaling of projected precipitation in the 21st century: indication of a wetter monsoon over the Upper Mahanadi Basin, India. Hydrological Sciences Journal 62(3):467-482. https://doi.org/10.1080/02626667.2016.1241882

Srivastava P., Islam T, Monika G., Petropoulos G. and Dai O. (2015) WRF dynamical downscaling and bias correction schemes for NCEP estimated hydrometeorological variables. Water Resources Management 29:2267-2284. https://doi.org/10.1007/s11269-015-0940-z

Wilby R.L., Dawson C.W. and Barrow E.M. (2002) SDSM - a decision support tool for the assessment of regional climate change impacts. Environmental Modelling and Software, 17(2):147-159. https://doi.org/10.1016/S1364-8152(01)00060-3

Wilby R.L. and Dawson C.W. (2013) The Statistical Downscaling Model: insights from one decade of application. International Journal of Climatology 33:1707-1719. https://doi.org/10.1002/joc.3544

Wilby R.L. and Wigley T.M.L. (2000) Precipitation Predictors for Downscaling: Observed and General Circulation Model Relationships. International Journal of Climatology 20:641-661. https://doi.org/10.1002/(SICI)1097-0088(200005)20:6<641::AID-JOC501>3.0.CO;2-1

Yang T., Li H., Wang W., Xu C.Y., Yu Z. (2012) Statistical downscaling of extreme daily precipitation, evaporation, and temperature and construction of future scenarios. Hydrological Processes 26:3510-3523. https://doi.org/10.1002/hyp.8427

Zheng Y., Bourassa M.A., Ali M.M. and Krishnamurti T.N. (2016) Distinctive features of rainfall over the Indian homogeneous rainfall regions between strong and weak Indian summer monsoons. Journal of Geophysical Research-Atmospheres 121:5631-5647. https://doi.org/10.1002/2016JD025135