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Drought Analysis of Chhatrapati Sambhajinagar District Using SDSM

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Abstract: *This study examines the expected changes in drought patterns in Chhatrapati Sambhajinagar, a semi-arid district in Maharashtra, by using the Statistical Down Scaling Model (SDSM) and the Standardized Precipitation Index (SPI). Due to increasing climate variability, the region faces growing challenges related to water availability and agriculture. The research evaluates drought frequency and intensity under future climate scenarios RCP 4.5 and RCP 8.5 for the period from 2024 to 2100. Using historical climate data from 1980 to 2023, the SDSM was applied to generate detailed projections of temperature and rainfall. These projections show a steady rise in temperature, particularly during summer and post-monsoon seasons, which may lead to higher water loss through evapotranspiration and more stress on agriculture. The results indicate that climate variability will continue to affect the district's water resources and crop production. The SPI method was effective for identifying drought conditions, while SDSM helped provide district-level future climate estimates. This study highlights the importance of adopting adaptive water management measures such as rainwater harvesting, recharging groundwater, and using climate-resilient agricultural methods to reduce the negative impacts of future droughts. The findings offer useful guidance for local authorities, planners, and farmers of chhatrapati sambhajinagar to make informed decisions for sustainable water and agricultural management in the face of climate change.*

Index Terms - Chhatrapati Sambhajinagar, Drought Projection, Climate Change Impact, SDSM, SPI

1. INTRODUCTION

Climate change has emerged as a major global concern, significantly impacting hydrological cycles, agricultural productivity, and regional water resources. Semi-arid regions like Chhatrapati Sambhajinagar district in Maharashtra are particularly vulnerable to these impacts due to their climatic sensitivity and heavy dependence on seasonal rainfall. In recent decades, the district has experienced frequent droughts, delayed monsoons, and erratic rainfall patterns, all of which have serious implications for water availability and agriculture. Drought is one of the most complex natural hazards to monitor and predict, especially under changing climatic conditions. Therefore, it is essential to assess future drought trends to support effective planning and resource management. The integration of statistical tools and climate models offers a scientific approach for understanding these patterns at a local scale. This study employs the Statistical Down Scaling Model (SDSM) to generate high-resolution projections of temperature and precipitation using historical climate data (1980–2023) and future emission scenarios, specifically RCP 4.5 and RCP 8.5. To assess drought severity and frequency, the Standardized Precipitation Index (SPI) is applied. This combined methodology allows for a detailed understanding of potential future drought conditions in the district. The Intergovernmental Panel on Climate Change (IPCC) has developed several Global Climate Models (GCMs) to project future climate trends across the globe. These models include different greenhouse gas emission scenarios known as Representative Concentration Pathways (RCPs), which represent varying levels of radiative forcing expected by the end of the 21st century. One such model, the CanESM2 developed by the Canadian Centre for Climate Modelling and Analysis (CCCma), is widely used and considered suitable for climate studies in various regions, including parts of Asia. In the context of climate change impact studies, this model can be used to estimate future precipitation patterns and analyze drought risks. The aim of the referenced study is to estimate rainfall trends for a 75 year period (2024–2099) and classify drought events using the Standardized Precipitation Index (SPI) based on climate projections under three RCP scenarios: RCP 4.5, and RCP 8.5.

2. STUDY AREA

Chhatrapati Sambhajinagar, formerly known as Aurangabad, is located in the Marathwada region of Maharashtra, India. Geographically positioned in the central part of the state, the district holds great historical and cultural importance. The region falls under arid to semi-arid climatic conditions and experiences a tropical climate with distinct hot summers, a monsoon season, and mild winters. The Marathwada region lies between latitudes 17°37′N to 20°39′N and longitudes 74°33′E to 78°22′E (Groundwater Surveys and Development Agency, 2017; ENVIS-Maharashtra, 2007). The district receives an average annual rainfall of approximately 825 mm**.** However, the rainfall is highly variable and unpredictable, making the region vulnerable to droughts and water scarcity. Chhatrapati Sambhajinagar district, part of the drought-prone Marathwada region, often experiences irregular rainfall, high temperatures, and frequent water shortages. Since most of the population depends on agriculture and monsoon rains, even slight changes in climate can lead to serious problems like crop failure and water scarcity.

Figure 1 Study Area

3. LITERATURE REVIEW

Drought is one of the major natural disasters worsened by climate change, with serious impacts on agriculture. To reduce future risks, it is important to predict drought events in advance. This study aims to estimate future rainfall for the next 25 years (2025–2049) and classify drought levels using the Standardized Precipitation Index (SPI) under three climate scenarios: RCP2.6, RCP4.5, and RCP8.5**.** Using SDSM version 4.2, precipitation was projected in 5-year intervals from 2025 to 2049. The 3-month SPI was then calculated for each scenario. Results showed the most severe drought conditions occurred during: 2040–2044 for RCP2.6, 2035–2039 for RCP4.5, and 2030–2034 for RCP8.5. These findings highlight the need for timely adaptation and drought mitigation strategies[8].

Small-scale farmers in Africa, who depend mainly on rain fed agriculture, are highly vulnerable to climate change due to limited adaptation resources (Ncoyini-Manciya & Savage, 2022). Their study used the Statistical Down Scaling Model (SDSM) to examine climate trends in South Africa's KZN Midlands. Under RCP4.5 and RCP8.5 scenarios, projections showed rising temperatures and changing rainfall patterns initially decreasing, then increasing by the 2050s. These findings highlight the need for local, adaptive strategies to protect farming, reduce poverty, and ensure food security [23].

A study conducted in Yazd province, Iran, assessed future meteorological drought using SPI and SPEI indices under climate change scenarios. Using CanESM2 (CMIP5) and 56 years of historical data, drought severity and duration were analyzed under RCP2.6, RCP4.5, and RCP8.5**.** Results showed that future droughts are expected to be more severe and longer than in the past, especially under RCP8.5**.** The SPEI index indicated more intense droughts compared to SPI, and droughts with longer return periods are likely to become more frequent in the future [21].

4. Data Collection

In this study, NCEP/NCAR reanalysis data and the CanESM2 Global Climate Model (GCM) were used to obtain the necessary climate predictors. The CanESM2 data was downloaded from the official Canadian climate scenario portal (https://climate- scenarios.canada.ca/tools/downscaling/canesm2)[30]. The model provides climate data on a grid with a spatial resolution of 2.5° × 2.5°, which was adjusted to match the geographic location of the study area. For this research, the specific grid points selected from the CanESM2 model correspond to grid coordinates 28X and 40Y, which are appropriate for representing the climate conditions of Chhatrapati Sambhajinagar district.

5. Precipitation Prediction Analysis

In this study, precipitation predictions were made using the CanESM2 climate model, which includes three future greenhouse gas emission scenarios known as RCP2.5, RCP4.5, and RCP8.5. These scenarios are defined based on their radiative forcing values (measured in W/m^2) by the end of the 21st century.

- RCP2.6 represents a low-emission scenario, where radiative forcing peaks at about 3 W/m^2 before 2100 and then gradually declines.
- RCP4.5 is a moderate scenario, with radiative forcing reaching about 4.5 W/m^2**,** stabilizing after 2100.
- RCP8.5 is a high-emission scenario, where radiative forcing rises to approximately 8.5 W/m^2 by 2100 and continues to increase beyond that.

These scenarios help in understanding how different levels of greenhouse gas emissions could impact future climate conditions, including rainfall patterns.

6. Stages of Analysis

Future precipitation in this study was estimated using the Statistical DownScaling Model (SDSM**)** software, version 4.2. The downscaling process involved five main steps under different RCP scenarios (RCP4.5, and RCP8.5)**,** as described below:

1. Quality Control**:** This step involves checking the daily precipitation data to ensure it is accurate and complete. The number of valid data points and any missing data are identified.

2. Screening of Variables: In this stage, the relationship between the predictor variables (from NCEP reanalysis data) and the predictand (local precipitation data) is analyzed. Among the 26 available predictors, those with the highest positive correlation and the lowest p-values are selected as "super predictors."
3. Calibration**:** Calibration helps in establishing regression parameters between the selected predictors and the observed precipitation data. Since precipitation data is non-linear, a conditional transformation method is applied for accurate modeling.

4. Weather Generation**:** Based on the selected predictors, synthetic weather data is generated for the calibration period (1988–2019). The accuracy of this generated data is assessed using statistical tools such as Root Mean Square Error (RMSE) and coefficient of determination (R^2).

5. Scenario Generation**:** Finally, precipitation data is simulated for future periods under RCP4.5, and RCP8.5 scenarios. The projections are divided into twenty five year blocks across a 25-year period: 2025–2050**,** 2051–2099.

Table 1. NCEP Predictors Variables

No.	Predictors	Description	No.	Predictors	Description
1	ncepmslpgl	Mean sea level pressure	14	ncepp5zhgl	500 hPa Divergence
2	ncepp1_fgl	1000 hPa Wind Speed	15	ncepp8_fgl	850 hPa Wind Speed
3	ncepp1_ugl	1000 hPa Zonal velocity	16	ncepp8_ugl	850 hPa Zonal velocity
4	ncepp1_vgl	1000 hPa Meridional velocity	17	ncepp8_vgl	850 hPa Meridional velocity
5	ncepp1_zgl	1000 hPa Vorticity	18	ncepp8_zgl	850 hPa Vorticity
6	ncepp1thgl	1000 hPa Wind direction	19	ncepp850gl	850 hPa Geopotential height
7	ncepp1zhgl	1000 hPa Divergence	20	ncepp8thgl	850 hPa Wind direction
8	ncepp5_fgl	500 hPa Wind Speed	21	ncepp8zhgl	850 hPa Divergence
9	ncepp5_ugl	500 hPa Zonal velocity	22	nceprcpgl	Precipitation
10	ncepp5_vgl	500 hPa Meridional velocity	23	nceps500gl	500 hPa Specific humidity
11	ncepp5_zgl	500 hPa Vorticity	24	nceps850gl	850 hPa Specific humidity
12	ncepp500gl	500 hPa Geopotential height	25	ncepshumgl	1000 hPa Specific humidity
13	ncepp5thgl	500 hPa Wind direction	26	nceptempgl	Screen (2m) air temperture

7. Standardized Precipitation Index (SPI) Analysis

The Standardized Precipitation Index (SPI) was used in this study to measure how much the precipitation deviates from the average over a specific time period. For this analysis, the SPI was calculated for a 3-month timescale, which helps in identifying short-term drought conditions. The SPI is determined using a gamma probability distribution, which fits the historical rainfall data. This distribution is used to calculate the SPI value using a specific mathematical formula, as shown in Equation (1).

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha T(\alpha)} \int_0^x t^{\alpha-1} e^{-x/\beta} dx \tag{1}$$

Beta and alpha values are estimated for each rain station using Eqs. (2) and (3):

$$\alpha = \frac{\overline{x}^2}{s^2} \tag{2}$$

$$\beta = \frac{\overline{x}}{s^2}, \text{ for x} > 0 \tag{3}$$

The gamma function is not defined for x = 0, so for precipitation that the value equal to 0 using the Eq. (4):

$$4\ H\ (x) = q + (1 - q) \cdot G(x) \quad (4)$$

where q is the number of rain data divided by the number of data (n). The SPI value is the change from the Gamma distribution of precipitation to a normal distribution using Eqs. 5 and 6.

$$Z = SPUI = -\left(t - \frac{c_0 + c_1 t + c_2 t}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0 < \mathrm{H}(x) \leq 0.5 \quad (5)$$

$$Z = SPUI = +\left(t - \frac{c_0 + c_1 t + c_2 t}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0.5 < \mathrm{H}(x) \leq 1.0 \quad (6)$$

where:

$$t = \sqrt{ln\left(\frac{1}{(H(x))^2}\right)} \text{ for } 0 < \mathrm{H}(x) \leq 0.5 \quad (7)$$

$$t = \sqrt{ln\left(\frac{1}{(1 - H(x))^2}\right)} \text{ for } 0.5 < \mathrm{H}(x) \leq 1.0 \quad (8)$$

where:

$$c_0 = 2.515517 \quad d_1 = 1.432788$$

$$c_1 = 0.802853 \quad d_2 = 0.189269$$

$$c_2 = 0.010328 \quad d_3 = 0.001038$$

The calculated SPI values are then categorized into different drought levels to assess the severity of drought in a particular area. These classifications help in identifying whether the region is experiencing normal, dry, or extremely dry conditions, as shown in Table 2.

Table 2. SPI value classification

SPI Values Range	Condition
>2.0	Extremely wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

Source: WMO 2012 Standardized Precipitation Index User Guide. Online: www.wamis.org/agm/pubs/SPI/WMO_1090_EN.pdf

8. Result and Discussion

8.1 Selected Predictors

Out of the 26 available NCEP predictors, those with a positive correlation (r > 0) and a significance level of 95% ($p < 0.05$) were selected for model development. The selected predictors for the chhatrapati sambhajinagar district are listed in Table 3, and their descriptions are provided in Table 1.

8.2 Model Calibration and Validation

Model calibration and validation were performed for the period 1980–2023 by comparing observed rainfall data with model-generated historical data. This process helps assess how accurately the model reflects real conditions. Validation results include RMSE, R^2, and the correlation coefficient. A lower RMSE value (closer to 0) and a higher R^2 value (closer to 1) indicate better model performance. The best results are those with the lowest RMSE and highest R^2.

Table 3. Selected NCEP Predictors

Parameters	Selected Predictors
Rainfall	ncepp1zhgl, ncepp5_fgl
Tmax	ncepp5_ugl, nceptempgl
Tmin	ncepp5_zgl, ncepshumgl

9. FUTURE PRECIPITATION

The projected rainfall data for the years 2024–2050 under RCP 4.5 and RCP 8.5 shows small but important changes compared to the historical average (1980–2023). In January, rainfall is slightly less under RCP 4.5 than in the past, while RCP 8.5 shows nearly the same amount. In February and March, rainfall is slightly higher in both scenarios than the historical data. April also shows a small increase. During the monsoon season (June to September), rainfall projections under RCP 4.5 and RCP 8.5 show slight changes compared to the historical average (1980–2023). In June, rainfall under both scenarios remains almost the same as historical values, with a slight decrease under RCP 8.5 (382.46 mm) compared to RCP 4.5 (384.79 mm). In July, rainfall slightly increases under RCP 4.5 (141.70 mm) but drops under RCP 8.5 (140.13 mm). For August, both scenarios show very little change, with rainfall remaining close to past levels. However, in September, a notable decline is seen under RCP 8.5 (131.25 mm), which is lower than both RCP 4.5 (133.45 mm) and the historical average (134.89 mm). These small variations suggest that while monsoon rainfall may stay mostly stable in the coming decades, RCP 8.5 could lead to a slight reduction in late monsoon rainfall, especially in September. This could affect crop water availability and groundwater recharge during the post-monsoon period, making long-term planning and water conservation strategies important.

During the monsoon season (June to September), rainfall projections under both RCP 4.5 and RCP 8.5 show only small differences compared to historical data. In June, rainfall slightly decreases under RCP 4.5 (382.42 mm) but remains nearly the same as historical values under RCP 8.5 (384.22 mm). In July, rainfall under RCP 4.5 (140.27 mm) is slightly lower than historical rainfall, while RCP 8.5 (143.13 mm) shows a small increase. August shows a slight drop under both scenarios compared to the past, but the difference is minimal. September remains stable, with both RCP 4.5 and RCP 8.5 showing rainfall close to historical values (around 134 mm). Overall, monsoon rainfall is expected to stay relatively stable, with only minor monthly shifts under future climate scenarios. Looking at the annual trend, the total rainfall from January to December under both RCP 4.5 and RCP 8.5 remains mostly consistent with the 1980–2023 average. However, some months like December show noticeable increases under both RCP 4.5 (380.26 mm) and RCP 8.5 (381.69 mm), compared to the historical average (376.76 mm). Minor decreases or increases across other months balance out over the year. These projections suggest that overall annual rainfall may remain steady, but monthly variations could impact water availability, especially during critical agricultural months. Continuous monitoring and adaptive water management will be important to handle these future changes.

9.1 Standardized Precipitation Index (SPI) Based on Climate Projection

The SPI drought index was analyzed using a 3-month timescale, as it effectively reflects short-term moisture conditions and seasonal rainfall trends. This duration is especially relevant for agriculture, where planting cycles typically occur every three months . The use of 3-month SPI helps in assessing drought risks during critical crop growth periods. The most severe drought values observed under different RCP scenarios are presented in Table 5**.** Based on the SPI graphs, droughts of varying intensity are expected throughout the future under the RCP 4.5 scenario. From 2024 to 2050, notable drought years include 2024, 2029, 2035, 2044, 2046, and 2050, with 2044 showing severe drought. Some years like 2027 and 2041 show wet conditions. Between 2051 and 2100, droughts continue to appear regularly, with severe dry years observed in 2052, 2056, 2071, 2091, and 2100. Although some wet years occur, the overall trend shows frequent moderate to severe droughts, highlighting the need for adaptive water and agricultural management**.**

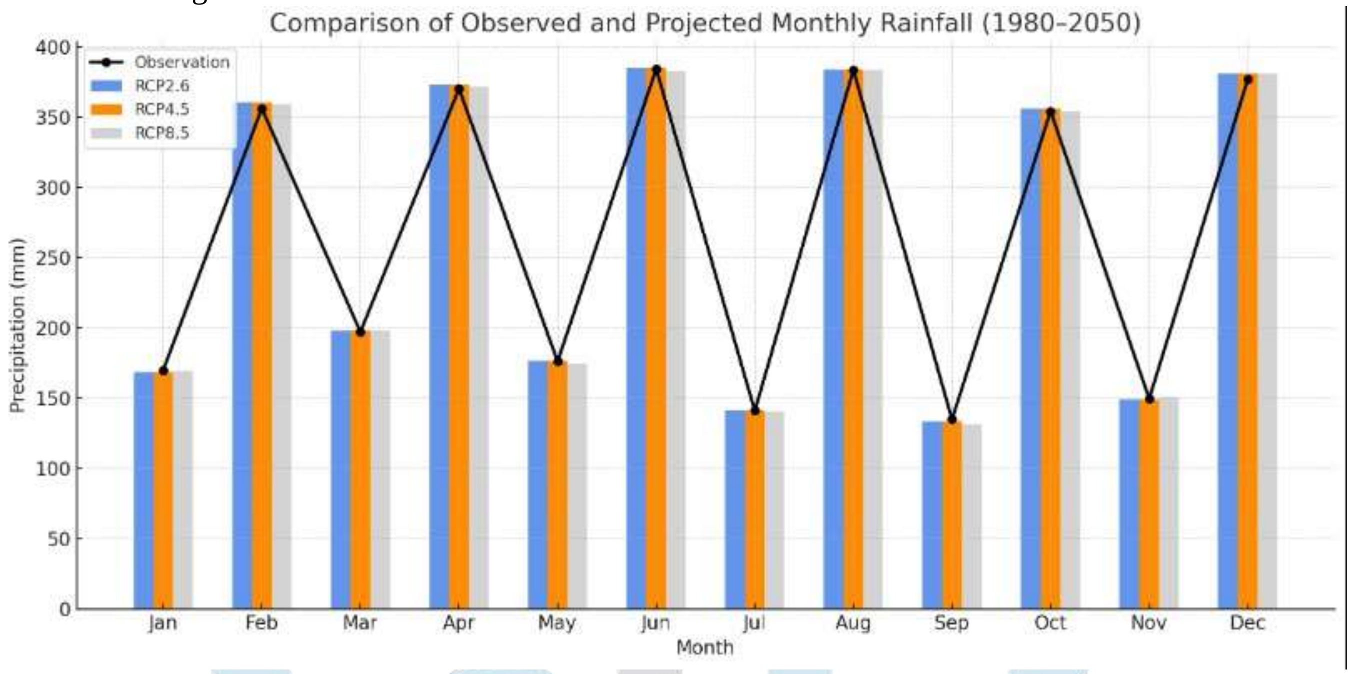

Figure 2. Comparasion between Observed (1980-2023) and projected rainfall for year (2024-2050)

Table 4. Average annual precipitation prediction based on RCP4.5, and RCP8.5 (mm)

Months	Rainfall 1980 – 2023	Rainfall RCP 4.5 2024-2050	Rainfall RCP 8.5 2024 2050	Rainfall RCP 4.5 2050-2100	Rainfall RCP 8.5 2050-20100
Jan	169.919	168.406	169.346	167.432	167.794
Feb	356.086	360.314	359.214	358.034	358.197
Mar	197.05	198.102	197.902	197.796	196.738
Apr	370.054	372.831	371.731	370.212	371.61
May	176.143	176.438	174.38	175.554	173.812
Jun	384.194	384.796	382.466	382.418	384.22
Jul	140.97		140.13	140.274	
Aug	383.349	383.822	383.522	382.385	381.068
Sep	134.899	133.458	131.258	134.488	134.049
Oct	354.069	355.907	354.487	354.421	354.032
Nov	149.58	149.156	150.756	149.494	150.502
Dec	376.757	381.008	380.908	380.258	381.692

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Table 5. SPI Values for 3- Month

Year	SPI for RCP 4.5	Drought/Wetness category	Year	SPI for RCP 4.5	Drought/Wetness category	Year	SPI for RCP 4.5	Drought/Wetness category
2024	-1.04581	modratly dry	**2051**	-0.79325	near normal	**2078**	0.823828	near normal
2025	-0.79325	near normal	**2052**	-0.23557	near normal	**2079**	1.118657	modratly wet
2026	-0.23557	near normal	**2053**	1.427102	modratly wet	**2080**	0.888944	near normal
2027	1.427102	modratly wet	**2054**	1.298007	modratly wet	**2081**	-1.05764	modratly dry
2028	1.298007	modratly wet	**2055**	-0.27182	near normal	**2082**	-1.05764	modratly dry
2029	-0.38333	near normal	**2056**	-0.57854	near normal	**2083**	-0.77879	near normal
2030	-0.69252	near normal	**2057**	-0.22937	near normal	**2084**	1.504301	very wet
2031	-0.31524	near normal	**2058**	0.975417	near normal	**2085**	1.42827	modratly wet
2032	0.830581	near normal	**2059**	1.086069	modratly wet	**2086**	1.088406	modratly wet
2033	0.969386	near normal	**2060**	-0.0308	near normal	**2087**	-0.25701	near normal
2034	-0.0484	near normal	**2061**	-0.85942	near normal	**2088**	-0.80086	near normal
2035	-0.94488	near normal	**2062**	-0.58344	near normal	**2089**	0.571872	near normal
2036	-0.65519	near normal	**2063**	1.170449	modratly wet	**2090**	1.150345	modratly wet
2037	1.058878	modratly wet	**2064**	1.276627	modratly wet	**2091**	0.985275	near normal
2038	1.164897	modratly wet	**2065**	-0.32714	near normal	**2092**	-0.93844	near normal
2039	-0.44157	near normal	**2066**	-1.14425	modratly dry	**2093**	-0.63045	near normal
2040	-1.2378	modratly dry	**2067**	-1.2009	modratly dry	**2094**	0.569041	near normal

2041	-1.26104	modratly dry	**2068**	1.253404	modratly wet	**2095**	1.208288	modratly wet
2042	1.127434	modratly wet	**2069**	1.282652	modratly wet	**2096**	1.125145	modratly wet
2043	1.162363	modratly wet	**2070**	0.190236	near normal	**2097**	-1.37281	modratly dry
2044	0.015517	near normal	**2071**	-1.23213	modratly dry	**2098**	-1.29962	modratly dry
2045	-1.31791	modratly dry	**2072**	-1.14656	modratly dry	**2099**	-0.01512	near normal
2046	-1.21419	modratly dry	**2073**	0.845629	near normal	**2100**	1.177926	modratly wet
2047	0.731126	near normal	**2074**	1.033292	modratly wet			
2048	0.904159	near normal	**2075**	0.043576	near normal			
2049	-0.10614	near normal	**2076**	-1.0345	modratly dry			
2050	-1.18325	modratly dry	**2077**	-0.95553	near normal			

Based on the SPI drought index values under the RCP 4.5 scenario for Chhatrapati Sambhajinagar district from 2024 to 2100, several key observations were made. The region experienced moderately dry conditions (SPI ≤ -1.0) in multiple years, notably in 2040, 2041, 2045, 2046, 2071, 2072, 2097, and 2098, indicating increased drought risk during these periods. Conversely, the majority of the years, including 2025 to 2035, 2051 to 2056, and 2083 to 2089, fell under the near normal category (SPI between -0.99 and 0.99), reflecting relatively stable rainfall conditions suitable for agriculture. Additionally, moderately to very wet conditions (SPI ≥ 1.0) were observed during 2027–2028, 2037–2038, 2042–2043, 2063–2064, and 2090–2096**,** suggesting periods of above-average precipitation which may benefit crop growth and water resource replenishment. Overall, this analysis highlights fluctuations in drought severity across decades and underscores the need for adaptive planning in agriculture and water management

10. CONCLUSION

This study presents a comprehensive analysis of future drought trends in Chhatrapati Sambhajinagar district by applying the Standardized Precipitation Index (SPI) to precipitation data downscaled using the Statistical Down Scaling Model (SDSM) under RCP 4.5 and RCP 8.5 scenarios, covering the period from 2024 to 2100. The results show that around 23% of the years are likely to experience moderately dry conditions, with a notable concentration of drought years during 2040–2046. In contrast, about 31% of the years are projected to be moderately to very wet, suggesting periodic recovery phases. However, increasing temperature trends—especially under RCP 8.5—are expected to worsen evapotranspiration and reduce soil moisture, leading to more frequent and prolonged hydrological droughts even when rainfall remains near average. Seasonal rainfall distribution also becomes more variable in the latter half of the century, increasing the risks of both droughts and flash floods. These findings emphasize the importance of region-specific climate assessments and demonstrate that the SDSM-SPI combination is a practical and reliable tool for drought monitoring, planning, and policy-making in water-stressed areas like Chhatrapati Sambhajinagar.

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