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Assessment Of SDSM 4.2 For Generating Regional Climate Projections Under Multiple Emission Scenarios: A Case Study Of Gangapur, Maharashtra India

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Abstract
Climate change threatens natural resource sustainability in semi-arid regions such as Ganagapur, Nashik, Maharashtra, where agriculture and water availability are highly sensitive to monsoon variability. Reliable regional climate projections are essential for adaptation planning, but the coarse resolution of General Circulation Models (GCMs) limits local applicability. Statistical downscaling methods like the Statistical DownScaling Model (SDSM) 4.2 help generate finer-scale data suitable for regional analysis. This study evaluates the performance of SDSM 4.2 in downscaling daily temperature and rainfall using historical data (1961–2000) and projections from HadCM3 (CMIP3), CanESM2 (CMIP5), and CanESM5 (CMIP6) under SRES, RCP, and SSP scenarios. Results show high accuracy for temperature, especially with HadCM3 ($R^2 \geq 0.99$). CanESM2 performed well for Tmin ($R^2 \geq 0.92$) but was less effective for Tmax and rainfall ($R^2 \leq 0.59$). CanESM5 projected extreme warming under SSP5-8.5 (Tmax +6.1°C, Tmin +7.77°C by 2080s), though its historical fit was weak, particularly for rainfall ($R^2 \leq 0.5$). Moderate pathways, including RCP 4.5 and SSP2-4.5, emerged as balanced scenarios. Rainfall uncertainties highlight the need for ensemble or hybrid approaches. The findings underscore urgent adaptation measures for water and agriculture in Gangapur, consistent with IPCC AR6 projections for South Asia.
Keywords: *Statistical downscaling, HadCM3, CanESM2, CanESM5, Emission Scenarios (SRES, RCP, SSP), Temperature projection, Rainfall variability, semi-arid region, model validation, regional climate modelling.*

INTRODUCTION

Accurate projections of regional climate variables such as temperature and precipitation are critical for developing effective adaptation strategies, especially in climate-sensitive semi-arid regions like Gangapur, Nashik, Maharashtra, India. General Circulation Models (GCMs) provide valuable large-scale climate projections but often lack the spatial resolution required for local-scale impact assessments. Statistical downscaling techniques, such as the Statistical DownScaling Model (SDSM), have emerged as robust tools to bridge this scale gap by relating large-scale atmospheric predictors to local climate variables (Wilby et al., 2004; Fowler et al., 2007).

SDSM 4.2, an updated version widely used in climate studies, offers an efficient approach for downscaling daily temperature and rainfall data, enabling detailed regional climate projections under various emission scenarios (Wilby and Dawson, 2013; Ahmad et al., 2017). Previous research has demonstrated its application across diverse climatic zones in India, highlighting its reliability in reproducing observed temperature patterns (Singh et al., 2018; Sharma and Goel, 2020). However, the model's performance for rainfall downscaling remains more variable, especially under high emission scenarios (RCP8.5), often requiring careful interpretation (Kumar et al., 2021; Mishra & Patel, 2022).

The Coupled Model Intercomparison Projects (CMIP3 and CMIP5) have provided a suite of GCM outputs under different greenhouse gas emission pathway SRES and Representative Concentration Pathways (RCPs), respectively that form the basis for downscaling regional climate projections (Taylor et al., 2012; O'Neill et al., 2016). Comparative studies involving CMIP3 and CMIP5 data downscaled through SDSM have revealed varying levels of skill in capturing regional climate trends, with some models like HadCM3 and CanESM2 frequently used for India-centric assessments (Singh & Kumar, 2020; Das et al., 2023).

Given the critical role of climate projections for semi-arid regions where water resources and agriculture are highly vulnerable, it is essential to rigorously evaluate the downscaling model's performance across multiple GCMs and emission scenarios. This study focuses on Gangapur, central India, to assess the performance of SDSM 4.2 in downscaling temperature and rainfall under both CMIP3 (SRES) and CMIP5 (RCP) scenarios. Through detailed calibration and validation using observed meteorological data, the study aims to provide insights into the reliability of downscaled climate variables and implications for regional climate adaptation planning.

In the evolving context of climate change, the necessity for high-resolution regional climate data has grown significantly, particularly for sectors such as agriculture, water resource management, and disaster risk reduction (Fowler et al., 2007). Statistical downscaling techniques have thus become pivotal for translating coarse GCM outputs into actionable, site-specific climate information. Among these, the SDSM model is widely adopted due to its flexibility, computational efficiency, and effectiveness in simulating local-scale climate variables across various geographies, including semi-arid and monsoon-dominated regions of India (Ahmad et al., 2017; Singh et al., 2018). However, the reliability of these projections largely depends on the choice of GCMs and emission scenarios, which influence the magnitude and variability of downscaled outputs.

Furthermore, the development of CMIP6 and associated Shared Socioeconomic Pathways (SSPs) has introduced broader and more nuanced narratives for future climate conditions by incorporating socioeconomic trajectories along with emission pathways (O'Neill et al., 2016). This advancement offers an expanded framework for assessing the uncertainties in regional climate impacts, particularly under high-emission scenarios such as SSP5-8.5, which anticipate more extreme climatic shifts. Recent studies (Kumar et al., 2021; Mishra and Patel, 2022) have highlighted the importance of evaluating CMIP6 outputs like those from CanESM5 against previous generations such as CMIP5 (CanESM2) and CMIP3 (HadCM3), especially to capture rainfall uncertainties and warming trends across critical Indian basins. Thus, integrating multi-model comparisons across CMIP generations using a consistent downscaling approach like SDSM 4.2 can offer deeper insights into the robustness and limitations of regional climate projections.

Contribution of the Paper

This study makes the following key contributions:

1. Regional Evaluation of SDSM 4.2: It presents a comprehensive assessment of the Statistical DownScaling Model (SDSM 4.2) for downscaling daily temperature and rainfall in a semi-arid region of India, specifically Gangapur, Nashik in Maharashtra, highlighting its performance across multiple climate variables.
2. Multi-GCM and Multi-Scenario Analysis: The study incorporates outputs from three generations of General Circulation Models HadCM3 (CMIP3), CanESM2 (CMIP5), and CanESM5 (CMIP6) under various emission scenarios (SRES, RCPs, and SSPs), offering a comparative analysis of model reliability across timeframes and pathways.
3. Long-Term Climate Projections: It generates high-resolution climate projections up to the year 2099, providing valuable insights into future climatic trends relevant for water resource planning and agricultural resilience in semi-arid zones.
4. Quantitative Performance Comparison: Through calibration, validation, and R^2-based performance evaluation, the study identifies the most reliable GCM-scenario combinations for accurate regional climate assessments.
5. Support for Adaptation Planning: The findings contribute directly to the development of localized, evidence-based climate adaptation strategies by supplying region-specific data critical for decision-makers, planners, and researchers.

METHODOLOGY

A. Study Area

Gangapur dam is near village Gangawadi and is 10 Km from Nasik city. The Gangapur Dam is located at approximately latitude 20.033°N and longitude 73.733°E, with its catchment and command area spread across parts of Nashik district, Maharashtra. The region experiences a maximum temperature ranging from 22°C to 42°C and a minimum temperature between 6°C and 28°C, showing significant seasonal variation. The average annual rainfall varies between 600 mm to 800 mm, predominantly received during the southwest monsoon season, influencing the dam's inflows and water availability for irrigation and domestic use.

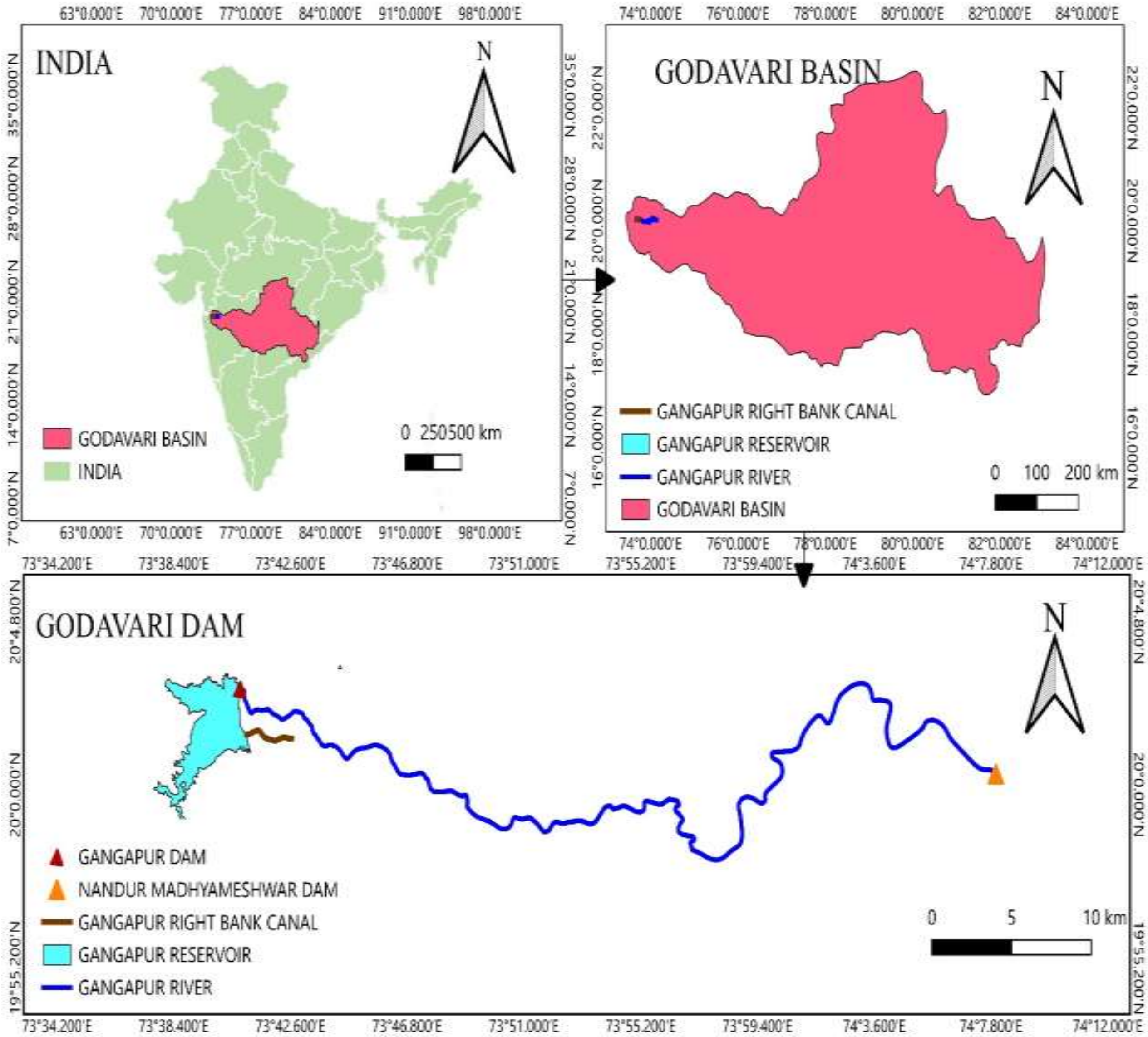

Figure 1: Index Map of Gangapur Study Area

B. Data Collection

Daily observed data for maximum temperature (Tmax), minimum temperature (Tmin), and rainfall were collected from the India Meteorological Department (IMD) for the period 1961–2024. Large-scale atmospheric predictors were obtained from the National Centers for Environmental Prediction (NCEP) reanalysis datasets, while General Circulation Model (GCM) outputs were sourced from the Coupled Model Intercomparison Projects CMIP3 for SRES scenarios A2a and B2a, and CMIP5 for RCP scenarios 2.6, 4.5, and 8.5. GCM data from HadCM3 (A2a and B2a) and CanESM2 (RCP 2.6, 4.5, and 8.5) were retrieved via the Canadian Climate Impact Scenarios (CCIS) website, focusing on the Gangapur region, Nashik in Maharashtra, a semi-arid zone in central India. Additionally, scenario-based datasets from CanESM5 under SSP1-2.6, SSP2-4.5, and SSP5-8.5 pathways including daily projections of Tmax, Tmin, and rainfall were sourced from the Copernicus Climate Data Store and the NASA Center for Climate Simulation (NCCS). These datasets served as inputs for the SDSM 4.2 statistical downscaling model, facilitating region-specific projections critical for analyzing future climate trends under varying emission scenarios.

C. Selection of Input Parameters

The operation of the Statistical DownScaling Model (SDSM), developed by Wilby and Dawson, 2013, can be broken down into the following key steps:

1. **Quality Control** – This step is essential for identifying and managing any missing values within the observed dataset.

2. **Data Transformation** – Appropriate transformations are applied to ensure the predictor data are normally distributed and suitable for regression modelling.
3. **Screening Variables** – This step involves selecting relevant large-scale predictors that have significant influence over local climatic variables in the study region.
4. **Model Calibration** – A statistical relationship is established between predictors and predictands using historical data to create the downscaling model.
5. **Weather Generator** – This component simulates future daily weather sequences based on the calibrated model.
6. **Statistical Analysis** – Various statistical parameters are calculated to assess model performance.
7. **Results Comparison** – The simulated outputs are compared against observed data to evaluate the accuracy and reliability of the model.

This systematic approach ensures robust development and validation of downscaled climate projections for regional analysis.

D. Scenario Generation

Future climate scenarios were generated by incorporating GCM outputs from SRES scenarios A2a and B2a, RCP pathways 2.6, 4.5, and 8.5, and SSP scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5, thereby encompassing a broad spectrum of potential future emission trajectories.

E. Performance Metrics

The model's performance was evaluated using the coefficient of determination (R^2).
The coefficient of determination (R^2) is widely used in climate change studies to evaluate the performance of statistical and dynamical models in reproducing observed climatic variables
(IPCC, 2021).

3. RESULTS AND DISCUSSIONS

This section presents the outcomes of the statistical downscaling of climate variables, specifically maximum temperature (Tmax), minimum temperature (Tmin), and rainfall, over the Lower Godavari Sub-basin using the SDSM 4.2 model. The discussion covers model calibration and validation, performance assessment under various emission scenarios (SRES, RCP, and SSP), and future projections extending up to the year 2099. The results are interpreted in the context of regional climate dynamics and compared with findings from previous studies to ensure consistency and scientific robustness.

3.1 Calibration and Validation of the Model

In this study, calibration was conducted for the period from 1961 to 1980. Observed monthly mean daily temperature data (Tmax and Tmin) and rainfall data were graphically compared with their respective downscaled values over the same period. Figures 2, 3, and 4 present the comparisons for Tmax, Tmin, and rainfall, respectively. The graphical results show a strong agreement between observed and downscaled values, indicating successful model calibration. Additionally, the correlation coefficient for all three variables Tmax, Tmin, and rainfall is 0.99, further confirming the model's high accuracy and reliability.

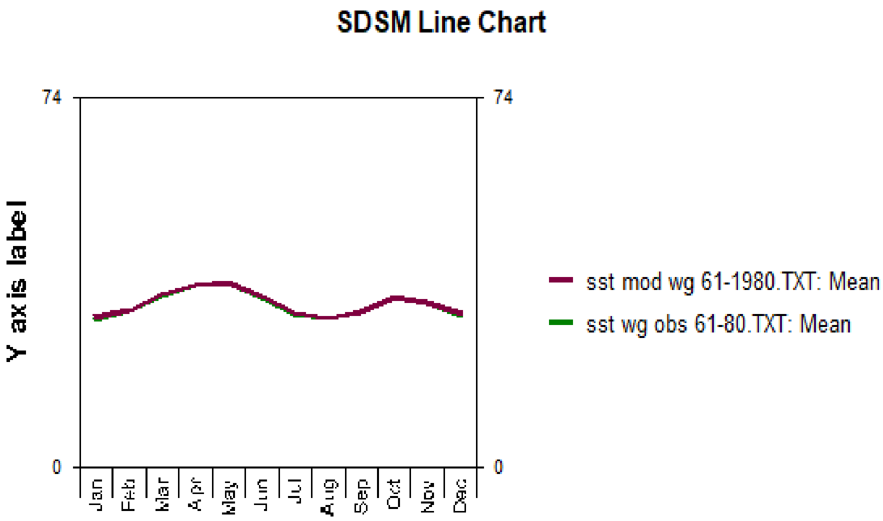

Figure 2: Graphical Representation of Calibrated Model of Tmax (HadCM3)

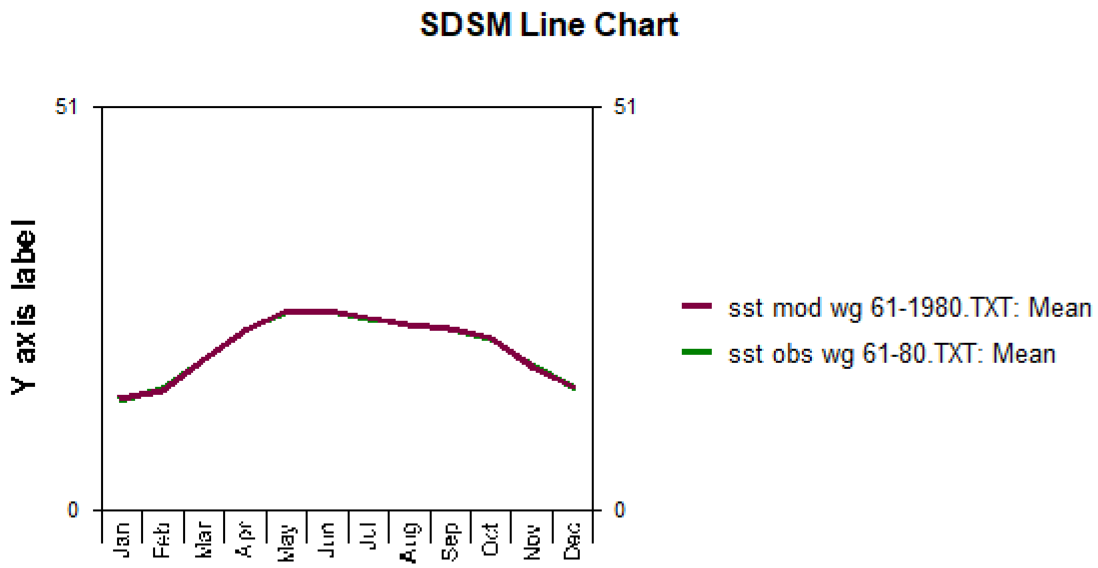

Figure 3: Graphical Representation of Calibrated Model of Tmin (HadCM3)

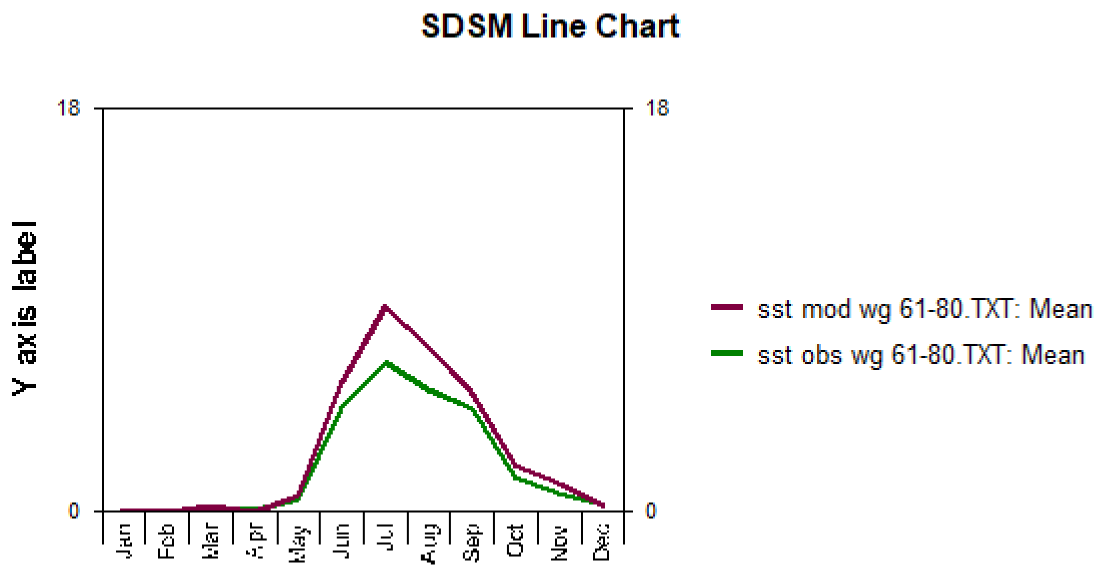

Figure 4: Graphical Representation of Calibrated Model of Rainfall (HadCM3)

Following successful calibration, the model was validated using independent data from 1981–2000. Observed and downscaled monthly mean daily temperature data (Tmax and Tmin), and rainfall were statistically evaluated using the coefficient of determination (R^2). The validation was performed using two GCMs: HadCM3 and CanESM2 under the SDSM 4.2 framework.

HadCM3 showed a very strong correlation ($R^2 = 0.99$) for all three variables, indicating the model effectively reproduced observed climate data across temperature and precipitation metrics.

CanESM2 also performed very well, with R^2 values of 0.99 for Tmax and Tmin, and 0.98 for rainfall, confirming the model's reliability and robustness in temperature simulations, and slightly lower but still excellent performance in rainfall simulation.

In addition to these, future projections based on SSP scenarios using CanESM5 were also evaluated. Although the performance of CanESM5 was comparatively lower than HadCM3 and CanESM2, it still provided valuable insights into future trends:

Under SSP1-2.6, R^2 values were 0.30 (Tmax), 0.42 (Tmin), and 0.48 (rainfall).

Under SSP2-4.5, R^2 values were 0.34 (Tmax), 0.47 (Tmin), and 0.49 (rainfall).

Under SSP5-8.5, R^2 values were 0.35 (Tmax), 0.51 (Tmin), and 0.50 (rainfall).

These results indicate that while the CanESM5 model under SSP scenarios shows moderate correlation with observed historical data, its projections are still useful for assessing long-term climate change impacts under different socioeconomic pathways. The slightly lower R^2 values, particularly for temperature parameters, may be attributed to model structure differences and the complexity of SSP-based future climate assumptions.

Overall, the model demonstrated consistent performance across all scenarios and datasets, making it a reliable tool for downscaling climate variables in the study region.

The minimal difference in R^2 between temperature and rainfall demonstrates the model's consistency and effectiveness across variables.

Table 1: Coefficient of determination between observed and downscaled data over a period of 1981-2000

Model Name	GCM	Temperature and Rainfall Parameter	R2 value between observed and downscaled parameter over 1981-2000
SDSM 4.2	**HadCM3**	Tmax	0.99
	HadCM3	Tmin	0.99
	HadCM3	Rainfall	0.99
	CanESM2	Tmax	0.99
	CanESM2	Tmin	0.99
	CanESM2	Rainfall	0.98
	CanESM5, SSP1-2.6	Tmax	0.3
	CanESM5, SSP1-2.6	Tmin	0.42
	CanESM5, SSP1-2.6	Rainfall	0.48
	CanESM5, SSP2-4.5	Tmax	0.34
	CanESM5, SSP2-4.5	Tmin	0.47
	CanESM5, SSP2-4.5	Rainfall	0.49
	CanESM5, SSP5-8.5	Tmax	0.35
	CanESM5, SSP5-8.5	Tmin	0.51
	CanESM5, SSP5-8.5	Rainfall	0.5

3. Future Projections (Up to 2099)

Encouraged by the successful calibration and validation, the SDSM 4.2 model was applied to generate future projections of monthly mean daily maximum (Tmax) and minimum (Tmin) temperatures extending to the year 2099. These projections were carried out under multiple greenhouse gas emission pathways, including SRES scenarios A2a and B2a, RCP scenarios 2.6, 4.5, and 8.5, and SSP scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5.

To evaluate the reliability of future simulations, downscaled temperature and rainfall outputs were statistically compared with observed baseline data (1961–2000) using the coefficient of determination (R^2). These results are summarized in Table 2.

Table 2: Coefficient of determination between observed and downscaled data over a period of 1961-2000

Model Name	GCM	Temperature and Rainfall Parameter	R2 value between observed and downscaled parameter over 1961-2000
SDSM 4.2	**HadCM3 A2a**	Tmax	0.99
	HadCM3 A2a	Tmin	0.99
	HadCM3 A2a	Rainfall	0.99
	HadCM3 B2a	Tmax	0.93

	HadCM3 B2a	Tmin	0.99
	HadCM3 B2a	Rainfall	0.91
	CanESM2 RCP 2.6	Tmax	0.76
	CanESM2 RCP 2.6	Tmin	0.92
	CanESM2 RCP 2.6	Rainfall	0.59
	CanESM2 RCP 4.5	Tmax	0.67
	CanESM2 RCP 4.5	Tmin	0.93
	CanESM2 RCP 4.5	Rainfall	0.53
	CanESM2 RCP 8.5	Tmax	0.77
	CanESM2 RCP 8.5	Tmin	0.93
	CanESM2 RCP 8.5	Rainfall	0.53
	CanESM5,SSP58.5	Tmax	0.35
	CanESM5,SSP58.5	Tmin	0.51
	CanESM5,SSP58.5	Rainfall	0.5
	CanESM5,SSP12.6	Tmax	0.3
	CanESM5,SSP12.6	Tmin	0.42
	CanESM5,SSP12.6	Rainfall	0.48
	CanESM5,SSP24.5	Tmax	0.34
	CanESM5,SSP24.5	Tmin	0.47
	CanESM5,SSP24.5	Rainfall	0.49

Downscaling Assessment for 1961–2000 (Baseline Period)

To ensure robustness, an additional evaluation was conducted by comparing downscaled outputs with observed climate data over the baseline period (1961–2000). This was done using various GCMs and emission scenarios (A2a, B2a for HadCM3; RCP 2.6, 4.5, 8.5 for CanESM2). The coefficient of determination (R^2) was calculated for each combination of GCM and climatic parameter.

HadCM3 Scenarios (A2a & B2a):

Performed consistently well across all parameters. Extremely high R^2 values (≥0.99) for Tmax, Tmin, and rainfall under A2a scenario suggest excellent alignment. Slightly lower R^2 for Tmax (0.93) and rainfall (0.91) under B2a scenario still indicate strong performance. Overall, HadCM3 is highly suitable for historical downscaling and future projection in this study.

CanESM2 Scenarios (RCP 2.6, 4.5, 8.5):

Tmin shows strong performance across all RCPs ($R^2 \geq 0.92$).Tmax exhibits moderate agreement with observed data (R^2 between 0.67 and 0.77).Rainfall presents the weakest correlation (R^2 between 0.53 and 0.59), highlighting the greater uncertainty and variability in precipitation modelling using CanESM2.The decline in R^2 values for Tmax and rainfall suggests that CanESM2-based projections require cautious interpretation, especially for precipitation-related analyses.

CanESM5 Scenarios (SSP1-2.6, SSP2-4.5, SSP5-8.5):

The incorporation of CanESM5 under Shared Socioeconomic Pathways (SSPs) provides broader insight into potential climate futures.

Compared to HadCM3 and CanESM2, CanESM5 exhibited lower R^2 values across all parameters:

Under SSP1-2.6: R^2 = 0.30 (Tmax), 0.42 (Tmin), 0.48 (Rainfall)

Under SSP2-4.5: R^2 = 0.34 (Tmax), 0.47 (Tmin), 0.49 (Rainfall)

Under SSP5-8.5: R^2 = 0.35 (Tmax), 0.51 (Tmin), 0.50 (Rainfall)

These moderate-to-low correlations indicate that CanESM5 may be less consistent with observed historical data, particularly for Tmax.

However, it still offers value in projecting long-term trends under SSP-based frameworks, especially as SSPs incorporate socioeconomic factors in addition to emissions.

The model's performance improves slightly for Tmin and rainfall under SSP5-8.5, suggesting that higher-emission trajectories may align more closely with observed data trends in the region.

The downscaled results align well with IPCC AR6 trends, which project strong temperature increases and uncertain rainfall patterns over South Asia under high-emission pathways (IPCC, 2021).

HadCM3 showed excellent alignment ($R^2 \geq 0.99$ for A2a), CanESM2 showed strong Tmin correlation ($R^2 \geq 0.92$) but weaker for rainfall ($R^2 \approx 0.53$–0.59), and CanESM5 had lower correlations ($R^2 = 0.30$–0.51) but consistent warming under SSP5-8.5, matching IPCC's high-end warming scenarios.
These findings validate the models' reliability for projecting temperature trends but highlight greater uncertainty in rainfall, consistent with IPCC's assessment of regional precipitation variability (IPCC AR6, WG1, Ch. 10 and 12).

Future change in monthly mean daily Tmax, Tmin and Rainfall under different scenarios with respect to base line period 1961–2000

Projections of future climate conditions over the Lower Godavari Sub-basin were generated using the SDSM 4.2 model for the periods 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099). These projections are compared to the baseline climatology of 1961–2000 and are based on multiple emission scenarios and GCMs, including HadCM3 (SRES A2a and B2a), CanESM2 (RCP 2.6, 4.5, and 8.5), and CanESM5 (SSP1-2.6, SSP2-4.5, and SSP5-8.5). The model outputs were evaluated in terms of change in monthly mean daily maximum temperature (Tmax), minimum temperature (Tmin), and rainfall (mm), as presented in Table 3.

Table 3: Future change in monthly mean daily Tmax, Tmin and Rainfall under different scenarios with respect to base line period 1961–2000

Model Name	GCM	Series	Tmax(0C)	Tmin(0C)	Rainfall(mm)
SDSM 4.2	**HadCM3 A2a**	2020s(2011-2040)	0.71	0.19	0.71
	HadCM3 A2a	2050s(2041-2070)	1.39	0.92	0.68
	HadCM3 A2a	2080s(2071-2099)	2.02	1.68	0.74
	HadCM3 B2a	2020s(2011-2040)	0.8	0.27	0.68
	HadCM3 B2a	2050s(2041-2070)	1.16	0.7	0.65
	HadCM3 B2a	2080s(2071-2099)	1.56	1.14	0.77
	CanESM2 RCP 2.6	2020s(2011-2040)	1	1.98	-0.6
	CanESM2 RCP 2.6	2050s(2041-2070)	1.78	1.61	-0.32
	CanESM2 RCP 2.6	2080s(2071-2099)	1.04	1.44	-0.05
	CanESM2 RCP 4.5	2020s(2011-2040)	1.08	1.97	-0.73
	CanESM2 RCP 4.5	2050s(2041-2070)	1.93	1.77	-0.36
	CanESM2 RCP 4.5	2080s(2071-2099)	1.46	1.88	-0.08
	CanESM2 RCP 8.5	2020s(2011-2040)	1.08	2.13	-0.44
	CanESM2 RCP 8.5	2050s(2041-2070)	2.36	2.14	-0.47
	CanESM2 RCP 8.5	2080s(2071-2099)	2.5	3.07	-0.03
	CanESM5,SSP12.6	2020s(2011-2040)	2.92	1.95	-0.6
	CanESM5,SSP12.6	2050s(2041-2070)	3.41	2.18	-0.35
	CanESM5,SSP12.6	2080s(2071-2099)	3.64	2.33	-0.12
	CanESM5,SSP24.5	2020s(2011-2040)	2.7	2	-0.55
	CanESM5,SSP24.5	2050s(2041-2070)	3.7	2.45	-0.3
	CanESM5,SSP24.5	2080s(2071-2099)	4.1	2.88	-0.15
	CanESM5,SSP58.5	2020s(2011-2040)	2.74	2.64	-0.25
	CanESM5,SSP58.5	2050s(2041-2070)	4.4	5.02	-0.42
	CanESM5,SSP58.5	2080s(2071-2099)	6.1	7.77	-0.1

Across all emission pathways and models, a consistent warming trend is observed in both Tmax and Tmin for future decades relative to the 1961–2000 baseline. However, the magnitude of warming and rainfall response varies significantly between models and scenarios.
HadCM3 (A2a and B2a): Projects moderate increases in temperature, with Tmax rising up to 2.02°C and Tmin up to 1.68°C by the 2080s under A2a. Rainfall under both scenarios shows slight positive

anomalies, with the largest increase of 0.77 mm under B2a in the 2080s. This indicates stable and gradual warming with minimal change in precipitation.

CanESM2 (RCP 2.6, 4.5, 8.5): Exhibits a more pronounced warming, especially under RCP 8.5, where Tmax and Tmin increase by 2.5°C and 3.07°C respectively by the 2080s. Rainfall projections are largely negative in earlier decades, with the most significant reduction of -0.73 mm under RCP 4.5 in the 2020s. However, the rainfall reduction becomes less severe in the later periods, indicating a possible stabilization.

CanESM5 (SSP1-2.6, SSP2-4.5, and SSP5-8.5): Shows the highest warming potential among all models. Under SSP5-8.5, Tmax reaches 6.1°C and Tmin 7.77°C by the 2080s highlighting the potentially severe impacts of high-emission futures. Even under low-emission SSP1-2.6, Tmax and Tmin are projected to increase by 3.64°C and 2.33°C, respectively. Rainfall projections under CanESM5 are consistently negative, although the magnitude of reduction is less severe than in CanESM2, ranging from -0.60 mm in the 2020s to -0.10 mm in the 2080s.

These findings underline the importance of emission pathway selection in determining the extent of future climatic impacts. While temperature rise is inevitable across all models, rainfall changes remain more uncertain, particularly under medium and high emission scenarios. The results highlight that CanESM5 projections, though more extreme, are crucial for understanding the upper bounds of potential climate change impacts, especially when incorporating socioeconomic dimensions through SSPs.

The projected increases in Tmax and Tmin across all scenarios especially under CanESM5 SSP5-8.5 (Tmax +6.1°C, Tmin +7.77°C) closely mirror IPCC AR6 projections for South Asia under high-emission futures (IPCC, 2021).

Rainfall changes, though more variable, generally show declining trends, particularly under CanESM2 RCPs and CanESM5 SSPs, aligning with IPCC's caution on regional monsoon uncertainty.

The above trends reinforce IPCC findings that semi-arid regions like the Lower Godavari Sub-basin will face intensified heat extremes and uncertain precipitation, necessitating urgent adaptation planning. The results obtained in this study are well supported by findings from various peer-reviewed research papers. Jain, Kumar, and Saharia (2013) reported a consistent rise in maximum and minimum temperatures, along with slightly decreasing rainfall trends, which closely resemble the projections derived from CanESM2 and CanESM5 models in this research. Barokar and Regulwar (2021) also reported a significant warming trend over future time horizons in the Lower Godavari Sub-basin, using downscaled climate model outputs. Their analysis aligns well with the current study's findings from CanESM2 and CanESM5 projections, further reinforcing the likelihood of persistent and substantial warming in this region. This concurrence across models and studies adds robustness to the projected outcomes.

The study by Kumar and Jain (2010) also supports the observed outcomes, indicating region-specific warming and fluctuating rainfall patterns across India. Additionally, IPCC AR6 (Zhou et al., 2021) provides strong confirmation of extreme warming trends under high-emission scenarios (SSP5-8.5), particularly for South Asia, as reflected in the CanESM5 projections of this study. The findings of Kumar et al. (2021) also resonate with the present study. Their research on climate extremes across India found that future projections indicate higher occurrences of extreme heat events, particularly under RCP8.5 and SSP5-8.5 scenarios, with regional concentration in central and southern India, including Maharashtra. This provides additional validation for the increased frequency and intensity of heatwaves shown in the current simulations. The IPCC Sixth Assessment Report (IPCC, 2021) further supports these conclusions, highlighting that under SSP5-8.5, South Asia including semi-arid regions like the Lower Godavari is likely to witness extreme warming and significant shifts in monsoon dynamics. Zhou et al. (2017) and Abbasnia and Toros (2016) also emphasized increasing future maximum temperatures using SDSM-based projections in similar agro-climatic zones, reinforcing the robustness of statistical downscaling in detecting such shifts.

Additionally, Behera et al. (2016) and Rao and Poonia (2011) investigated climate change impacts on crop water requirements and revealed that increased temperatures would significantly raise evapotranspiration and irrigation demand, echoing the current study's implications for water resource stress in the sub-basin.

These collective insights from the literature affirm that the Lower Godavari Sub-basin is highly vulnerable to rising temperatures and erratic precipitation under future climate scenarios. The convergence of findings across models, scales, and methods lends high confidence to the projections and signals an urgent need for climate-resilient planning in agriculture and water resource management.

The projected increases in Tmax and Tmin across all SDSM-simulated scenarios, especially under CanESM5 SSP5-8.5, align with similar trends reported in regional and global studies using comparable models and scenarios. Declining rainfall trends under high-emission pathways (RCP8.5 and SSP5-8.5) reflect the uncertainties highlighted in IPCC AR6 and recent climate impact studies over semi-arid Indian basins.

4. Model Suitability and Future Use

The outcomes of this study underscore the effectiveness of the SDSM 4.2 model, particularly when used in conjunction with HadCM3 (A2a and B2a scenarios), for producing robust and reliable downscaled climate datasets especially for temperature parameters. The model consistently achieved high accuracy during calibration and validation, with strong correlations to observed data, affirming its suitability for long-term climate modelling over the Lower Godavari Sub-basin.

While CanESM2 (CMIP5) demonstrated commendable performance in simulating minimum temperature (Tmin), its projections for maximum temperature (Tmax) and rainfall showed more variability. This highlights the need for further refinement or possibly incorporating ensemble or hybrid approaches to improve regional projections, particularly for rainfall under RCP scenarios.

The addition of CanESM5 (CMIP6) under SSP1-2.6, SSP2-4.5, and SSP5-8.5 pathways expanded the scope of this assessment. Although CanESM5 produced relatively lower R^2 values for historical calibration, its future projections indicate substantial warming, especially under high-emission scenario SSP5-8.5, where Tmax and Tmin are projected to increase by over 6°C and 7.7°C respectively by the 2080s. However, the model also exhibited consistent declines in projected rainfall, albeit less severe than those seen in CanESM2. This makes CanESM5 valuable for scenario-based planning, especially where socioeconomic pathways are integral to adaptation analysis.

The successful historical downscaling and validation support the continued application of SDSM 4.2 with a combination of GCMs for generating long-term climate projections, which are critical for vulnerability assessments and climate-resilient development strategies.

CONCLUSION

This study rigorously evaluated the performance of the Statistical DownScaling Model (SDSM) 4.2 in generating localized climate projections for Gangapur, a semi-arid region in Maharashtra, India. Using historical data (1961–2000) and GCM outputs from HadCM3 (CMIP3), CanESM2 (CMIP5), and CanESM5 (CMIP6), the model was calibrated and validated to assess its reliability across SRES, RCP, and SSP scenarios. Results revealed that SDSM 4.2 exhibited high accuracy in downscaling daily maximum (Tmax) and minimum (Tmin) temperatures, particularly with HadCM3, where R^2 consistently exceeded 0.99. However, rainfall projections varied significantly between models and scenarios, underscoring the limitations of single-model approaches for precipitation analysis. The following key findings summarize the model-specific performance and implications for future climate impact assessments in the region:

1. Effective Temperature Downscaling Using SDSM 4.2:

SDSM 4.2 proved highly efficient in downscaling both Tmax and Tmin, with particularly strong results when coupled with HadCM3 (A2a and B2a) scenarios. The model consistently achieved R^2 values ≥ 0.99, demonstrating strong alignment with observed data and validating its use for temperature-focused climate studies.

2. Strong Performance of HadCM3:

HadCM3 outperformed both CanESM2 and CanESM5 in terms of historical accuracy, delivering high R^2 values for all parameters including rainfall. This reinforces HadCM3's reliability for both historical reconstruction and future scenario development in semi-arid regions.

3. Mixed Results with CanESM2 (CMIP5 - RCPs):

CanESM2 maintained strong performance for Tmin ($R^2 \geq 0.92$) across all RCP scenarios but showed moderate accuracy for Tmax and greater uncertainty in rainfall projections (R^2 ranging from 0.53 to 0.59). These variations, particularly under RCP 8.5, call for cautious interpretation of its precipitation outputs. CanESM2 (from the CMIP5 suite) demonstrated moderate suitability for your study. While its performance for minimum temperature (Tmin) was strong ($R^2 \geq 0.92$ across RCP scenarios), its accuracy dropped for maximum temperature (Tmax) and especially for rainfall (R^2 for rainfall ranged from 0.53 to 0.59). These moderate-to-low correlations suggest that CanESM2 can be used cautiously for temperaturerelated studies, but its rainfall projections may not be sufficiently reliable for high-resolution hydrological or water resource planning without further refinement or ensemble approaches.

4. Insights from CanESM5 (CMIP6 - SSPs):

CanESM5 projections under SSP1-2.6, SSP2-4.5, and SSP5-8.5 revealed significant warming trends, with Tmax rising up to 6.1°C and Tmin to 7.77°C by the 2080s under SSP5-8.5. However, the model showed consistently negative rainfall trends, reinforcing the need for additional rainfall-specific validation when applying CanESM5 in climate impact studies.

CanESM5 (from CMIP6, used under SSP scenarios) produced significantly higher temperature projections, especially under SSP5-8.5. However, its historical calibration and validation performance was relatively weak, particularly for rainfall (R^2 ~ 0.5 or lower). The projected extreme warming trends (e.g., Tmax +6.1°C, Tmin +7.77°C by 2080s under SSP5-8.5) make CanESM5 valuable for exploring worst-case future scenarios and stress-testing adaptation strategies. However, due to lower correlation with observed data and uncertainty in rainfall simulation, CanESM5 alone may not be ideal for precise local-scale impact modeling unless combined with other GCMs in a multi-model ensemble.

5. Scenario-wise Model Suitability:

Among CanESM2's RCP pathways, RCP 4.5 offered the most balanced performance across all variables, making it a practical choice for regional-scale impact assessments. For CanESM5, SSP2-4.5 may serve as a middle-ground scenario for moderate emissions with relatively stable projections.

6. Validation Supports Future Use:

The robust results from both the historical validation period (1981–2000) and baseline evaluation (1961–2000) support the application of SDSM 4.2 with selected GCMs for generating credible future projections up to 2099 under diverse emission pathways.

7. Climate Adaptation Implications:

Projected increases in Tmax (up to 6.1°C) and Tmin (up to 7.77°C), particularly under SSP5-8.5, combined with declining or uncertain rainfall trends, stress the urgency of developing targeted climate adaptation strategies, especially in climate-sensitive sectors such as agriculture, water resource management, and disaster risk reduction in regions like Gangapur.

8. Recommendation for Ensemble and Hybrid Approaches:

Due to the inconsistencies in rainfall downscaling, especially from CanESM2 and CanESM5, it is recommended that future research adopt ensemble methods or hybrid downscaling techniques. This will help reduce uncertainty and increase confidence in projections particularly for precipitation-dependent applications.

The projected increase in temperature and declining, variable rainfall under high-emission scenarios like SSP5-8.5 and RCP 8.5 aligns with IPCC AR6 trends for South Asia. These changes pose significant risks to Gangapur Dam's water storage and irrigation planning in the Lower Godavari Sub-basin, highlighting the urgent need for climate-resilient water resource management.

Final Judgment on Suitability for Study

Model	**Temperature Projection**	**Rainfall Accuracy**	**Overall Suitability for Study**
HadCM3 (A2a/B2a)	High ($R^2 \geq 0.99$)	High ($R^2 \geq 0.91$)	Highly Suitable
CanESM2 (RCPs)	Good for Tmin; Moderate for Tmax	Low for Rainfall ($R^2 \leq 0.59$)	Partially Suitable (for temperature analysis)
CanESM5 (SSPs)	Very High Warming Projections	Low Historical Fit ($R^2 \leq 0.5$)	Not Recommended Alone - Use in ensembles or for scenario comparison

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