Plant Archives **Vol. 25, Special Issue (ICTPAIRS-JAU, Junagadh) Jan. 2025 pp. 157-172**

e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org

DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2025.v25.SP.ICTPAIRS-027

TEMPERATURE DYNAMICS IN JUNAGADH, GUJARAT UNDER CLIMATE CHANGE: INSIGHTS FROM REGIONAL CLIMATE MODELS

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ABSTRACT

This research demonstrates the effectiveness of Gaussian distribution method in aligning Regional Climate Model (RCM) outputs with historical temperature data from India Meteorological Department (IMD), Pune. The study focuses on applying bias correction, primarily on mean and coefficient of variation statistics, for daily maximum and minimum temperatures using the RCA4 RCM for Junagadh district of Saurashtra region, Gujarat. For the period 1951-2005, raw RCM data consistently underestimated the observed IMD temperatures. Post-correction, the R^2 values improved significantly—from 0.917 to 1 for maximum temperatures and from 0.879 to 1 for minimum temperatures during calibration period, and from 0.92 to 0.99 and 0.875 to 0.999, respectively, during validation period. Similarly, the alignment of the coefficient of variation improved, with R^2 values increasing from 0.868 to 1 and 0.661 to 1 for calibration, and from 0.814 to 0.978 and 0.597 to 0.995 for validation. Despite these improvements, skewness remained negative in most months, and positive kurtosis persisted in certain months, indicating areas for further refinement. For future period (2006-2100), under RCP 2.6, bias-corrected mean temperatures ranged from 29.50°C to 31.85°C for maximum temperatures and from 13.71°C to 27.26°C for minimum temperatures, compared to raw RCM projections of 14.65°C to 15.64°C and 2.03°C to 24.15°C, respectively. Under RCP 4.5 and RCP 8.5, similar trends were observed, with mean temperatures, standard deviation, and CV showing consistent patterns. There was positive skewness in winter and negative skewness in summer, along with positive kurtosis in both colder and warmer months. The study reveals, bias correction significantly improved the accuracy of the RCA4 RCM in simulating daily maximum and minimum temperatures during both the calibration (1951-1995) and validation (1996-2005) periods, aligning the corrected data closely with IMD observations. Projections under various RCPs indicate a warming trend with continued skewness and kurtosis, suggesting a potential for more extreme temperature events in future.

***Key words*: ** Bias Correction, Gaussian distribution Method, Regional Climate Model (RCM), Temperature Variability.

Introduction

Climate change refers to alterations in expected weather patterns. The IPCC's fourth assessment report states that "warming of climate system is evident" based on observed increases in global air and ocean temperatures, widespread snow and ice melting, and rising sea levels. Climate may change in different ways, over different time scales and at different geographical scales. Since climate is changing, scientists have grown interest in global warming, due to mankind's impact on climate system, through the enhancement of natural greenhouse effect. Carbon dioxide concentration scenarios project an increase in CO_2 from 372 ppm to between 500 and 950 ppm by the year 2100, and the potential effect on temperature, humidity, and plant responses to environmental factors are complex and becoming topic for our concern. For 2100, mean daily temperature is projected to be increase in range from 1.2^{o}C to 6.8^{o}C depending on greenhouse gas emissions (Snyder *et al.*, 2013). On the bad side, higher temperatures are often associated with increases in evapotranspiration (ET), heat stress, and pest infestations. Climate change study for 21st century was carried out by Kohli *et al.,* (2006) and it revealed that PRECIS simulated marked increase in temperature towards the end of the 21st century for India.

Lunagaria *et al.,* (2012) have reported that there is a large scale of uncertainty in trends of different climatic parameters in the state of Gujarat. GCMs are widely used for projection of future climatic data (Ahmed *et al.,* 2019 and Sonali and Kumar 2020). General Circulation Models (GCMs) are often affected by uncertainties mainly due to low resolutions (approximately 100-250 Km) that inevitably lack regional scale details (Randall *et al.,* 2007). Several downscaling methods have been developed to mutate the large-scale information of GCMs to finer scales (25-50 Km), resulting in RCMs (Teutschbein and Seibert, 2012; Maraun, 2016). The Regional Climate Models (RCM) is also known as a limited area model. It is the best-known toll for the downscaling of climatic data from the output of a GCM and it makes the prediction for a particular region. It has a higher spatial resolution and provides more reliable results on a regional scale as compared to GCMs (Chen *et al.,* 2013).

The advantages of RCM over GCM are: RCMs have higher spatial resolution (10-50 km) compared to GCMs (100-250 km), enabling better representation of local topography and regional features. This higher resolution allows RCMs to more accurately simulate local climate processes and extreme weather events (Hulme *et al.,* 2001). RCMs also provide finer temporal resolution, improving short-term climate analysis. They are excellent for dynamical downscaling, taking broad-scale GCM outputs and producing detailed regional climate projections. RCMs can be customized to focus on specific regions, using region-specific parameterizations for greater accuracy. This makes RCMs invaluable for localized climate projections, impact studies, and informing regional policy and adaptation strategies.

Bhatu and Rank (2017) used RCM data to simulate climate for Jamnagar, revealing an significant warming trends in both daily minimum and maximum temperatures from 1961 to 2100. The study highlighted a stronger warming trend in daily minimum temperatures, underscoring regional climate shifts projected by RCMs.

Rank *et al.,* (2022) demonstrated that Gaussian distribution mapping effectively corrected the mean and coefficient of variation (Cv) in RCA4 RCM-simulated temperatures for Junagadh, Gujarat, achieving a strong goodness of fit in both calibration and validation periods. The approach maintained original skewness (Cs) and kurtosis (Ck) values, making it a robust method for RCM temperature bias correction in future scenarios.

Several authors have discussed about the limitations of RCM (Christensen *et al.,*, 1998; Varis *et al.,*, 2004; Deque, 2007; Teutschbein and Seibert, 2012), in terms of incorrectly yield extreme temperatures. For this reason, several bias-correction (BC) methods were developed to overcome the significant bias in RCMs, adapting simulated data to local observations in terms of mean and variance (scaling methods) or distribution probabilities. There are various types of BC methods such as the difference method (DM), linear scaling (LS) or statistical methods (Lenderink *et al.,* 2007), quantile mapping (QM) (Buonomo *et al.,* 2007), and probability density functions (Piani *et al.,* 2010) to correct the biases present in GCM-RCM outputs for various impact studies (Enayati *et al.,* 2021).

CORDEX (Coordinated Regional Climate Downscaling Experiment) https://cordex.org data often contain biases, necessitating correction for accurate future climate simulations. This study analyses temperature projections from RCA4 RCM under RCP 2.6, RCP 4.5, and RCP 8.5 scenarios, comparing future data (post-2006) against historical values (1961-2005). The RCPs reflect varying greenhouse gas emission pathways, with RCP 8.5 being the most pessimistic, RCP 4.5 showing stabilization by 2100, and RCP 2.6 representing significant emission reductions. With rising extreme climate events, evaluating bias correction methods, such as distribution mapping, is essential to improve model reliability and understand climate change impacts.

Material and Methods

Study Area

The study area is Junagadh, a city in Gujarat. Junagadh (21.5222° N, 70.4579° E), is located at the base of the Girnar hills. It has a tropical savanna climate, featuring hot summers (March to June), a monsoon season (July to September), and mild winters (October to February). Average temperatures range from about 20°C in winter to 40°C in summer.

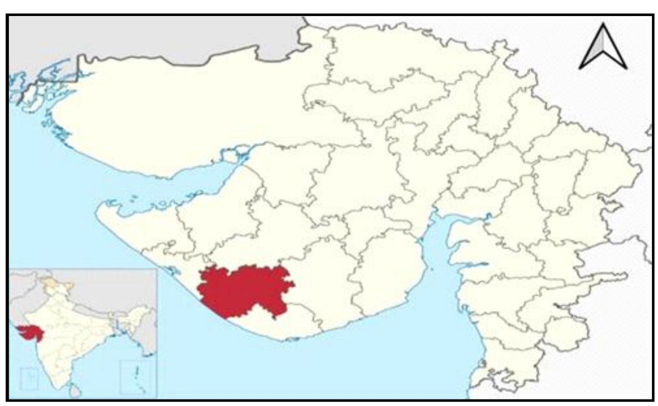

Fig. 1: Study area map showing Junagadh District.

Data Collection

Gridded data of temperature prepared by Indian Meteorological Department (IMD) for the Indian regions was used in this research work. Daily Gridded data of daily maximum & minimum temperature data 0.5 × 0.5 degree was collected. The data from IMD is available in Network Common Data Format (NetCDF). The add in called netcd4excel can be downloaded and installed to access the data in NetCDF. The in Network Common Data Format (NetCDF) data was then converted to Excel format in Arc-GIS.

Climatic data was used to study the future prediction of climate change. Regional climate models are best models to understand and project the changes in climate. Climate change data was downloaded from CORDEX-South Asia Multi Models Output site (http://cccr.tropmet.res.in/cordex/files/downloads.jsp). The CORDEX data given by Centre for Climate Change Research, Indian Institute of Tropical Meteorology, Pune. The CORDEX regional climate model (RCM) simulations for the European domain (EURO-CORDEX) are conducted at two different spatial resolutions, the general CORDEX resolution of 0.44 degree (EUR-44, ~50 km) and additionally the finer resolution of 0.11 degree (EUR-11, ~12.5km). These include projected changes in daily Temperature (°C) using Representative Concentration Pathway (RCP) 2.6 Scenario, 4.5 scenario and 8.5 scenario, for historical period as well as for future period.

Historical records of daily maximum and minimum temperature of 55 years (1951-2005) were obtained from IMD and maximum and minimum simulated temperature for Junagadh was obtained by CORDEX for different RCPs. Baseline period (1951-2005) was compared to and that of during the future periods (2006-2100) for the RCP 2.6, RCP 4.5 and 8.5 scenario were used for the future projection. RCM simulations of temperature require careful handling due to their tendency to exhibit significant biases, primarily stemming from systematic model errors, such as imperfect conceptualization, discretization, and spatial averaging within grid cells. These biases complicate the direct use of RCM outputs for hydrological impact studies. A recommended approach to address these issues is the use of an ensemble of RCM simulations combined with bias correction techniques. Bias correction methods adjust the simulated data to align more closely with observed values. In this context, data from 1951 to 1995 were used for calibration, while the period from 1996 to 2005 served for validation. A probability distribution-based scaling method adjusted RCM-simulated temperatures to observed values by modeling the annual temperature cycle as a normal distribution with monthly-specific means and standard deviations.

Distribution Mapping Method

The Distribution Mapping (DM) method aims to align the distribution function of raw data with that of observed data, adjusting the mean, standard deviation, and quantiles while preserving extreme values. Despite its effectiveness, the method has limitations due to assumption that both observed and raw meteorological variables follow the same proposed distribution, potentially introducing new biases. For temperature time series, the Gaussian distribution, characterized by the location parameter μ (mean) and scale parameterσ (standard deviation), is typically assumed to be the best fit. The scale parameter ó influences the spread of the distribution: a smaller σ results in a more compressed distribution with lower probabilities of extreme values, whereas a larger σ results in a more stretched distribution with higher probabilities of extremes. The location parameter μ directly affects the mean, thereby determining the position of the distribution. For temperature adjustments, the process involves using the Gaussian (normal) CDF (F_N) cumulative distribution function (CDF) and its inverse (F_N^{-1}).

$$T^*_{contr} = F_N^{-1}(F_N(T_{contr}(d) \mid \mu_{contr,m}, \sigma^2_{contr,m}) \mid \mu_{obs,m}, \sigma^2_{obs,m}) \qquad (1)$$

$$T^*_{scen} = F_N^{-1}(F_N(T_{scen}(d) \mid \mu_{contr,m}, \sigma^2_{contr,m}) \mid \mu_{obs,m}, \sigma^2_{obs,m}) \qquad (2)$$

Where,

T^*_{contr} = corrected value of temperature of control period

T_{contr} = uncorrected value of temperature of control period

T^*_{scen} = corrected value of temperature for scenario period

T_{scen} = uncorrected value of temperature of scenario period

F_N = Gaussian CDF

F^{-1}_N = Inverse Gaussian CDF

μ_{contr} = monthly mean of simulated time series of daily temperature during for control period

σ^2_{obs} = monthly standard deviation of observed time series of temperature during control period

μ_{obs} = monthly mean of observed time series of daily temperature during control period

σ^2_{contr} = monthly standard deviation of simulated time series of daily temperature during control period.

Results and Discussion

Study focused on bias corrections for daily maximum and minimum temperatures, covering both a baseline period (1951-2005) and future scenarios (2006-2100). It involved calibration (1951-1995) and validation (1996-2005) phases, comparing simulated data with actual

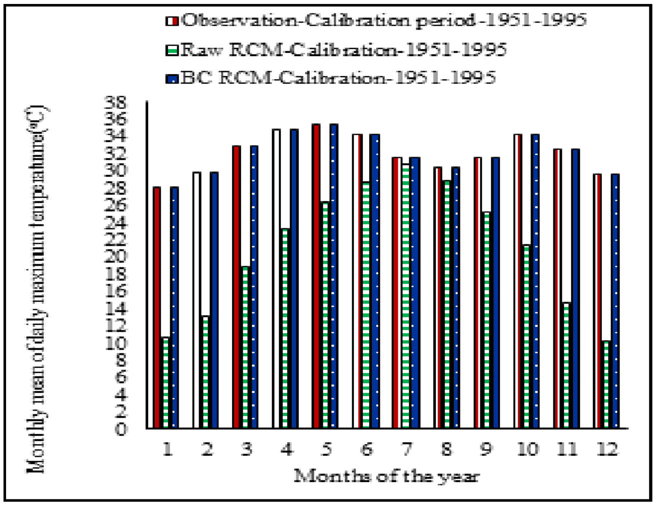

Fig. 2: Comparison of monthly mean of observed, raw and bias corrected daily maximum temperature during calibration period-1951-1995.

observations. Specifically, bias correction was applied to temperatures simulated by RCA4 for Junagadh, using observed data for comparison. The analysis provided temperature data for both control period (1951-2005) and projected future period (2006-2100).

Control Period (1951-2005)

Daily maximum temperature

Fig. 2 and 3 display the computed monthly mean of daily observed maximum temperatures alongside Raw RCM and Bias corrected RCM values for Junagadh during the calibration period (1951-1995) and validation period (1996-2005). The bias correction utilized Gaussian distribution method, focusing on mean and coefficient of variation statistics.

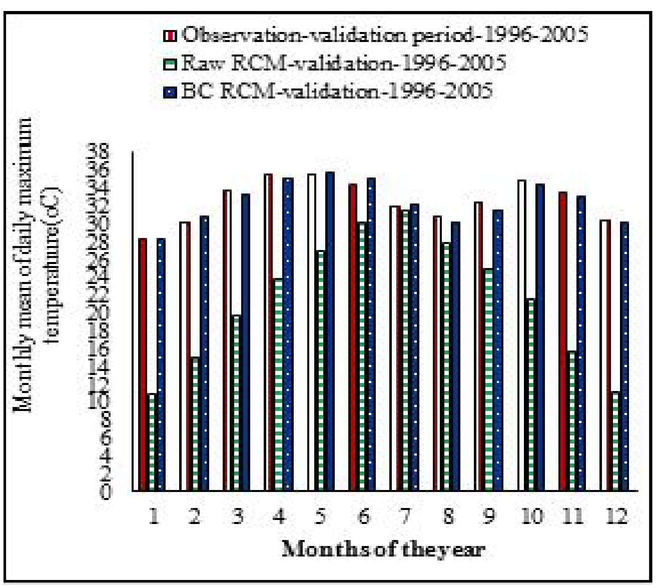

Fig. 3: Comparison of monthly mean of observed, raw and bias corrected daily maximum temperature during validation period-1996-2005.

In Fig. 2, Raw RCM consistently underestimated observed monthly maximum temperatures throughout the calibration period. This trend persisted in Fig. 3 during the validation period. However, following the application of Gaussian bias correction method, both calibration (Fig. 2) and validation (Fig. 3) periods showed improved agreement between Bias corrected RCM and observed temperatures across all 12 months of the year. This adjustment indicates that Gaussian distribution method effectively aligned the monthly mean values of daily maximum temperatures from the RCM with actual observed values for Junagadh, enhancing the model's performance in reflecting real-world conditions.

Fig. 4 and 5 illustrate the relationship between the monthly mean of observed maximum temperatures, Raw RCM, and Bias corrected RCM values for Junagadh

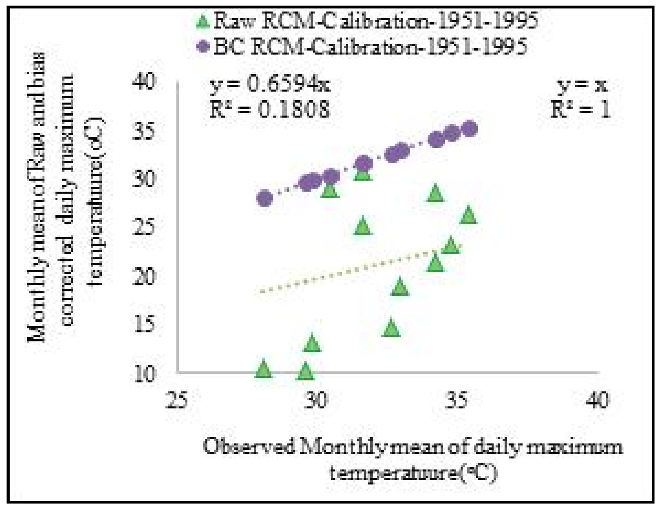

Fig. 4: Comparison of monthly mean of observed, raw and bias corrected daily maximum temperature during calibration period-1951-1995.

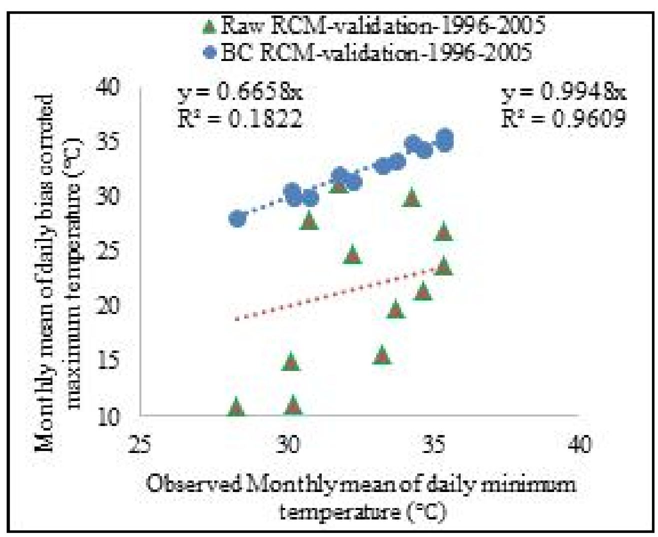

Fig. 5: Comparison of monthly mean of observed, raw and bias corrected daily maximum temperature during validation period-1996-2005.

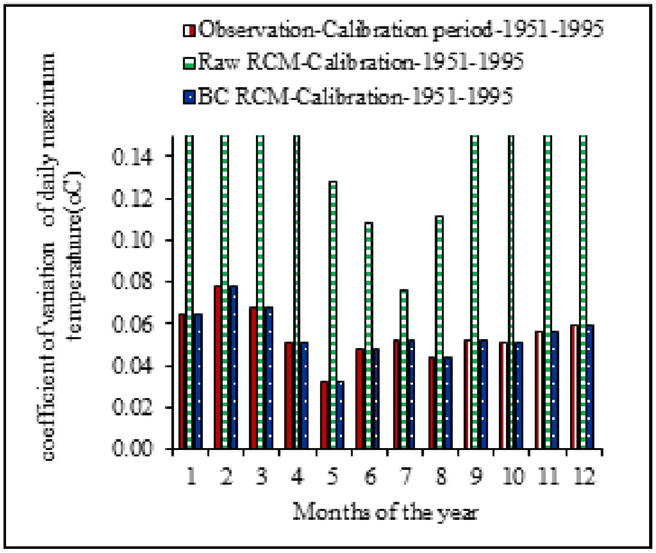

Fig. 6: Comparison of Coefficient of Variation observed, raw and bias corrected daily maximum temperature during Calibration period-1951-1995.

during the calibration period (1951-1995) and validation period (1996-2005). The evaluation includes the goodness of fit (R^2) between Raw RCM and Bias corrected RCM.

In Fig. 4, the goodness of fit (R^2) between Raw RCM and Bias corrected RCM was 0.917 and 1 for calibration period (1951-1995), respectively. Similarly, Fig. 5 shows R^2 values of 0.92 and 0.99 for validation period (1996-2005). These results indicate that the Gaussian distribution method effectively corrected the first moment (mean), aligning Raw RCM values closely with Bias corrected RCM and observed temperatures.

Fig. 6 and 7 present coefficient of variation for observed maximum temperatures, Raw RCM, and Bias corrected RCM values in Junagadh during the calibration

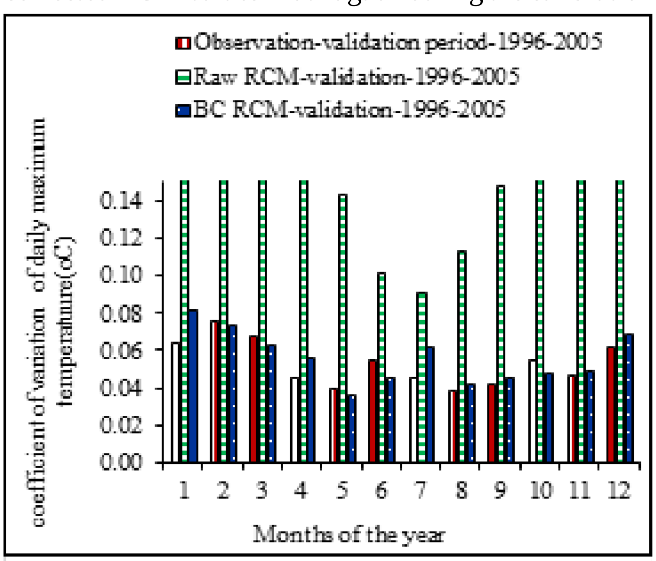

Fig. 7: Comparison of Coefficient of Variation observed, raw and bias corrected daily maximum temperature during Validation period-1996-2005.

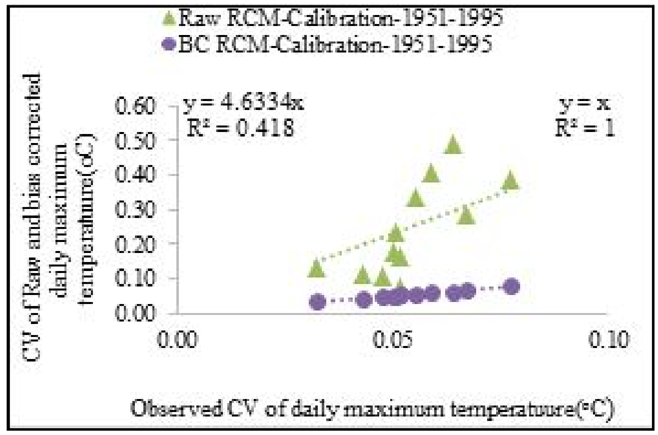

Fig. 8: Comparison of Coefficient of Variation observed, raw and bias corrected daily maximum temperature during Calibration period-1951-1995.

and validation periods. The coefficient of variation measures variability relative to the mean.

In Fig. 6, Raw RCM daily maximum temperatures exhibited a higher CV compared to observed maximum temperatures across all months during the calibration period. However, after applying bias correction, the CV of Bias corrected RCM aligned closely with observed values, indicating improved accuracy in capturing variability.

Similarly, in Fig. 7 for the validation period (1996-2005), both observed and bias corrected RCM showed lower coefficient of variation compared to Raw RCM for all months. Post-correction, Bias corrected RCM CV closely matched observed values, underscoring the effectiveness of the bias correction method in aligning model outputs with observed variability.

Fig. 8 and 9 depict the relationship between the monthly CV of observed maximum temperatures, Raw RCM, and Bias corrected RCM values for Junagadh during the calibration period (1951-1995) and validation

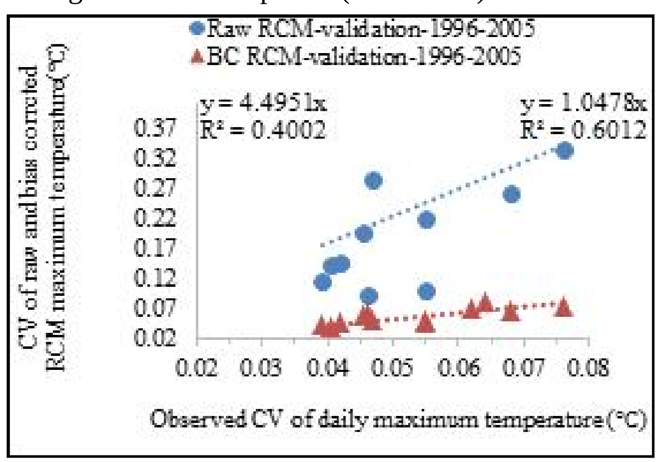

Fig. 9: Comparison of Coefficient of Variation observed, raw and bias corrected daily maximum temperature during Validation period-1996-2005.

period (1996-2005). The assessment includes the goodness of fit (R^2) between Raw RCM and Bias corrected RCM.

In Fig. 8, the goodness of fit (R^2) between Raw RCM and Bias corrected RCM was 0.868 and 1 for the calibration period (1951-1995), respectively, indicating a close match between the datasets. Conversely, Fig. 9 shows R^2 values of 0.814 and 0.978 for the validation

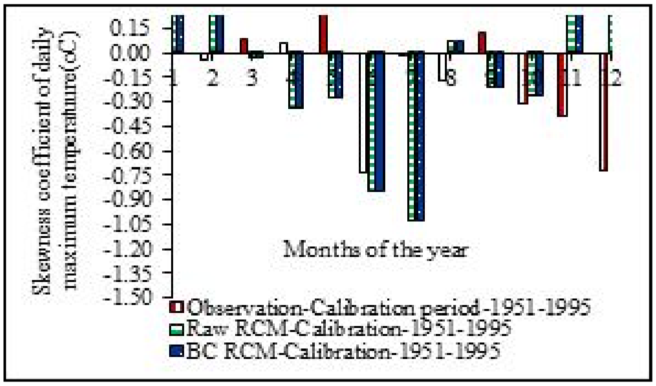

Fig. 10: Comparison of Skewness Coefficient of observed, raw and bias corrected daily maximum temperature during Calibration Period-1951-1995.

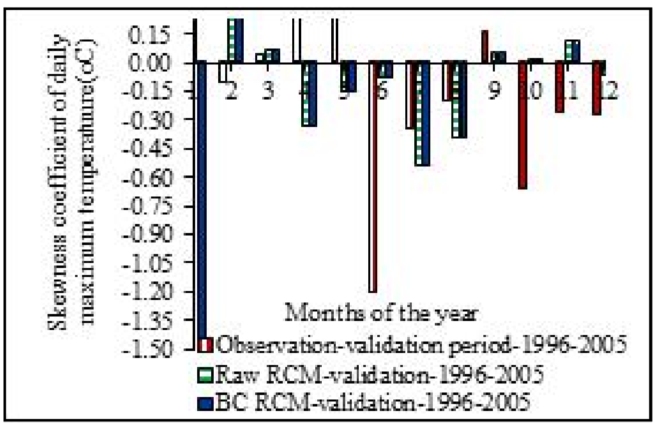

Fig. 11: Comparison of Skewness Coefficient of observed, raw and bias corrected daily maximum temperature during Validation Period-1996-2005.

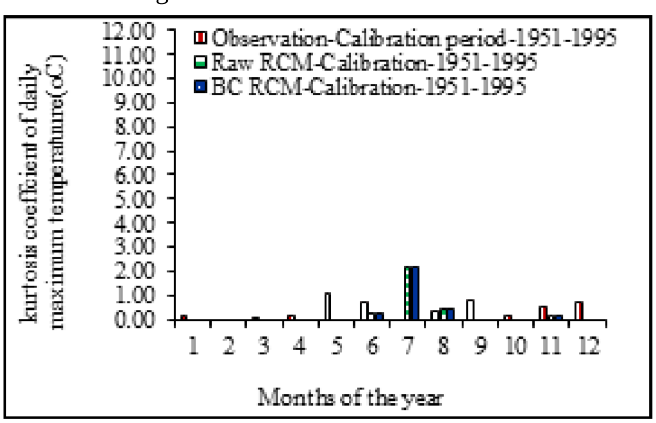

Fig. 12: Comparison of Kurtosis Coefficient of observed, raw and bias corrected daily maximum temperature during Calibration Period-1951-1995.

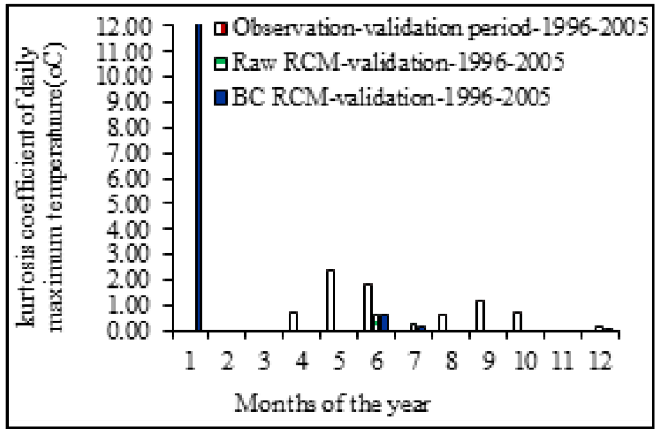

Fig. 13: Comparison of Skewness Coefficient of observed, raw and bias corrected daily maximum temperature during Validation Period-1996-2005.

period (1996-2005). These results suggest that while Gaussian distribution method corrected the CV effectively in the calibration period, there were some discrepancies observed in the validation period.

Fig. 10 and 11 illustrate the comparison of skewness coefficients (Cs) for observed maximum temperatures, Raw RCM, and Bias corrected RCM values in Junagadh during the calibration and validation periods. Skewness measures the asymmetry of the distribution.

In the calibration period (Fig. 10), skewness coefficients were negative for all months across Raw RCM and Bias corrected RCM, indicating a tendency towards lower values relative to the mean. However, in the validation period (Fig. 11), skewness coefficients were positive for March and September and negative for other months. This pattern suggests a departure from normality in these months, which the Gaussian bias correction method did not fully correct.

Fig. 12 and 13 depict the comparison of kurtosis coefficients (Ck) for observed maximum temperatures,

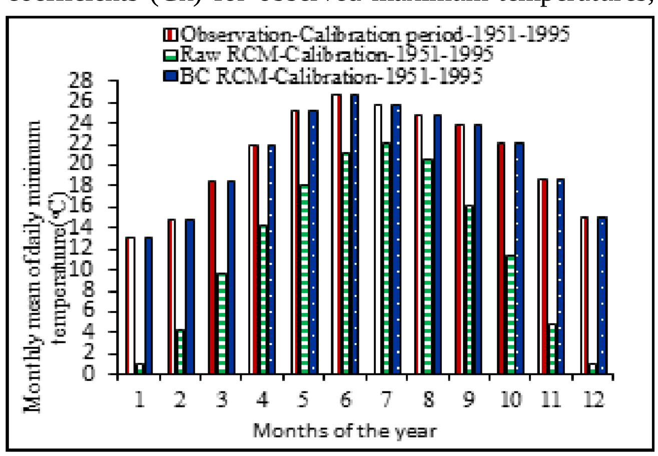

Fig. 14: Comparison of monthly mean of observed, raw and bias corrected daily minimum temperature during calibration period-1951-1995.

Raw RCM, and Bias corrected RCM values in Junagadh during the calibration and validation periods. Kurtosis measures the "tailedness" of the distribution, specifically the thickness of the tails relative to the normal distribution.

In the calibration period (Fig. 12), kurtosis coefficients were positive for all months across Raw RCM and Bias corrected RCM, indicating heavier tails in the distribution compared to the normal distribution. Similarly, in the validation period (Fig. 13), kurtosis coefficients remained positive across all months, suggesting persistent deviations from normality. These results indicate that while the Gaussian bias correction method effectively adjusted the mean and variability (first and second moments), it did not fully correct the skewness (third moment) and kurtosis (fourth moment) of the distribution.

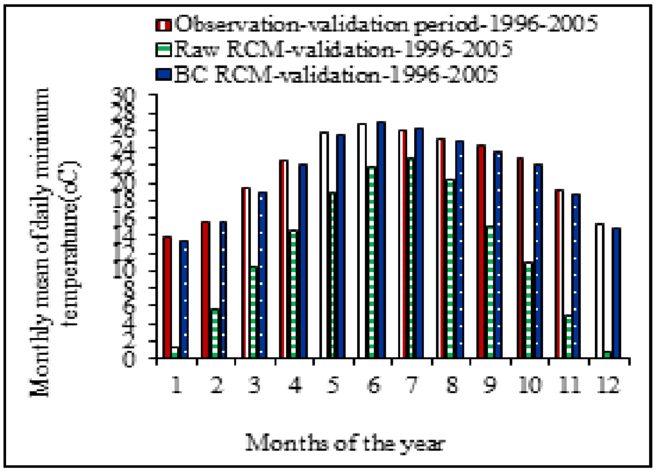

Fig. 15: Comparison of monthly mean of observed, raw and bias corrected daily minimum temperature during validation period-1996-2005.

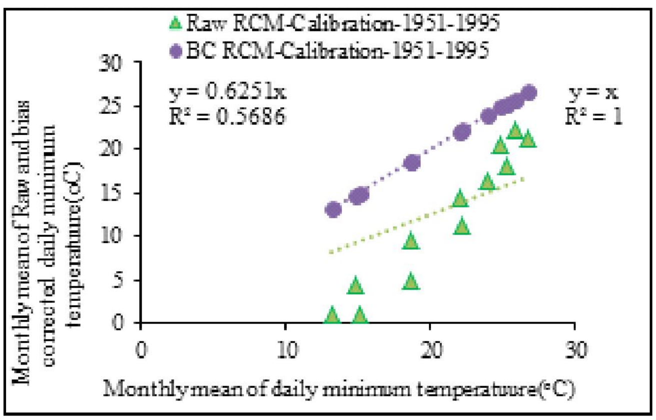

Fig. 16: Comparison of monthly mean of observed, raw and bias corrected daily minimum temperature during calibration period-1951-1995.

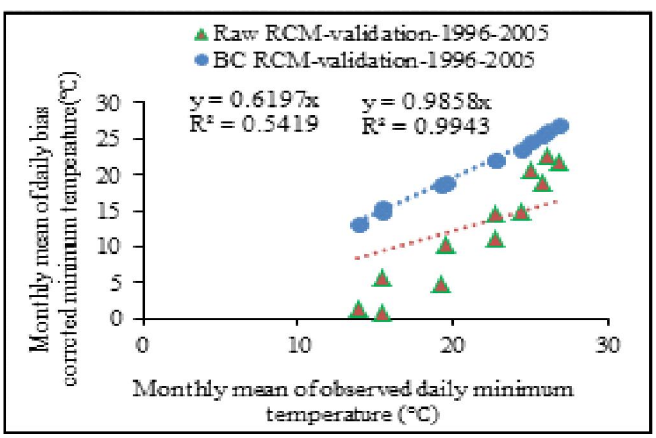

Fig. 17: Comparison of monthly mean of observed, raw and bias corrected daily minimum temperature during validation period-1996-2005.

Daily minimum temperature

Fig. 14 and 15 display the computed monthly mean of daily observed minimum temperatures, Raw RCM, and Bias corrected RCM values for Junagadh during the calibration period (1951-1995) and validation period (1996-2005), respectively. The bias correction employed the Gaussian distribution mapping method, focusing on mean and coefficient of variation statistics.

Fig. 14 shows that Raw RCM underestimated the observed monthly minimum temperatures across all months during the calibration period. A similar trend is observed in Fig. 15 for the validation period. However, after applying Gaussian bias correction method, the monthly means for both calibration (Fig. 14) and validation periods (Fig. 15) of daily minimum temperatures aligned closely with the actual observed values across all 12 months of the year.

Fig. 16 and 17 illustrate the relationship between the monthly mean of observed minimum temperatures, Raw RCM, and Bias corrected RCM values for Junagadh during calibration period (1951-1995) and validation period (1996-2005). The evaluation includes the goodness of fit (R^2) between Raw RCM and Bias corrected RCM.

In Fig. 16, the goodness of fit (R^2) between Raw RCM and Bias corrected RCM was 0.879 and 1, respectively, for calibration period (1951-1995). Similarly, Fig. 17 shows R^2 values of 0.875 and 0.999 for validation

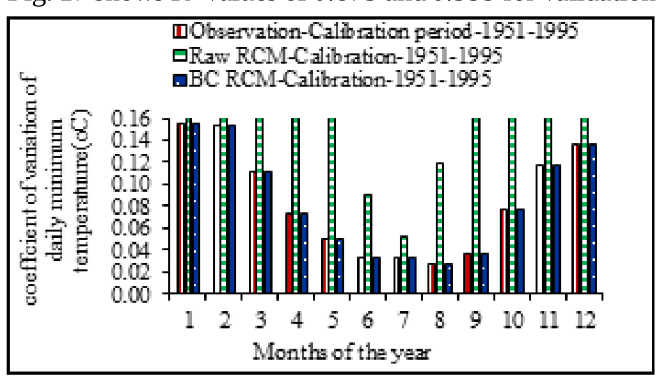

Fig. 18: Comparison of Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Calibration Period 1951-1995.

period (1996-2005). These results indicate that the Gaussian distribution method effectively corrected the first moment (mean), aligning Raw RCM values closely with Bias corrected RCM and observed minimum temperatures.

Fig. 18 and 19 present the CV for observed minimum temperatures, Raw RCM, and Bias corrected RCM values in Junagadh during the calibration and validation periods.

In Fig. 18, Raw RCM daily minimum temperatures exhibited a higher CV compared to observed minimum temperatures across all months during the calibration period. However, after applying bias correction, the coefficient of variation of Bias corrected RCM closely matched observed values, indicating improved accuracy in capturing variability.

Similarly, in Fig. 19 for validation period (1996-2005), both observed and bias corrected RCM showed lower CV compared to Raw RCM for all months. Post-correction, Bias corrected RCM closely aligned with observed values, underscoring the effectiveness of the bias correction method in aligning model outputs with observed variability.

Fig. 20 and 21 depict the relationship between the monthly CV of observed minimum temperatures, Raw RCM, and Bias corrected RCM values for Junagadh during calibration period (1951-1995) and validation period (1996-2005). The analysis includes the goodness of fit (R^2) between Raw RCM and Bias corrected RCM.

In Fig. 20, the goodness of fit (R^2) between Raw RCM and Bias corrected RCM was 0.661 and 1, respectively, for the calibration period (1951-1995),

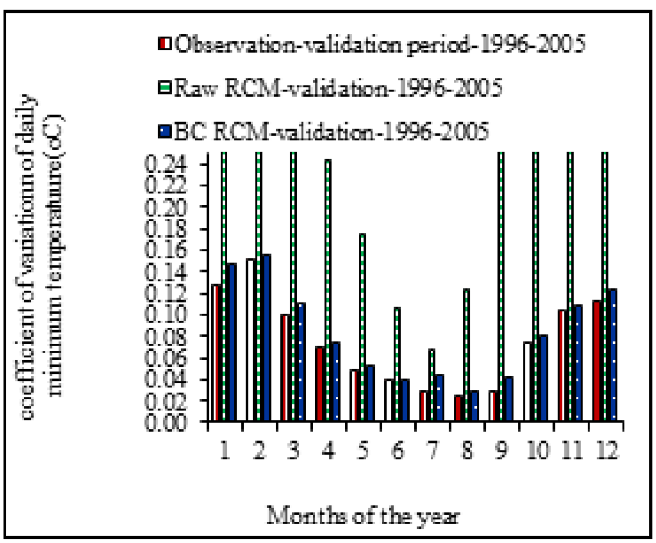

Fig. 19: Comparison of Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Validation Period 1996-2005.

indicating a strong alignment between the datasets. Conversely, Fig. 21 shows R^2 values of 0.597 and 0.995 for the validation period (1996-2005). These results suggest that while the Gaussian distribution method corrected the CV effectively in calibration period, there were some discrepancies observed in the validation period.

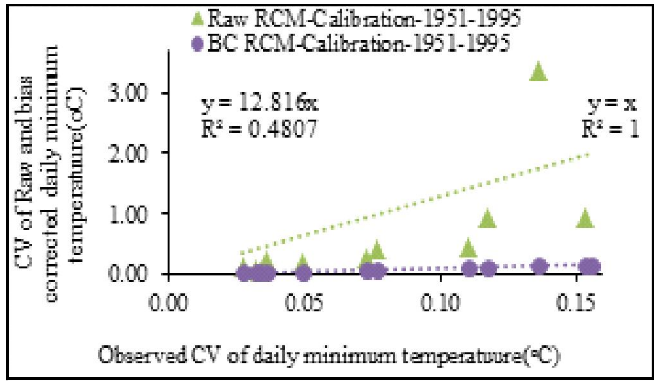

Fig. 20: Comparison of Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Calibration Period 1951-1995.

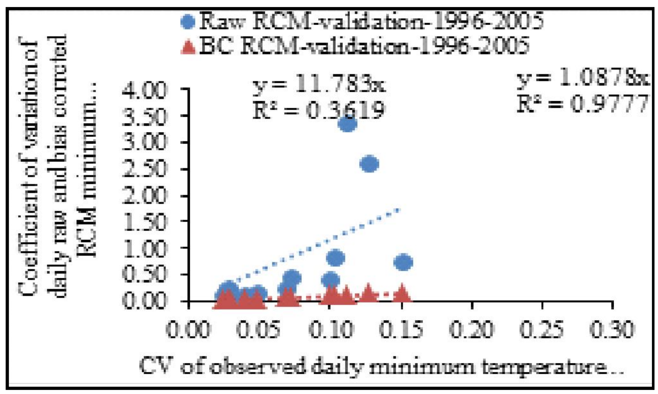

Fig. 21: Comparison of Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Validation Period 1996-2005.

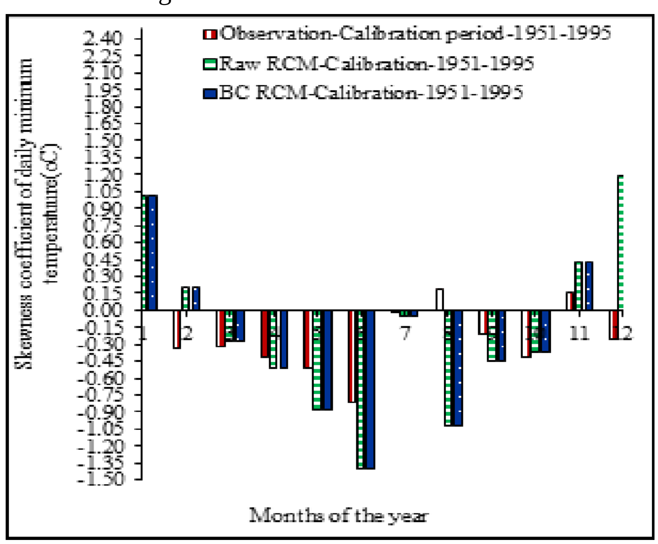

Fig. 22: Comparison of Skewnwss Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Calibration Period 1951-1995.

Fig. 22 and 23 illustrate the comparison of skewness coefficients (C_s) for observed minimum temperatures, Raw RCM, and Bias corrected RCM values in Junagadh during the calibration and validation periods. Skewness measures the asymmetry of the distribution.

In the calibration period (Fig. 22), skewness coefficients were negative for all months except November across Raw RCM and Bias corrected RCM, indicating a tendency towards lower values relative to the mean. However, in the validation period (Fig. 23), skewness coefficients were positive for November and negative for the remaining months. This pattern suggests deviations from normality, which the Gaussian bias correction method did not fully address.

Fig. 24 and 25 depict the comparison of kurtosis coefficients (Ck) for observed minimum temperatures, Raw RCM, and Bias corrected RCM values in Junagadh during the calibration and validation periods.

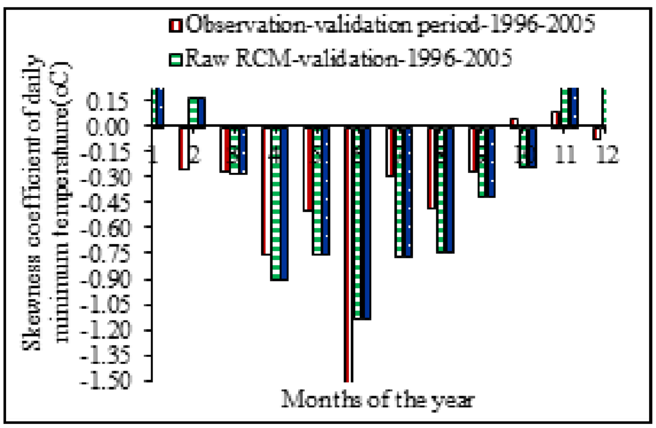

Fig. 23: Comparison of Skewnwss Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Validation Period 1996-2005.

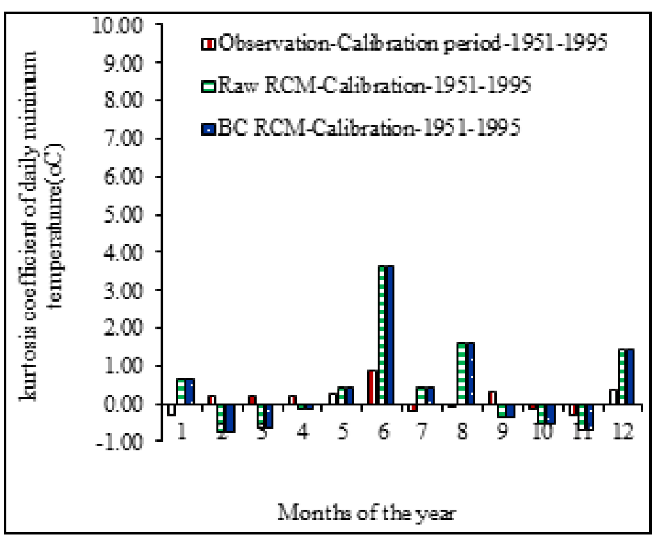

Fig. 24: Comparison of Kurtosis Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Calibration Period 1951-1995.

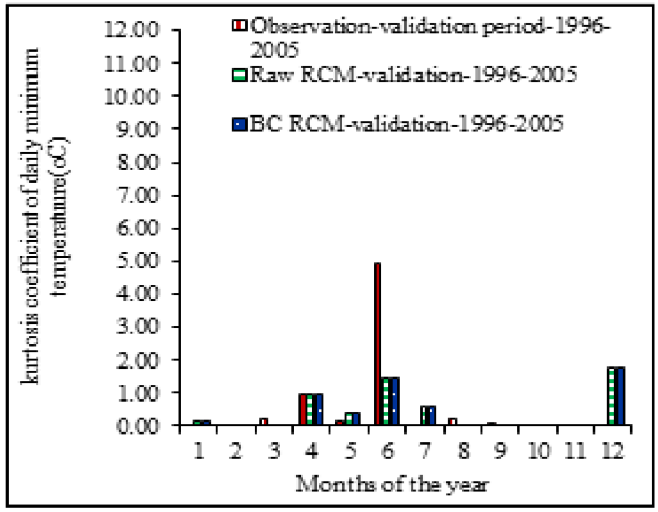

Fig. 25: Comparison of Kurtosis Coefficient of Variation of observed, raw and bias corrected daily minimum temperature during Validation Period 1996-2005.

In the calibration period (Fig. 24), kurtosis coefficients were positive for May to August and December, indicating heavier tails in the distribution compared to the normal distribution. For the remaining months, kurtosis coefficients were negative, suggesting a lighter tail distribution. Similarly, in the validation period (Fig. 25), kurtosis coefficients were positive for all months, indicating persistent deviations from normality.

These results indicate that while the Gaussian bias correction method effectively adjusted the mean and variability (first and second moments), it did not fully correct the skewness (third moment) and kurtosis (fourth moment) of the distribution.

Future Period (2006-2100)

RCP 2.6

Daily maximum temperature

Fig. 26, 27, 28 and 29 shows the statistical

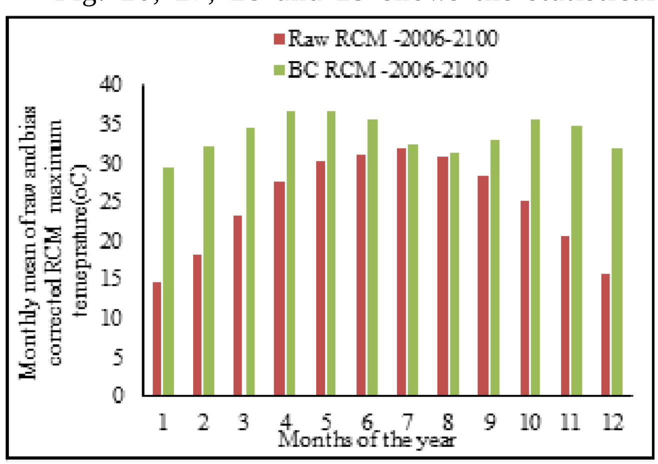

Fig. 26: Comparison of raw and bias corrected RCM monthly mean of daily maximum temperature during future Period 2006-2100 for RCP 2.6

characteristics of raw and bias-corrected regional climate model (RCM) simulations from 2006 to 2100. Fig. 26 shows the mean temperatures, the raw RCM shows lower values throughout the year, ranging from 14.65°C in January to 15.64°C in December, while the bias-corrected (BC) RCM exhibits consistently higher mean temperatures, ranging from 29.50°C in January to 31.85°C in December. This illustrates the impact of bias correction, which generally increases the mean temperature projections.

The standard deviation (SD), the raw RCM displays higher variability in temperature with values ranging from 3.09 to 5.46 across the months. In contrast, the SD values for the BC RCM are lower, ranging from 1.25 to 2.48, indicating that bias correction reduces the variability in temperature projections.

Fig. 27 shows the coefficient of variation (C_v), which normalizes SD by the mean, also shows differences between the two models. The raw RCM has higher Cv values ranging from 0.10 to 0.32, reflecting relatively higher variability compared to the BC RCM, which shows Cv values ranging from 0.04 to 0.08.

Fig. 28 examining skewness coefficient (C_s), both models exhibit similar patterns with positive skewness values in January, February, November, and December, and negative values from March to October. This indicates a distribution skewed towards higher temperatures during winter months and lower temperatures during summer months in both raw and bias-corrected simulations.

Fig. 29 shows Kurtosis coefficient (C_k) reveals varying distributions across months. Both models show positive kurtosis in certain summer months (June and July) and negative kurtosis in other months, suggesting differences in the likelihood of extreme temperature events between seasons.

Daily minimum temperature

Fig. 30, 31, 32 and 33 shows the statistical characteristics of raw and bias-corrected regional climate model (RCM) simulations from 2006 to 2100. Fig. 30 shows the mean temperatures across both datasets show distinct seasonal variations, with January experiencing the lowest temperatures ranging from 2.03°C in raw data to 13.71°C in bias-corrected data, and July recording the highest temperatures ranging from 24.15°C in raw data to 27.26°C in bias-corrected data. This overall increase

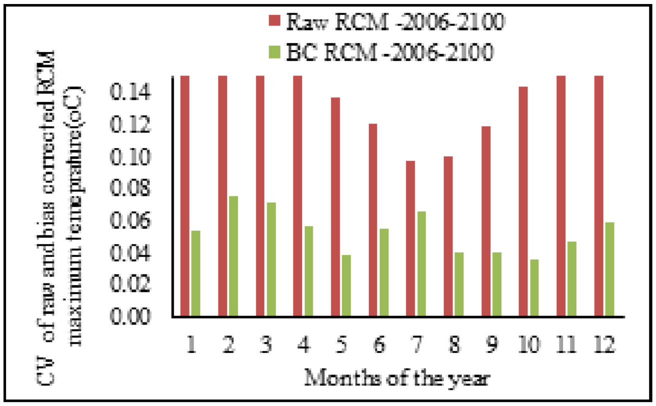

Fig. 27: Comparison of CV of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 2.6.

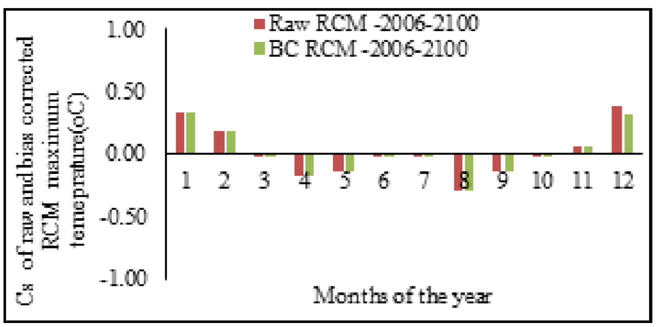

Fig. 28: Comparison of Skewness Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 2.6.

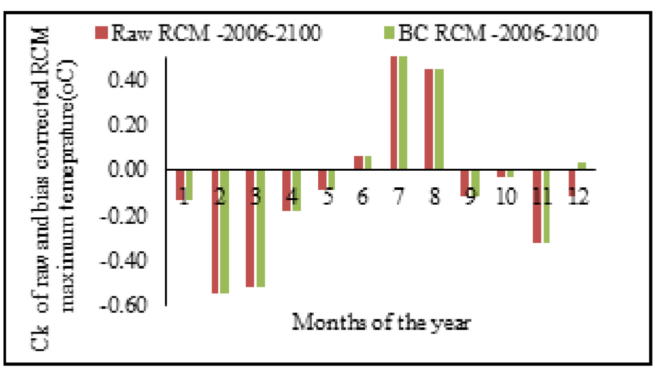

Fig. 29: Comparison of Kurtosis Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 2.6.

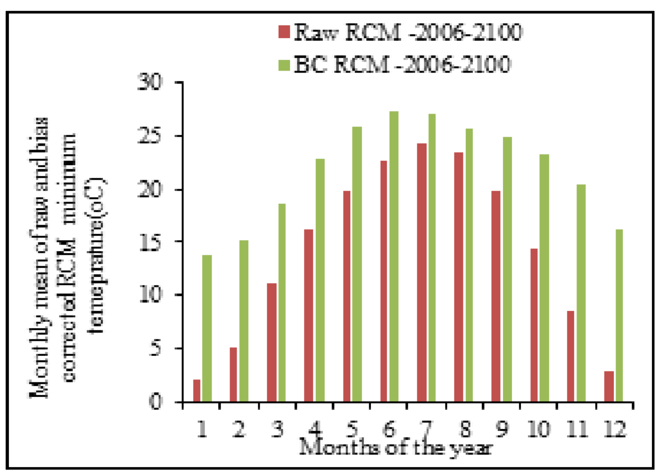

Fig. 30: Comparison of raw and bias corrected RCM monthly mean of daily minimum temperature during future Period 2006-2100 for RCP 2.6

in mean temperatures after bias correction underscores warming trend projected throughout the century.

Standard deviation (SD) values across months exhibit notable differences between raw and bias-corrected data. Raw RCM data shows wider variability, with SD ranging from 1.61°C to 4.74°C, indicative of higher uncertainty in temperature projections. In contrast, bias-corrected RCM data shows a narrower range of SD values from 0.54°C to 2.50°C, suggesting that bias correction has effectively reduced the spread of temperature projections and improved consistency across months.

Fig. 31 shows the coefficients of variation (Cv) which provides the additional insights into the relative variability of temperatures. In the raw RCM data, Cv values range from 0.07 to 1.72, reflecting varied levels of deviation from the mean temperature. Bias correction significantly lowers Cv values, narrowing the range from 0.02 to 0.15, indicating a more uniform distribution of temperatures and greater predictability in climate model outputs.

Despite these adjustments in mean and variability, (Fig. 32) skewness coefficient (Cs) and (Fig. 33) kurtosis coefficient (Ck) values remain largely consistent between raw and bias-corrected data. Skewness ranges from -1.27 to 1.15 across both datasets, indicating similar distribution shapes with occasional deviations towards higher or lower temperatures in specific months. Kurtosis values, ranging from -0.79 to 2.46, suggest that while bias correction adjusts mean temperatures, it does not significantly alter the likelihood of extreme temperature events within the projected climate scenarios.

RCP 4.5

Daily maximum temperature

Fig. 34, 35, 36 and 37 shows the statistical characteristics of raw and bias-corrected regional climate model (RCM) simulations for the period 2006-2100. Fig. 34 shows the mean daily maximum temperatures, the raw RCM ranges from 13.50°C in January to 33.78°C in July, with a distinct seasonal variation showing warmer temperatures in summer and cooler temperatures in winter. In contrast, the bias-corrected (BC) RCM consistently shows higher mean temperatures across all months, ranging from 29.10°C in January to 35.58°C in July, reflecting the adjustments made through bias correction to better align model outputs with observed data.

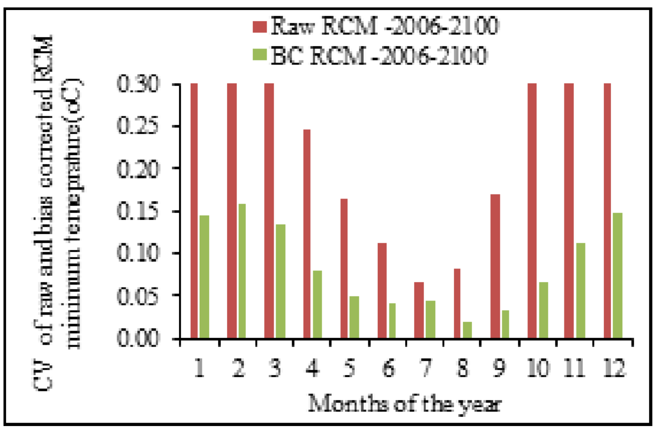

Fig. 31: Comparison of CV of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 2.6.

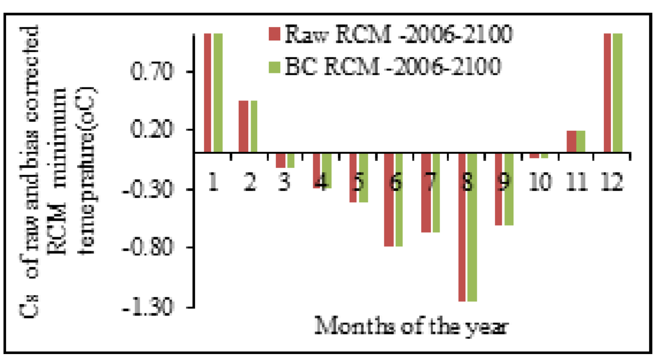

Fig. 32: Comparison of Skewness Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 2.6.

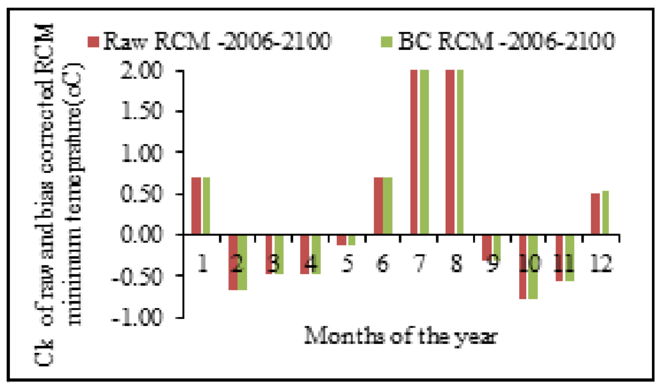

Fig. 33: Comparison of Kurtosis Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 2.6.

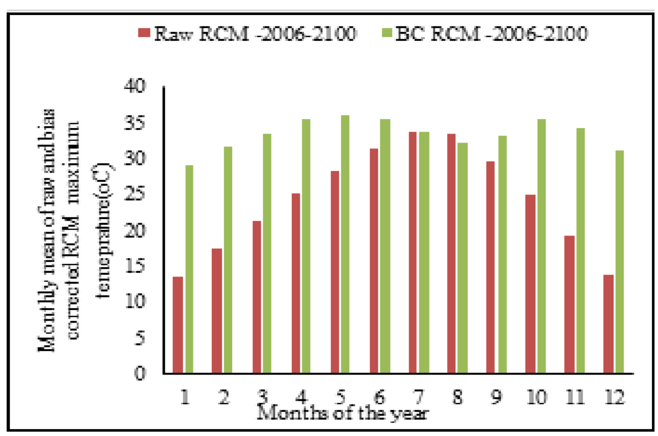

Fig. 34: Comparison of raw and bias corrected RCM monthly mean of daily maximum temperature during future Period 2006-2100 for RCP 4.5.

The standard deviation (SD) of daily maximum temperatures is generally higher in the raw RCM compared to the BC RCM. For example, SD ranges from 1.15 to 4.97 in the raw RCM and from 1.15 to 2.31 in the BC RCM. This indicates that bias correction reduces the variability in temperature projections, leading to smoother and more consistent model outputs.

Fig. 35 shows coefficient of variation (Cv), which normalizes SD by the mean, also shows differences between the two models. The raw RCM exhibits higher Cv values ranging from 0.09 to 0.29, while the BC RCM displays lower Cv values ranging from 0.03 to 0.07, further emphasizing the reduction in variability after bias correction.

Fig. 36 and 37 shows the Skewness coefficient (Cs) and kurtosis coefficient (Ck) coefficients, which provide insights into the shape and tails of the temperature distribution. Cs values show positive skewness in January, February, and December, indicating a distribution skewed towards higher temperatures during these months. Conversely, negative Cs values from March to November suggest a distribution skewed towards lower temperatures. Ck values indicate varying degrees of kurtosis across months, with positive values in June and July.

Daily minimum temperature

Fig. 38, 39, 40 and 41 shows the statistical characteristics of raw and bias-corrected regional climate model (RCM) simulations for the period 2006-2100. Fig 38 shows the raw RCM data begins with lower mean temperatures, starting at 1.29°C in 2006 and gradually rising to 2.99°C by 2100. In contrast, the bias-corrected RCM data starts with substantially higher mean temperatures of 13.29°C in 2006, reaching 16.26°C by 2100 after the bias correction process adjusts the model outputs to better align with observed data.

The raw RCM data exhibits higher initial standard deviation (SD) at 2.97°C in 2006, which decreases to 4.01°C by 2100. The bias-corrected RCM data, however, starts with lower variability, indicated by an SD of 1.70°C in 2006, remaining relatively stable over the century. This reduction in variability post-bias correction enhances the reliability of temperature projections, making them more consistent and useful for local climate impact assessments.

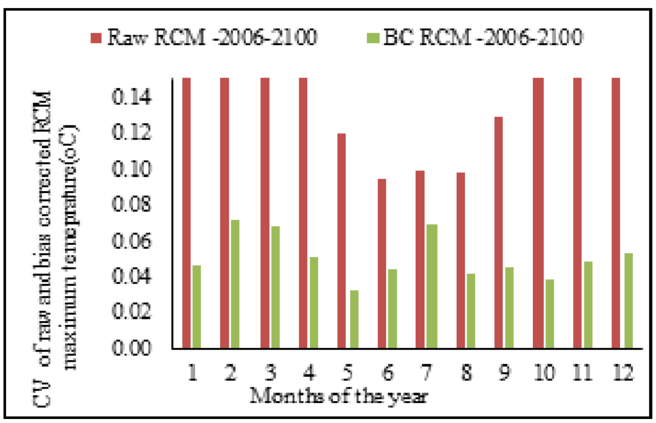

Fig. 35: Comparison of CV of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 4.5.

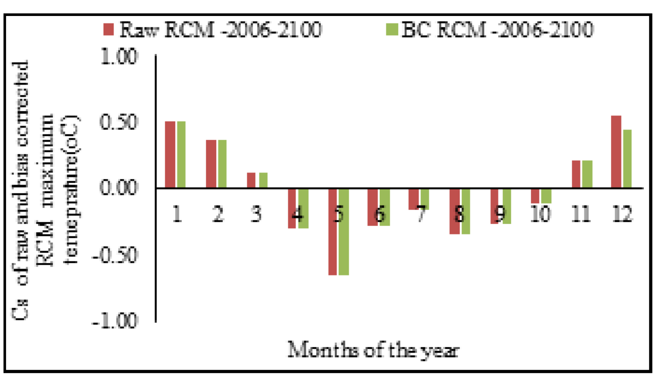

Fig. 36: Comparison of Skewness Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 4.5.

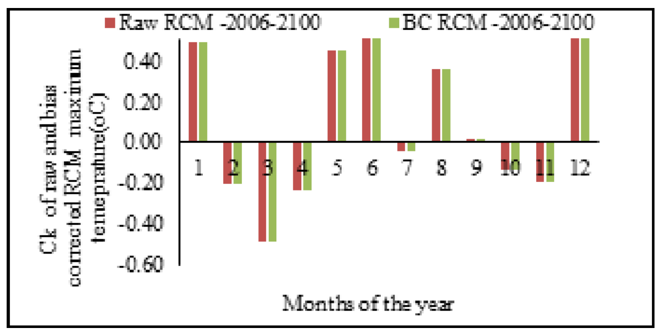

Fig. 37: Comparison of Kurtosis Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 4.5.

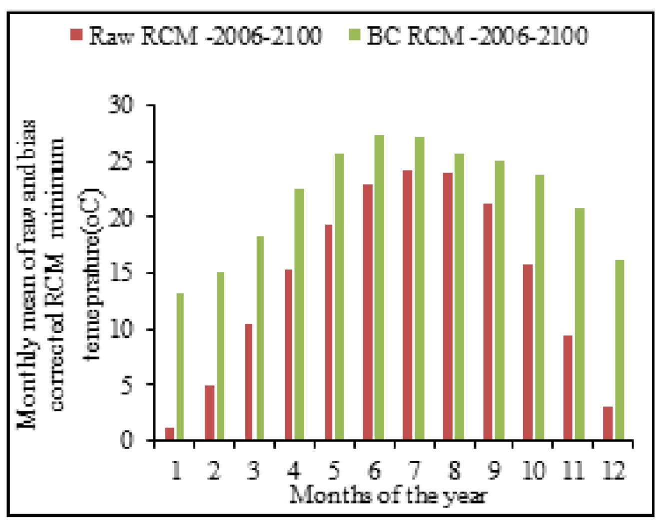

Fig. 38: Comparison of raw and bias corrected RCM monthly mean of daily minimum temperature during future Period 2006-2100 for RCP 4.5.

Fig. 39 shows combined data shows a notable difference in Cv between the raw and bias-corrected RCM datasets. The raw RCM data starts with a Cv of 2.31 in 2006, indicating higher variability relative to mean temperatures, which decreases gradually over time. In contrast, the bias-corrected RCM data begins with a significantly lower Cv of 0.13 in 2006 and maintains this low variability throughout the century.

(Fig. 40) Skewness coefficient (Cs) and (Fig. 41) kurtosis coefficient (Ck) values exhibit minimal change between the raw and bias-corrected RCM data, indicating that while bias correction adjusts mean temperatures and reduces variability, it preserves the overall shape of the temperature distribution. Cs tends to be positive in winter and negative in summer months for both raw and bias-corrected data, indicating asymmetry in temperature distributions while Ck shows positive values during colder

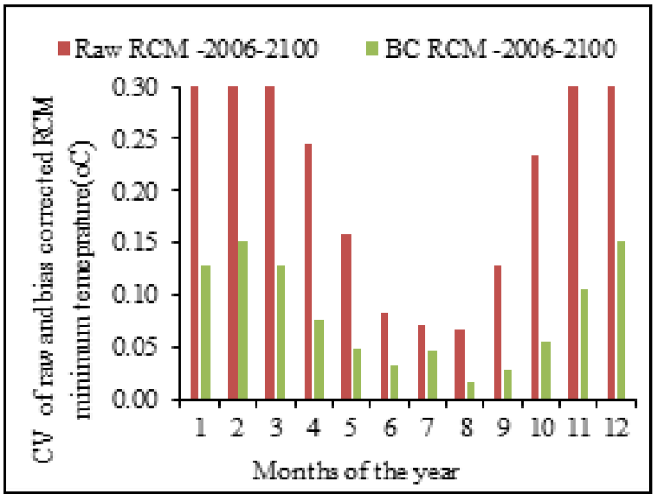

Fig. 39: Comparison of CV of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 4.5.

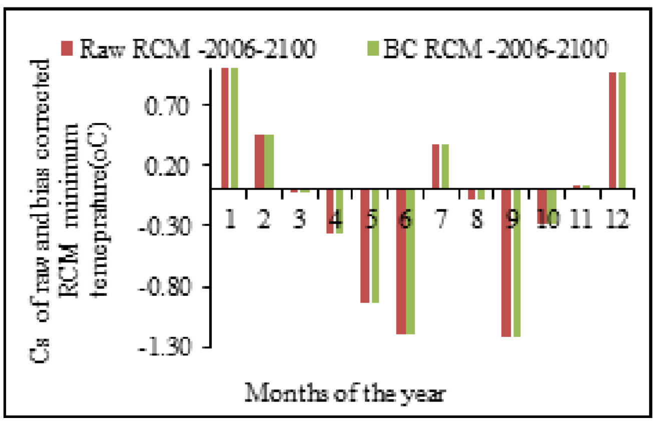

Fig. 40: Comparison of Skewness Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 4.5.

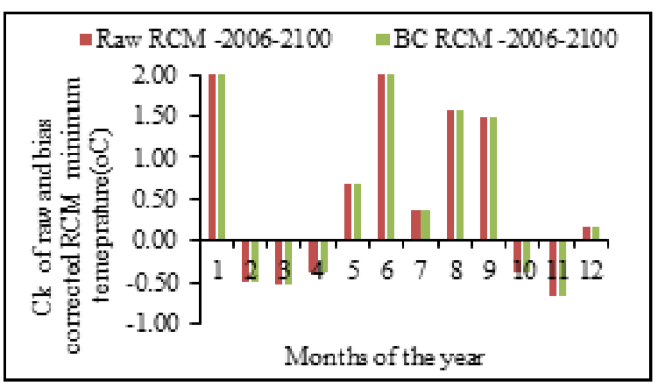

Fig. 41: Comparison of Kurtosis Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 4.5.

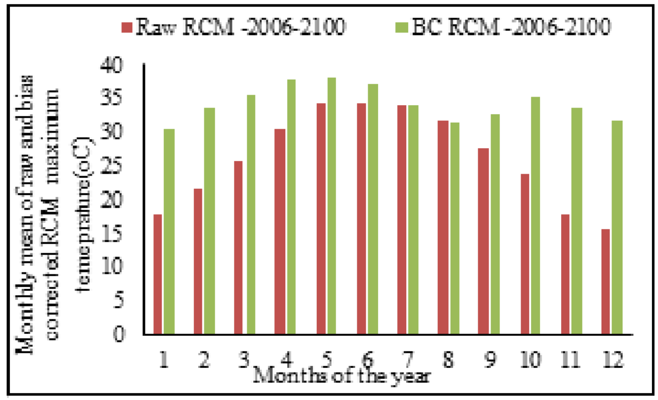

Fig. 42: Comparison of raw and bias corrected RCM monthly mean of daily maximum temperature during future Period 2006-2100 for RCP 8.5

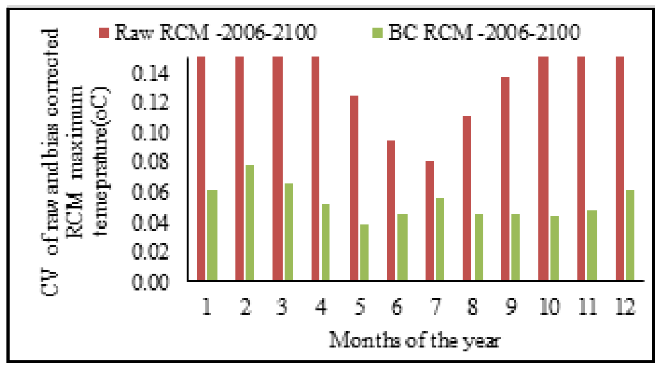

Fig. 43: Comparison of CV of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 8.5.

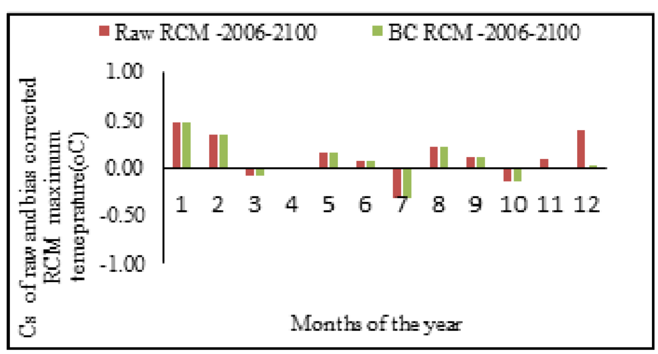

Fig. 44: Comparison of Skewness Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 8.5.

and warmer months and negative values during transitional periods.

RCP 8.5

Daily maximum temperature

Fig. 42, 43, 44 and 45 shows the statistical characteristics of raw and bias-corrected regional climate

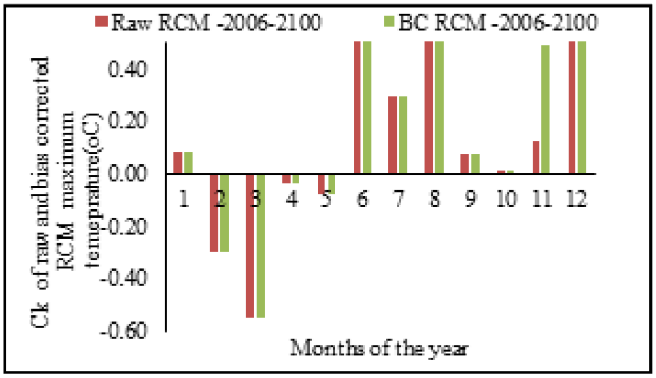

Fig. 45: Comparison of Kurtosis Coefficient of raw and BC RCM maximum temperature during future Period 2006-2100 for RCP 8.5.

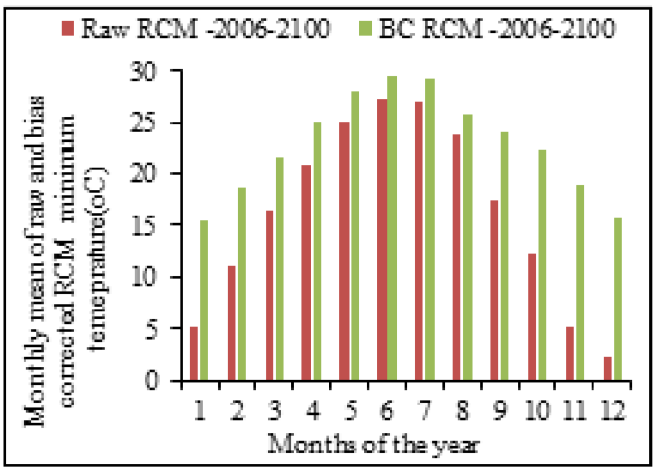

Fig. 46: Comparison of raw and bias corrected RCM monthly mean of daily minimum temperature during future Period 2006-2100 for RCP 8.5

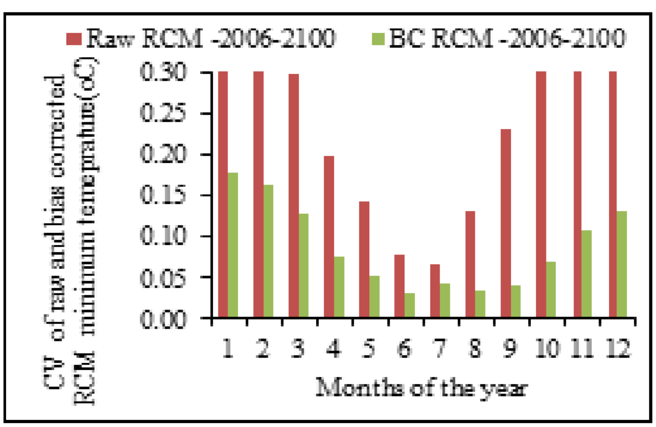

Fig. 47: Comparison of CV of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 8.5.

model (RCM) simulations for the period 2006-2100, focusing on daily maximum temperatures. Fig. 42 shows that the raw RCM shows a progression of mean temperatures from 17.80°C in January to 15.57°C in December, exhibiting a typical seasonal variation with warmer temperatures in summer and cooler temperatures in winter. In contrast, the bias-corrected (BC) RCM consistently projects higher mean temperatures across all months, ranging from 30.59°C in January to 31.77°C in December, reflecting adjustments made through bias correction to better align model outputs with observed data.

Regarding variability, the standard deviation (SD) of daily maximum temperatures is generally higher in the raw RCM compared to the BC RCM. For instance, SD ranges from 1.45 to 5.82 in the raw RCM and from 1.42 to 2.64 in the BC RCM, indicating that bias correction reduces the variability in temperature projections, resulting in more consistent model outputs.

Fig. 43 shows coefficient of variation (Cv), which normalizes SD by the mean, shows lower values in the

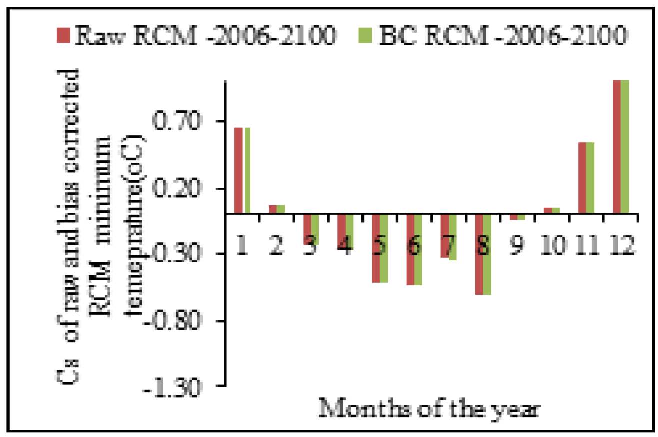

Fig. 48: Comparison of Skewness Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 8.5.

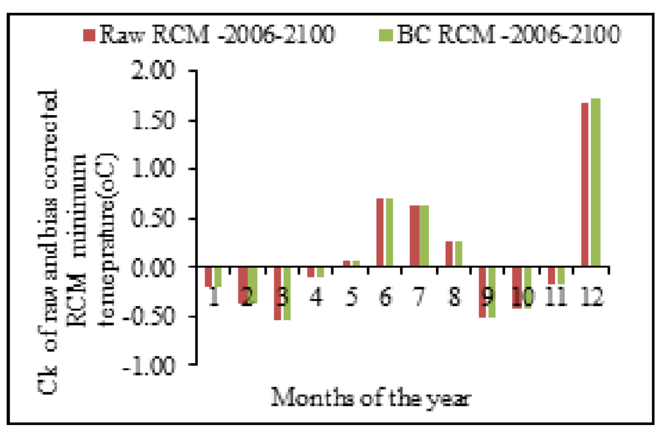

Fig. 49: Comparison of Kurtosis Coefficient of raw and BC RCM minimum temperature during future Period 2006-2100 for RCP 8.5.

BC RCM compared to the raw RCM. Cv values range from 0.04 to 0.31 in the raw RCM and from 0.04 to 0.08 in the BC RCM, highlighting the reduction in variability after bias correction.

Fig. 44 and 45 shows the Skewness coefficient (Cs) and kurtosis coefficient (Ck) coefficients, which provide insights into the distribution shape and tails of the temperature data. Cs values indicate positive skewness in January, February, April, May, and December, suggesting a distribution skewed towards higher temperatures during these months. Conversely, negative Cs values in rest of months suggest a distribution skewed towards lower temperatures. Ck values vary across months, with positive values indicating heavier tails and an increased likelihood of extreme temperature events, particularly noticeable in the BC RCM during June, July, and August.

Daily minimum temperature

Fig. 46, 47, 48 and 49 shows the statistical characteristics of raw and bias-corrected regional climate model (RCM) simulations for the period 2006-2100, focusing on daily minimum temperature. Fig 46 shows that in raw RCM, mean temperatures range from 2.33°C in December to 27.25°C in June, displaying typical seasonal variability with warmer temperatures in summer and cooler temperatures in winter. Bias-corrected (BC) RCM Shows consistently higher mean temperatures across all months, ranging from 15.84°C in December to 29.39°C in June. Bias correction adjusts temperatures upwards, aligning model outputs more closely with observed data.

For raw RCM, SD ranges from 1.79°C in July to 5.37°C in February, indicating variability in temperature projections throughout the year whereas for Bias-corrected RCM, SD values are generally lower compared to raw RCMs, ranging from 0.96°C in July to 3.00°C in February. This reduction suggests that bias correction smooths out variability in temperature predictions.

Fig. 47 shows that for raw RCM, Cv values range from 0.07 to 1.44, indicating higher variability relative to mean temperatures across months whereas for BC RCM, Cv values are consistently lower compared to raw RCMs, ranging from 0.03 to 0.18. This indicates that bias correction reduces variability in temperature projections, making them more consistent and reliable.

Fig. 48 shows positive Cs values in winter months (January, February) and December suggest a distribution skewed towards higher temperatures during these periods. Negative Cs values in other months indicate skewness towards lower temperatures.

Fig. 49 shows Positive Ck values in several months, particularly in July and August for both raw and bias-corrected RCMs, suggest heavier tails and a higher likelihood of extreme temperature events during these periods.

Conclusion

Based on the comprehensive bias correction analysis conducted for daily maximum and minimum temperatures in Junagadh, Gujarat, across both historical (1951-2005) and future climate change scenarios (2006-2100), several key findings emerge. The study employed the Gaussian distribution method to correct simulated temperatures from the RCA4 regional climate model, enhancing alignment with observed data. Results for the control period indicated significant underestimation by raw RCM outputs, particularly in maximum temperatures, which were effectively remedied by bias correction. This adjustment improved mean temperature accuracy and reduced variability, as evidenced by decreased coefficients of variation and improved goodness of fit metrics (R^2 values) across both calibration and validation periods. However, the study noted limitations in fully correcting skewness and kurtosis, especially in extreme temperature events, suggesting areas for further refinement in bias correction techniques. In the future period analysis, under different RCP scenarios, bias correction consistently elevated mean temperature projections while stabilizing variability, thereby enhancing the reliability of long-term climate projections for Junagadh.

In conclusion, the study underscores the effectiveness of the Gaussian bias correction method in improving the accuracy of regional climate model outputs for Junagadh's temperature profiles. This approach not only aligned simulated temperatures more closely with observed data but also enhanced the model's ability to predict future climate scenarios under various emission pathways. While the method successfully adjusted mean values and reduced variability, challenges remain in fully capturing the distribution's skewness and kurtosis, particularly in extreme temperature months. Future research could focus on refining bias correction techniques to address these nuances and further enhance the reliability of climate projections crucial for local and regional climate change adaptation strategies.

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