e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

EFFECTIVENESS OF GAUSSIAN DISTRIBUTION MAPPING FOR BIAS CORRECTION OF RCM SIMULATED TEMPERATURE FOR JUNAGADH REGION

P.H. Rank[*1], H.D. Rank[*2], PB Vekariya[*3], R.J. Patel[*4], G. Kar[*5]

[*1]Senior Research Assistant, Irrigation And Drainage Engineering Department, College Of Agricultural Engineering & Technology, JAU, Junagadh, India.

[*2]AICRP On Irrigation Water Management & Head Of Department, College Of Agricultural Engineering & Technology, JAU, Junagadh, India.

[*3,4]Assistant Professor, Soil And Water Conservation Engineering Department, College Of Agricultural Engineering & Technology, JAU, Junagadh, India.

[*5]Principal Scientist ICAR-Indian Institute Of Water Management – Bhubaneswar, India.

(*Correspondence Email: prasangpatel83@gmail.com;)

DOI : https://www.doi.org/10.56726/IRJMETS31007

ABSTRACT

The Gaussian distribution mapping approach was adopted to correct the biases in the simulation of temperature data by RCA4 RCM. It included the bias correction of temperature for the baseline period (1951-2005) and future scenarios (2006-2100). The bias correction also included calibration (1965-1995) and validation (1996-2005) by comparing it with actual observation. The bias correction improved the mean and coefficient of variation (Cv) for the calibration period with goodness of fit near to 1.0 and with reasonable goodness of fit during the validation period for RCA4 (IPCHEC) RCMs. The statistical properties like skewness coefficient (Cs) and kurtosis coefficient (Ck) were not altered because of using normal distribution for bias correction of temperature for calibration, validation and future scenario. The mean and coefficient of variation (Cv) of simulated daily temperature by RCA4 (IPCHEC) for the future scenario were required to get corrected. The Gaussian distribution mapping approach was found very effective tool for the bias correction of the RCA4 RCM simulated temperature for the Junagadh region of the Gujarat state of India.

Keywords: Distribution Mapping, Climate Change, Temperature, RCM, Simulation).

I. INTRODUCTION

Anthropogenic greenhouse gas emissions have increased since the pre-industrial era, driven largely by economic and population growth, and are now higher than ever. This has led to atmospheric concentrations of carbon dioxide, methane and nitrous oxide that are unprecedented in at least the last 800,000 years. Limiting climate change would require substantial and sustained reductions in greenhouse gas emissions which, together with adaptation, can limit climate change risks. Cumulative emissions of CO_2 largely determine global mean surface warming by the late 21st century and beyond. Climate change and agriculture are interrelated processes, both of which take place on a global scale. Climate change affects agriculture in a number of ways, including through changes in average temperatures, rainfall, and climate extremes (e.g., heat waves); changes in pests and diseases; changes in atmospheric carbon dioxide and ground-level ozone concentrations; changes in the nutritional quality of some foods; and changes in sea level. Climate change is already affecting agriculture, with effects unevenly distributed across the world. Future climate change will likely negatively affect crop production in low latitude countries, while effects in northern latitudes may be positive or negative. Climate change will probably increase the risk of food insecurity for some vulnerable groups, such as the poor.

Climate change and agriculture are interrelated processes, both of which take place on a global scale. Climate change affects agriculture in a number of ways, including through changes in average temperatures, rainfall, and climate extremes (e.g., heat waves); changes in pests and diseases; changes in atmospheric carbon dioxide and ground-level ozone concentrations; changes in the nutritional quality of some foods; and changes in sea level. The increased in the extremities due to climate change impacts will reduce the water resources (Taylor, et al, 2013). Therefore, the limited water resources have to be managed judiciously in the region having dependability on groundwater. The conditions for achieving water security, sustainable and climate resilient

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

development can be achieved through system transformations (Caretta et al., 2022). The water scarcity in the coastal area of Suarshtra region of Gujarat state of India, is the major issue which can be further worsened in the future under the threat of climate change (Rank, et al, 2020; Caretta et al., 2022). The ever-increasing population has forced to produce more from limited inputs. This can be possible only through various technological interventions like MIS, automated pulsed drip irrigation (Rank and Vishnu, 2019; Rank and Vishnu, 2021a, Rank and Vishnu, 2021b), aerated subsurface drip irrigation, optimal irrigation/fertigation schedules and mulches (Rank and Satasiya, 2022). The optimal irrigation schedules will depend on plant and soil moisture retention characteristics (Rank and Vishnu, 2022). The utmost care is required for the selection and design of these technologies considering the soil types, climate and crops for the successful outcomes (Rank, et al, 2019). The technological intervention are always costly to adopt but its proper selection, design and operation can make it profitable (Rank, et al, 2022a). The water management for any crop requires smart decisions based on the climate for getting the maximum input use efficiencies of all inputs. The crop modelling tools can be the best decision supports for maximizing the profits (Rank et al, 2022b). The climate change have positive as well as negative impact for different crops. The benefit cost ratio for wheat, cumin and green gram grown by utilizing recharged water was found higher, so one can go for bore well recharging for getting higher yield (Patel et al., 2014).

The events of climate extremities observed in the world in the recent years are witnesses of climate change. Under the climate change, noting is certain except uncertainties. Therefore, the analysis of the future climate simulated by RCM under various scenarios should be made. However, the RCM simulated climate data are always biased more or less. Therefore it should be bias corrected using appropriate methods. Therefore, it was attempted to assess the suitability of distribution mapping for the bias corrections of RCA4 RCM simulated temperature data for the study area.

II. STUDY AREA

The study area is Junagadh city of Gujarat state located at 21.52 N in latitude and 70.45 E in longitude. The Junagadh is one of the ancient city of India and located at the foot hill of Girnar. This region is follow in semiarid climate. The mean maximum temperature and minimum temperature are found for duration 1965-2005 is 38.86 0C and 10.53 0C respectively. January and May are coldest and hottest month of the year respectively.

III. DATA COLLECTION

The RCA4 RCM simulated daily maximum/minimum temperature and rainfall data(50kmx50km) for the base line period (1951-2005) and future scenario (2006-2100) for the IPCC SRES rcp4.5 for one grid points falling in Junagadh region were taken from the IITM, Pune. RCA4 were obtained from the World Climate Change Programme (WCRP) Coordinated Regional Climate Downscaling experiment (CORDEX) datasets for south Asia region derived from the Atmospheric-Ocean Coupled General Circulation Model (AOGCM) runs conducted under the Coupled Model Inter Comparison phase 5 (CMIP5) (Taylor et al. 2012) for one of four greenhouse gas emission scenario known as Representative Concentration Pathways (RCPs) (Meinshausen et al. 2011). The CMIP5 AOGCM runs were developed in support of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5). The RCM Rossby Center regional atmospheric model version 4 (RCA4) were obtained from the driving GCM Irish Center for High-End Computing (ICHEC) and European Consortium ESM (EC- Earth; Hazeleger et. al. 2012) contributing agency from the Rossy Center, Swedish Meteorological and Hydrological Institute (SMHI), Sweden. In the Present study RCA4 were taken from the Center for Climate Change Center (CCCR), Indian Institute of Tropical Management (IITM), Pune. The GCM EC-Earth is a recent earth-system model developed by a consortium of European research institutions and researchers, based on state-of-the-art models for the atmosphere, the ocean, sea ice and the biosphere. In particular, the model is based on the concept of "seamless predictions": numerical weather prediction (NWP) models are sophisticated state-of-the art models which, being based on the same physical principles may provide advanced atmospheric components for climate models. The historical observed data of minimum and maximum temperature from the year 1965 to 2005 was collected from weather observatory station at Junagadh Agricultural University, Junagadh.

IRJMETS

e-ISSN: 2582-5208

International Research Journal of Modernization in Engineering Technology and Science

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

IV. METHODOLOGY

The historical records of daily maximum and minimum temperature of 365 days of 40 years (1965-2005) for Junagadh station were collected from the JAU observatory, Junagadh and the maximum and minimum daily temperature simulated for the grid point (21.27N and 70.36E) nearest to Junagadh station by RCA4 (Rossby Centre Regional Atmospheric Model Version 4) RCM driven by Irish Centre for High-End Computing(ICHEC), European Consortium ESM (EC Earth Hazeleger et al., 2012) during the baseline period (1951-2005) were compared and that of during the future periods (2006-2100) for the RCP4.5 SRES scenario were used for the future projection. RCM simulations of temperature must be handled with caution as they often show significant biases. The reasons for such biases include systematic model errors caused by imperfect conceptualization, discretization and spatial averaging within grid cells. This makes the use of RCM simulations as direct input data for hydrological impact studies more complicated. One recommendation is to use an ensemble of RCM simulations together with bias correction methods. Bias correction methods are applied to help remedy the various problems with biased RCM output. The observed and simulated data of baseline during the period 1965-1995 were used for the calibration and period 1995-2005 were used as validation. Within probability distribution based scaling method, temperature simulated by RCM was adjusted to better reflect actual observations using cumulative distribution functions. Because the annual temperature cycle was symmetric, it could be described by normal distribution with daily mean and standard deviation which were calculated separately for each month.

Distribution Mapping

The DM method was to match the distribution function of the raw data to that of the observations. It was used to adjust mean, standard deviation and quantiles. Furthermore, it preserved the extremes. However, it also had its limitation due to the assumption that both the observed and raw meteorological variables followed the same proposed distribution, which might introduce potential new biases. For temperature time series, the Gaussian distribution with location parameter μ and scale parameter σ was usually assumed to fit best. The scale parameter σ determined the standard deviation, i.e., how much the range of the Gaussian distribution was stretched or compressed. A smaller value for σ resulted in a more compressed distribution with lower probabilities of extreme values. Contrary, a larger value for σ indicated a stretched shape with higher probabilities of extreme values. The location parameter μ directly controlled the mean and, therefore, the location of the distribution. For temperature, the procedure could be be expressed in terms of the Gaussian (normal) CDF (F_N) and its inverse (F_N^{-1}) as:

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

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

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 CD, σ^2_{contr} = monthly standard deviation for control period, σ^2_{obs} = monthly standard deviation for observe period, μ_{contr}= monthly mean for control period, μ_{obs}= monthly mean for observe period.

V. RESULTS AND DISCUSSION

The analysis was made on the bias corrections of daily maximum, minimum and mean temperature. It included the bias correction of temperature for the baseline period (1951-2005) and future scenarios (2006-2100). The bias correction also included calibration (1965-1995) and validation (1996-2005) by comparing it with actual observation. The maximum and minimum daily temperature simulated for the grid point (21.27N and 70.36E) nearest to Junagadh station by RCA4 was bias corrected by comparing it with observed data of Junagadh station. Temperature analysis is given for control period (1951-2005) and future period (2006-2100).

Daily Minimum Temperature (Tmin)

(A) Control period (1965-1995)

The comparison of observed, RCM simulated and bias corrected daily minimum temperature during the control period 1965-1995 is shown in Fig. 1.1 It could be seen that the RCM simulated daily minimum temperature

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

estimated lower than observed data except the month of July to September. However, after bias correction by distribution mapping (DM method), the bias corrected data during all the months were well matched with observed data. It could also be seen from the Fig. 1.2 that goodness of fit (R^2) between raw RCM and bias corrected RCM are 0.93 and 1.0 respectively, which shows quintile mapping method are corrected exactly the first moment about the mean. The Fig. 1.3 showed that the coefficient of variation (CV) of RCM simulated data were higher than that of observed data during months of January and December while that of during the rest of months had lower. After applying bias correction, Coefficient of Variance of bias corrected RCM had same value as observed data of temperature except December. So, it has also corrected the second moment. It could be seen in Fig. 1.4 that the goodness of fit of raw RCM and bias corrected RCM with observed data were 0.68 and 1.0 respectively. The skewness coefficient(C_s) of observed, corrected and RCM simulated daily minimum temperature data were also compared. It was found that skewness coefficient was positive in January, February and December for corrected and uncorrected data, while rest of month, that of were negative. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The kurtosis coefficient(C_k) of observed, raw and bias corrected daily minimum temperature data simulated by RCM were compared. Kurtosis coefficient was found positive for observation data for all months except November. It also showed that after applying bias corrections, kurtosis coefficient could be modified. The kurtosis coefficient(C_k) of raw and bias corrected RCM simulated daily minimum temperature were positive for January, February, August and September, while rest of the month, that of were negative.

(B) Validation Period (1996-2005)

Validation of the base period was taken from 1996-2005. The comparison of mean of raw RCM simulated, corrected RCM simulated and observed data is shown in Fig. 1.5. In validation period, as it could be seen in Fig. 1.5 that the RCM simulated uncorrected minimum temperature data were lower for all months as compared to that of observed data. However after applying bias correction, the bias corrected data were well matched with observed data. It could be seen from Fig. 1.6 that the goodness of fit for the raw RCM and corrected RCM with observation data of minimum temperature were 0.91 and 0.97 respectively. It clearly indicated that the bias correction method was found efficient for correction of mean of raw RCM data. Comparison of coefficient of variance(CV) of the simulated RCM, bias corrected RCM and observation were found as shown in Fig. 1.7 for the validation period from the 1996-2005. The coefficient of variation(CV) of RCM simulated data was higher from month of January, February, September, November and December as compared to observed data. After applying bias correction, CV of bias corrected data were reduced as compared to raw RCM for the month January, while rest of months, that of have higher values. It could be seen from the Fig. 1.8 that the goodness of fit for the Raw RCM and bias corrected RCM with observed data were 0.42 and 0.92 respectively. So, it indicated that the value of CV was not exactly matched for the duration of validation period 1996-2005. The skewness coefficient(Cs) for RCM simulated and bias corrected minimum temperature data was positive for the month of January, March, August, November and December, while that of the rest of months were negative. It revealed from the results that there was no correction of skewness coefficient(Cs) through bias corrections. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The comparison of kurtosis coefficient (C_k) of observed, raw RCM and bias corrected were made. The kurtosis coefficient (C_k) was found negative for raw RCM and corrected RCM minimum temperature data in March, April and June to December, while rest were positive. C_k value of observed were positive for the month of March to August. There were no correction of C_k value after bias correction. It clearly showed that Gaussian distribution could not correct the fourth moment of the temperature distribution.

(C) Future Period (2006-2100)

The comparison of RCM simulated corrected and uncorrected daily minimum temperature during the future period 2006-2100 is depicted in Fig. 1.9 and it was seen that the bias corrected minimum temperature was higher in January to November than the RCM uncorrected data and was same for month of December. The coefficient of variation (CV) of RCM simulated corrected data was higher from Feb to Sept, while same for Oct and November and reduced for January to December (Fig. 1.10). The skewness coefficient was positive in January, February and December, while that of the rest months, it were found were negative. The kurtosis coefficient was positive for January, February, April to June and August, while lower for the rest of months.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

Daily Maximum Temperature (Tmax)

(A) Control period (1965-1995)

The comparison of observed, RCM simulated and bias corrected daily maximum temperature during the control period 1965-1995 was found shown in Fig. 2.1 It could be seen that the RCM simulated daily maximum temperature estimated lower than observed data for the all months. It could be seen from the Fig. 2.2 that goodness of fit (R^2) between raw RCM and bias corrected RCM were 0.84 and 1.0 respectively, which showed that the quintile mapping method had corrected the first moment. The Fig. 2.3 showed that the coefficient of variation (CV) of RCM simulated data was higher than that of observed data during months of January, February and September to December, While that of during the rest of month were lower. After applying bias correction, the coefficient of variation of bias corrected RCM had same value as observed data of temperature. So, it had corrected the second moment also. It could be seen in Fig. 2.4 that the goodness of fit for the raw RCM and bias corrected RCM with observed data were -0.05 and 1.0 respectively.

The skewness coefficient of observed, corrected and RCM simulated data were compared. The skewness coefficient was positive for months of January, February, August, September and December, while that of during the rest months were negative for observation data. It clearly showed that there was no bias correction effects on skewness coefficient. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The kurtosis coefficient of observed data, simulated RCM and bias corrected RCM were also compared. The kurtosis coefficient were positive for observation data from January, March to June and August to December. While that of during the rest of month of the year, was negative. It also showed from that after applying bias correction, the kurtosis coefficient did not change. It clearly showed that Gaussian distribution could not correct the fourth moment of the temperature distribution.

(B) Validation Period (1996-2005)

The validation of the base period was taken from 1996-2005. The comparison of mean among RCM simulated uncorrected, corrected and observed data was found as shown in Fig. 2.5. In validation period, as it could be seen in Fig.2.5 that the RCM simulated uncorrected data were lower for all months as compared to observed data. After applying bias correction, the mean of corrected RCM were well matched with observed data. It could be seen from Fig. 2.6 that the goodness of fit for the raw RCM and corrected RCM with observation data were 0.7 and 0.9 respectively. It clearly indicated that bias correction method was found efficient for correction of mean of RCM data. The comparison of coefficient of variance (CV) of the simulated RCM, bias corrected RCM and observation were found as shown in Fig. 2.7 for the validation period for the 1996-2005. The coefficient of variation(CV) of RCM simulated data was higher for month of January to April and September to December as compared to observed data. After applying bias correction, the coefficient of variation of bias corrected data were higher compared to raw RCM for the month March to August. It could be seen from the Fig. 2.8 that the goodness of fit for the raw RCM and bias corrected RCM with observed data were 0.02 and -2.6 respectively. So, it indicated that the value of CV was not exactly corrected for the duration of validation period of 1996-2005.

The skewness coefficient(Cs) for RCM simulated and bias corrected data was Positive for the month of March, June, September and October, while that during the rest of months, it was negative. It revealed that there was no correction of Cs. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The comparison of kurtosis coefficient (Ck) of Observed, raw RCM and bias corrected were also compared. The kurtosis coefficient (Ck) was found negative for raw RCM and corrected RCM data in January, February, April, May, July, August, November and December, while that of during the rest of month were positive. It showed that there was no correction of Ck value after bias correction. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution.

(C) Future Period (2006-2100)

The comparison of RCM simulated corrected and uncorrected daily maximum temperature during the future period 2006-2100 was found as depicted in Fig. 2.9 and it could be seen that the bias corrected maximum temperature was higher for all the months. The coefficient of variation (CV) of RCM simulated corrected data was higher during April to August as shown in Fig. 2.10. The skewness coefficient was found positive in August to October and Kurtosis coefficient was positive in August to October, while during the rest of month, that of was negative. The kurtosis coefficient was negative for March, while that of during the rest of month was positive.

Daily Mean Temperature (Tmean)

(A) Control period (1965-1995)

The comparison of monthly mean of observed, RCM simulated and bias corrected daily mean temperature during the control period 1965-1995 was found as shown in Fig. 3.1. It could be seen that the RCM simulated daily mean temperature estimated lower than that of observed data. However, after bias corrected by distribution mapping (DM method), the bias corrected data during all the months were matched with observed data. It could also be seen from the Fig. 3.2 that the goodness of fit (R^2) for raw RCM and bias corrected RCM with actual observations were 0.92 and 1.0 respectively, which showed that the quintile mapping method had corrected the first moment. The Fig. 3.3 showed that the coefficient of variation (CV) of RCM simulated data was higher than that of observed data during months of January to March and October to December, while that of during the rest of months, had lower. After applying bias correction, the coefficient of variation of bias corrected RCM had same value as observed data of temperature. So, it had also corrected the second moment. It could be seen from Fig. 3.4 that the goodness of fit of Raw RCM and bias corrected RCM with observed data were 0.55 and 1.0 respectively

The skewness coefficient of observed, corrected and RCM simulated data were compared. It could be seen that the skewness coefficient was positive in January, March, May, September, October and December for corrected and uncorrected data, while that of during the rest of months were negative. It also showed that the skewness coefficient was positive only for month of January, March, April and while was negative for December. It clearly showed that there was no effects of bias correction on skewness coefficient. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The kurtosis coefficient of observed data, simulated RCM and bias corrected RCM were also compared. The kurtosis coefficient was positive for observation data for all months except November. It also showed that after applying bias correction, the kurtosis coefficient did not change. The kurtosis coefficient of simulated RCM and bias corrected RCM were positive for April, May and September and November while that of during the rest of the month were negative. It clearly showed that Gaussian distribution could not correct the fourth moment of the temperature distribution.

(B) Validation Period (1996-2005)

The validation of the base period was taken from 1996-2005. The comparison of mean among RCM simulated uncorrected, corrected data and observed data was found as shown in Fig. 3.5. In validation period, as it could be seen in Fig.3.5 that the RCM simulated uncorrected data was lower in all month as compared to observed data. After applying bias correction, mean of corrected RCM were higher than the RCM simulated data. Also, it could be seen from Fig.3.5 that the value of corrected RCM were higher during January, May to August and October than that of the actual observed data. It could be seen from Fig. 3.6 that the goodness of fit for the raw RCM and corrected RCM with observation data were 0.97 and 0.89 respectively. It clearly indicated that DM bias correction method was efficient for correction of mean of RCM data. The comparison of coefficient of variation(CV) of the simulated RCM, bias corrected RCM and observation were found as shown in Fig. 3.7 for the validation period from the 1996-2005. The coefficient of variation(CV) of RCM simulated data was higher in month of January to April and September to December as compared to that of observed data. After applying bias correction, coefficient of variation(CV) of bias corrected data was reduced as compared to raw RCM for the month January to March and October to December while rest of month it had higher. It could be seen from the Fig. 3.8 that the goodness of fit for the Raw RCM and bias corrected RCM with observed data were 0.36 and 0.85 respectively. So, it indicated that the value of coefficient of variation(CV) was not exactly matched for the validation period-1996-2005.

The skewness coefficient(Cs) for RCM simulated and bias corrected data was positive for the month of March, May, June, September, October, and December, while that of during the rest of month were negative. It revealed that there is no correction of Cs through nias correction by DM method. It clearly showed that Gaussian distribution could not correct the third moment of the temperature distribution. The comparison of kurtosis coefficient (C_k) of observed, raw RCM and bias corrected were also made. The kurtosis coefficient (C_k) was

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

found negative for raw RCM and corrected RCM data in March, May, July to September and November while that of during the rest were positive. kurtosis coefficient (C_k) value of observed data were positive for the month of March to June and August to October. It showed that there was no correction of kurtosis coefficient (C_k) after bias correction. It clearly showed that Gaussian distribution could not correct the fourth moment of the temperature distribution

(C) Future Period (2006-2100)

The comparison of corrected and uncorrected daily mean temperature simulated by RCM during the future period 2006-2100 was fond as depicted in Fig. 3.9 and it could be seen that the bias corrected mean temperature were higher during all of the months. The coefficient of variation (CV) of RCM simulated corrected data was higher in April to September (Fig. 3.10).

The skewness coefficient was positive in August and September and the kurtosis coefficient was positive in January, February, May and October and negative in rest of the months.

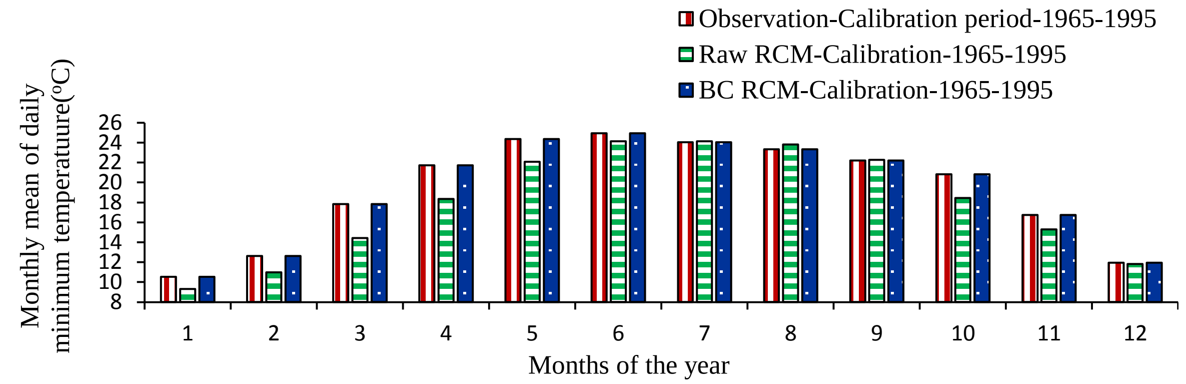

Fig 1.1: Comparison of the monthly mean of observed, raw and bias corrected daily minimum temperature during calibration period-1965-1995

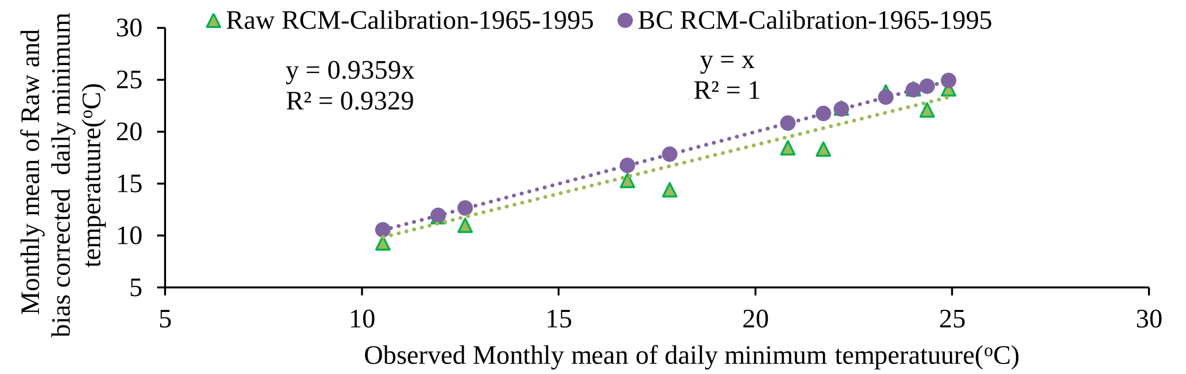

Fig 1.2: Comparison of the monthly mean of observed, raw and bias corrected daily minimum temperature during calibration period-1965-1995

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

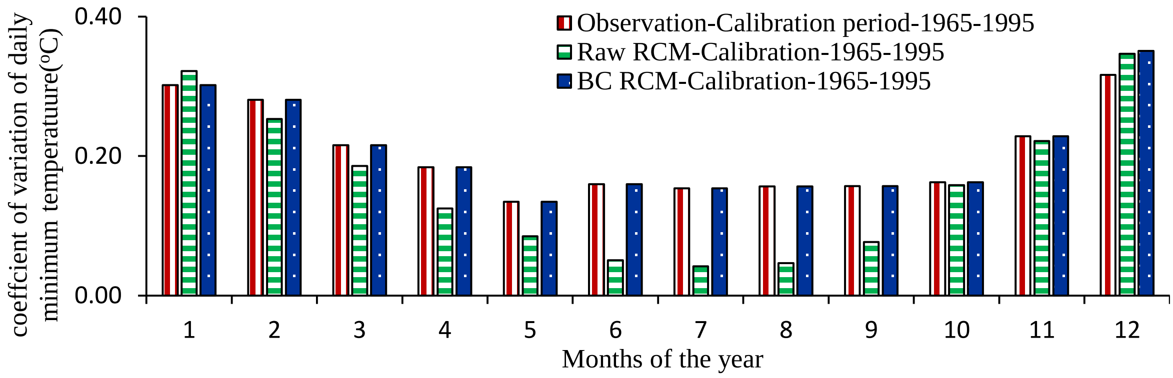

Fig 1.3: Comparison of the coefficient of variation of observed, raw and bias corrected daily minimum temperature during calibration period-1965-1995

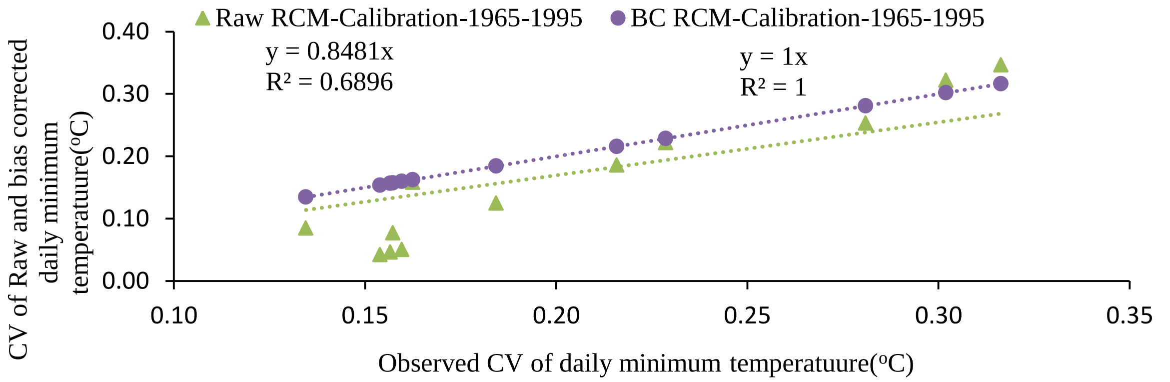

Fig 1.4: Comparison of the coefficient of variation of observed, raw and bias corrected daily minimum temperature during calibration period-1965-1995

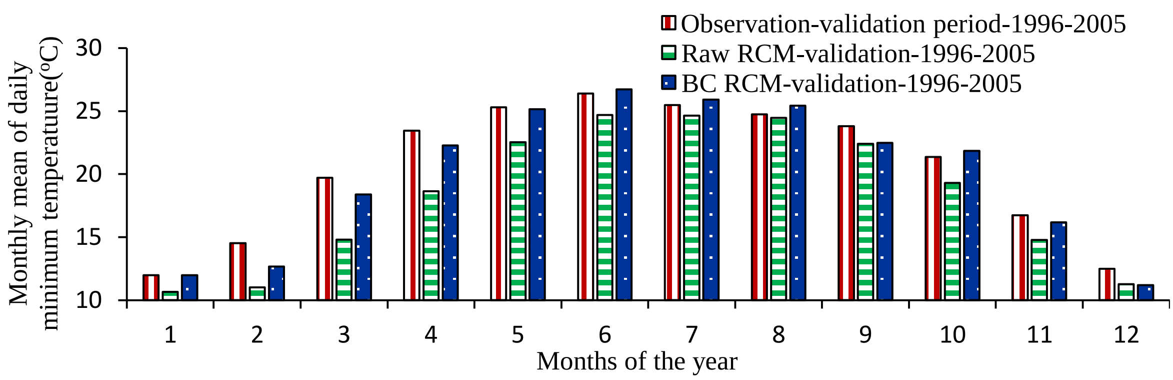

Fig 1.5: Comparison of the monthly mean of observed, raw and bias corrected daily minimum temperature during validation period-1996-2005

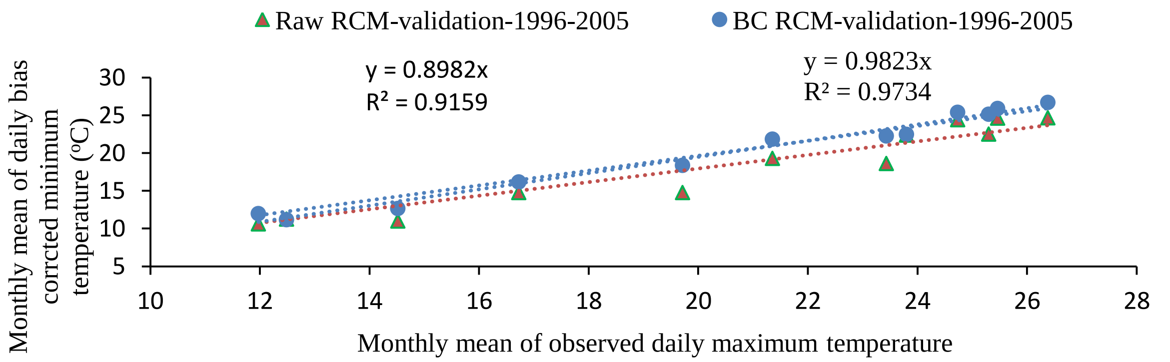

Fig 1.6: Comparison of the monthly mean of observed, raw and bias corrected daily minimum temperature during validation period-1996-2005

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

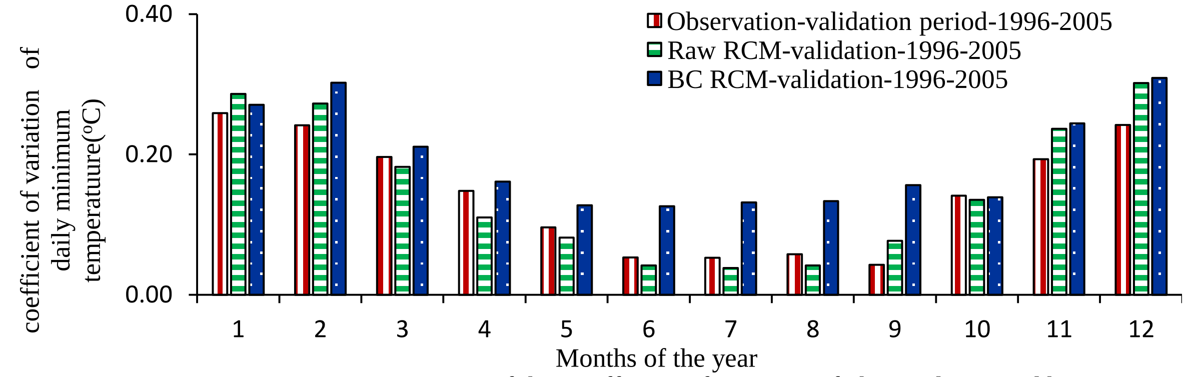

Fig 1.7: Comparison of the coefficient of variation of observed, raw and bias corrected daily minimum temperature during validation period-1996-2005

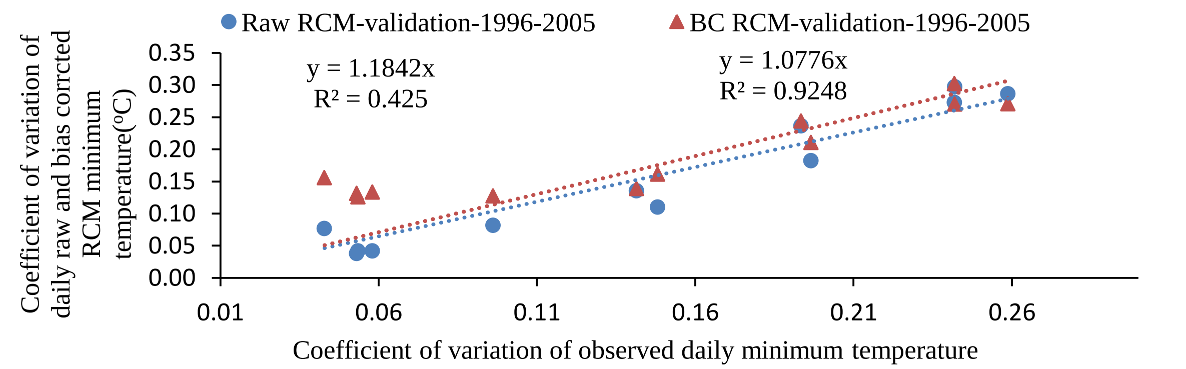

Fig. 1.8: Comparison of the coefficient of variation of observed minimum temperature during validation period-1996-2005

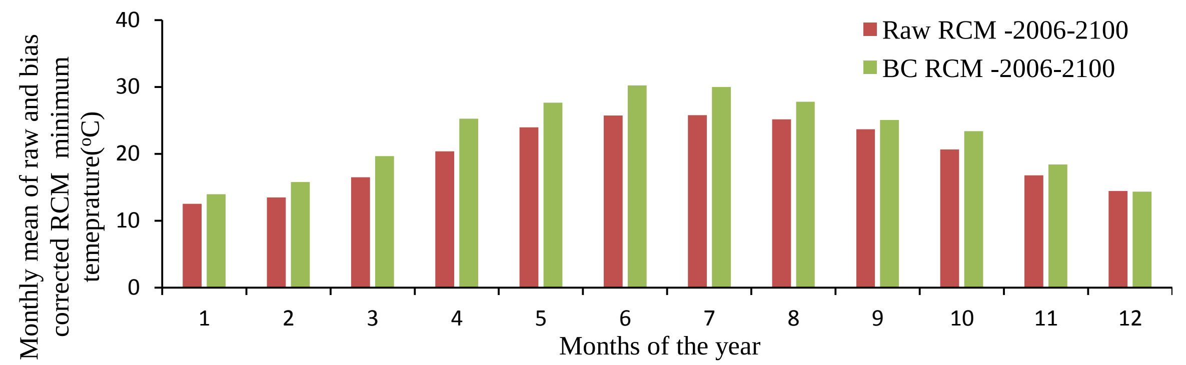

Fig. 1.9: Comparison of raw and bias corrected RCM monthly mean of daily minimum temperature during future period-2006-2100

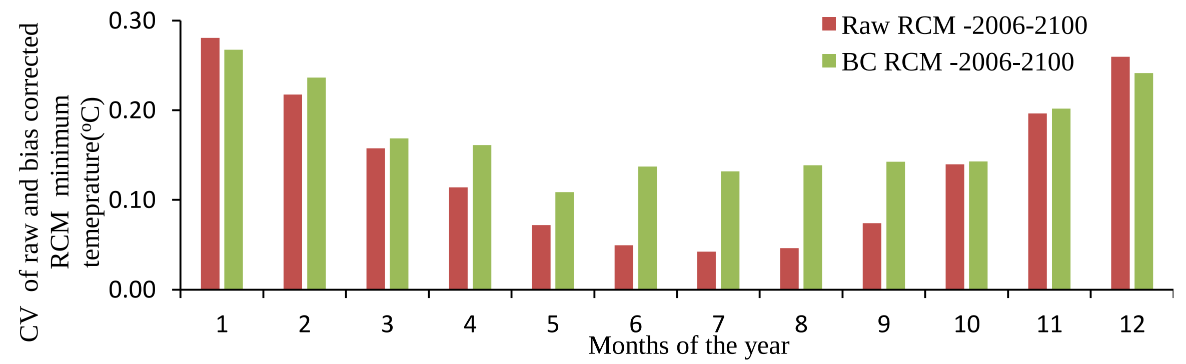

Fig. 1.10: Comparison of CV of raw and bias corrected RCM daily minimum temperature during future period-2006-2100

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

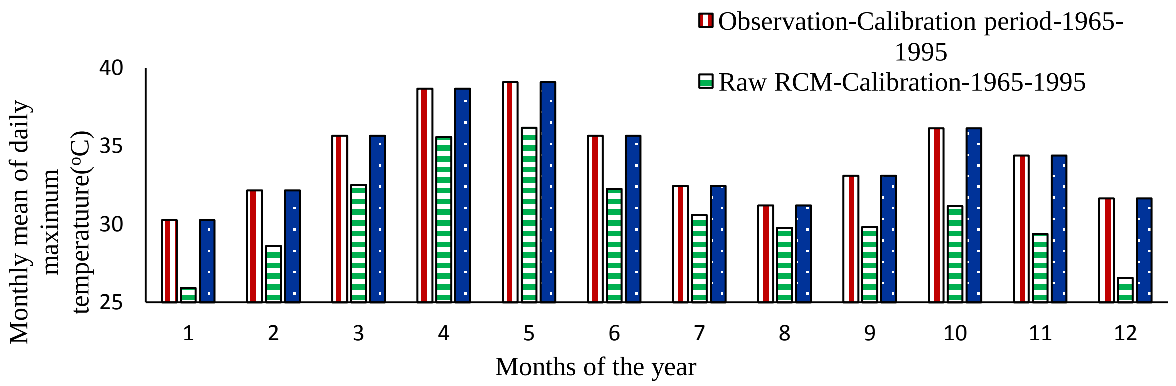

Fig 2.1.: Comparison of the monthly mean of observed, raw and bias corrected daily maximum temperature during calibration period-1965-1995

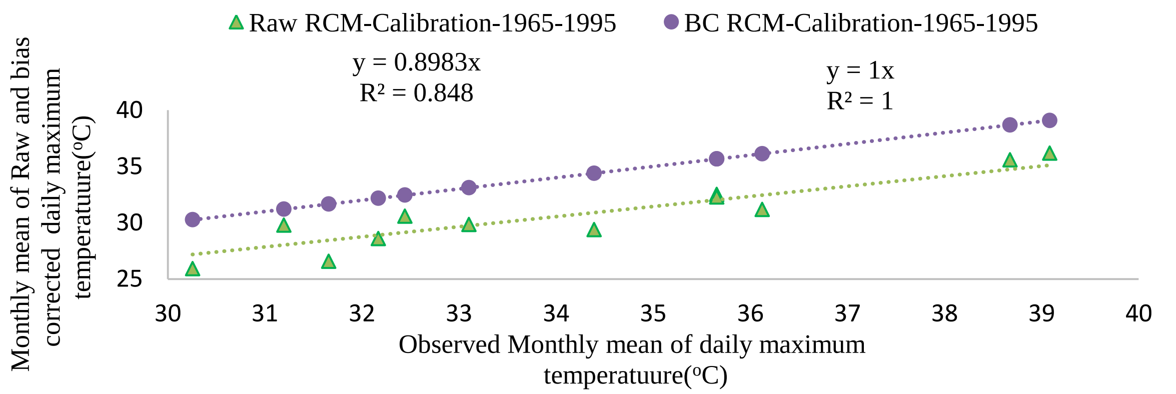

Fig 2.2: Comparison of the monthly mean of observed, raw and bias corrected daily maximum temperature during calibration period-1965-1995

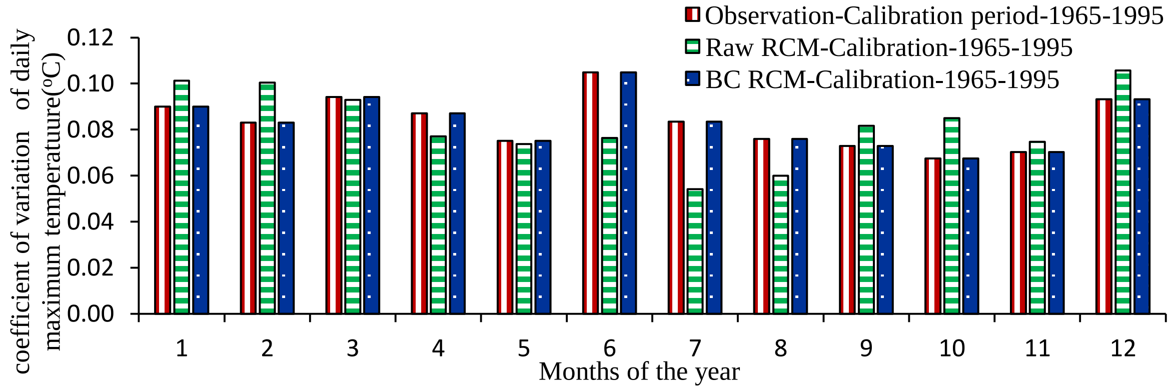

Fig 2.3: Comparison of the coefficient of variation of observed, raw and bias corrected daily maximum temperature during calibration period-1965-1995

IRJMETS
e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

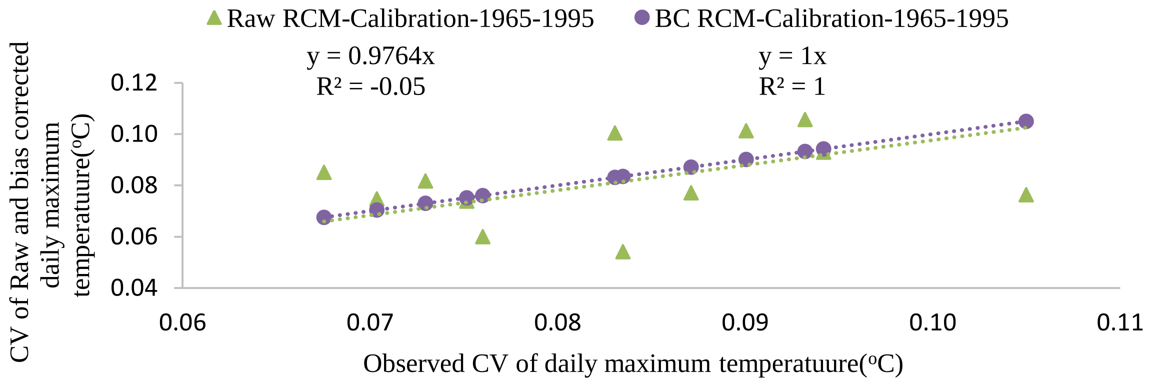

Fig 2.4: Comparison of the coefficient of variation of observed, raw and bias corrected daily maximum temperature during calibration period-1965-1995

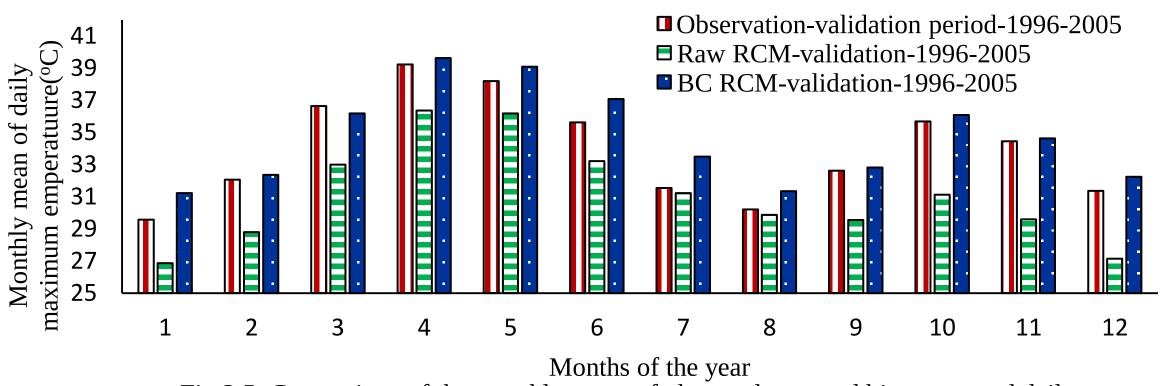

Fig 2.5: Comparison of the monthly mean of observed, raw and bias corrected daily maximum temperature during validation period-1996-2005

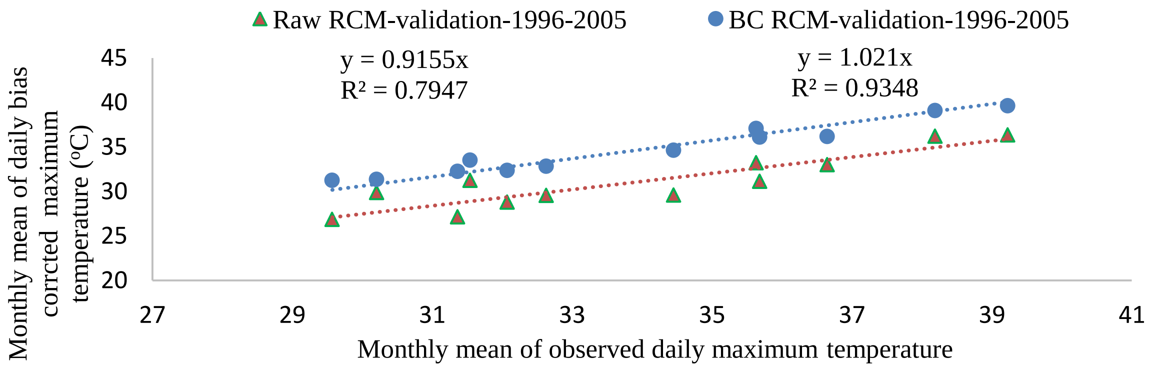

Fig 2.6: Comparison of the monthly mean of observed, raw and bias corrected daily maximum temperature during validation period-1996-2005

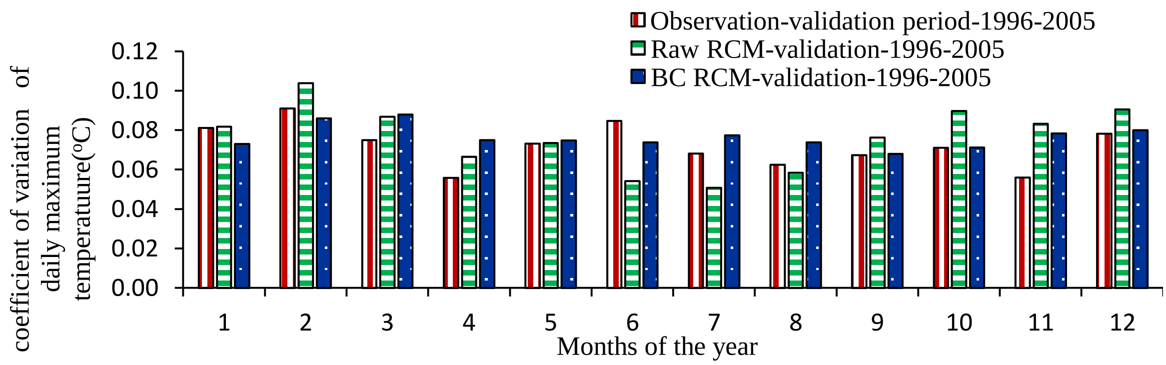

Fig 2.7: Comparison of the monthly mean of observed, raw and bias corrected daily maximum temperature during validation period-1996-2005

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

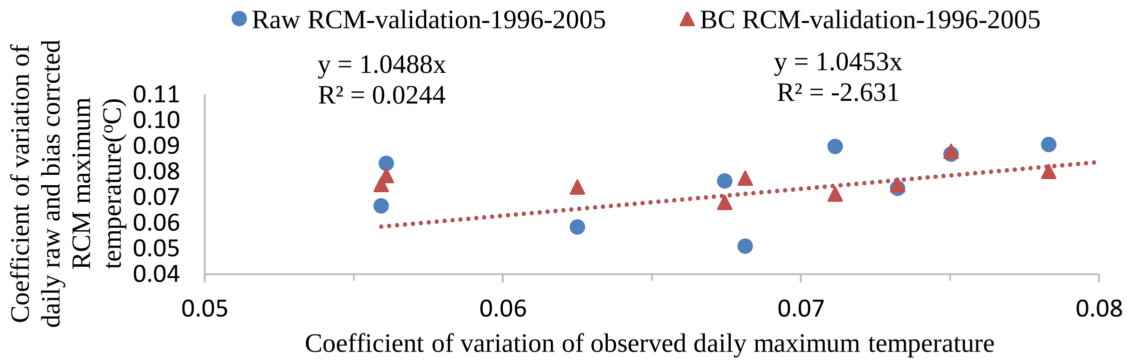

Fig. 2.8: Comparison of the coefficient of variation of observed maximum temperature during validation period-1996-2005 of Junagadh

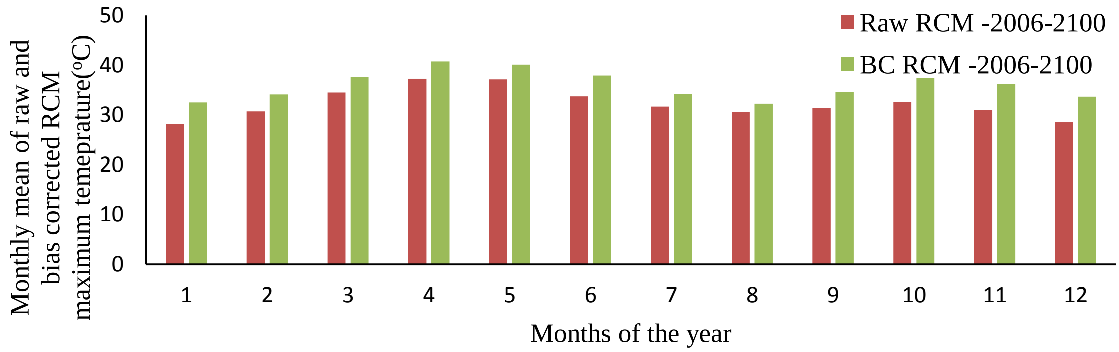

Fig. 2.9: Comparison of raw and bias corrected RCM monthly mean of daily maximum temperaturedurng future scenario-2006-2100

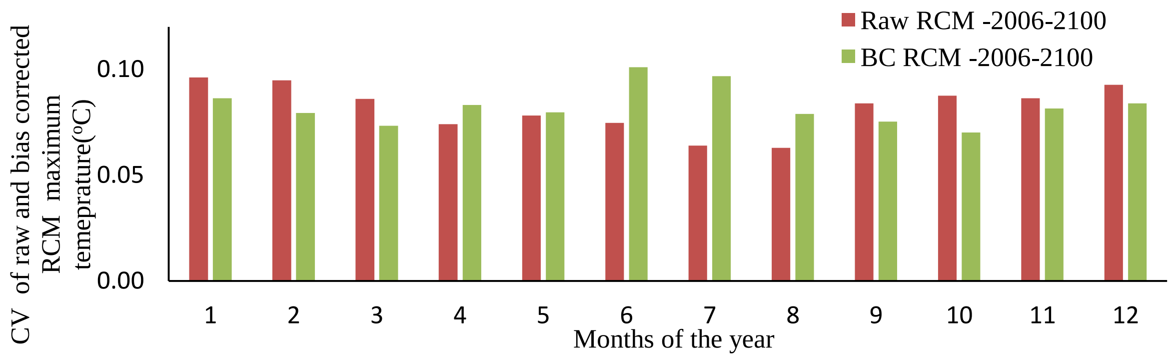

Fig. 2.10: Comparison of CV of raw and bias corrected RCM daily maximum temperature during future period-2006-2100

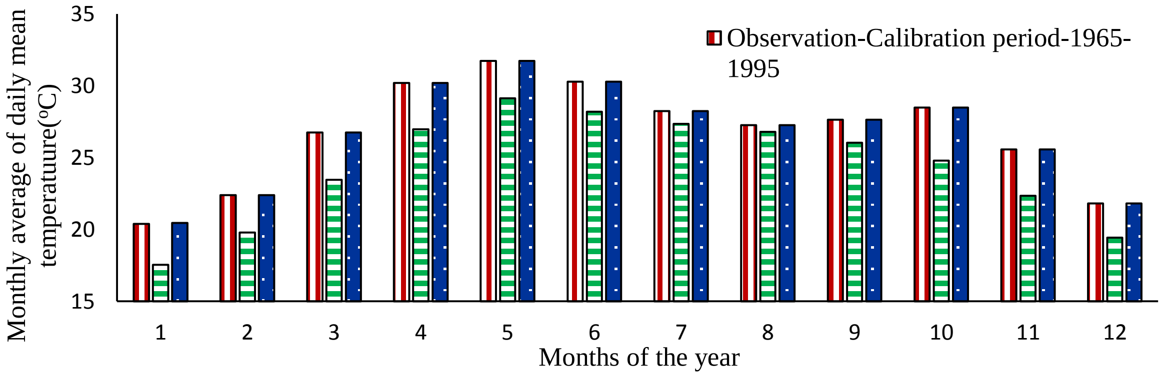

Fig 3.1: Comparison of the monthly mean of observed, raw and bias corrected RCM simulated daily mean temperature during calibration period 1965-1995

IRJMETS

e-ISSN: 2582-5208

International Research Journal of Modernization in Engineering Technology and Science

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

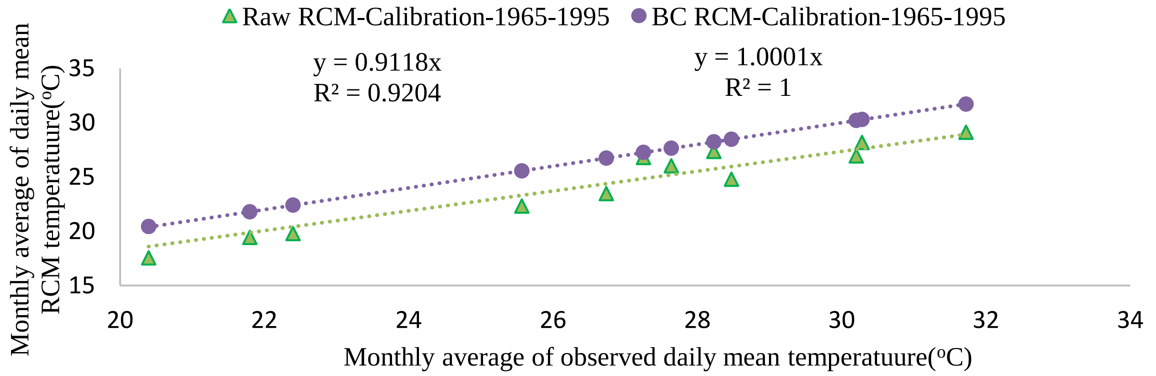

Fig 3.2: Comparison of the monthly mean of observed, raw and bias corrected daily mean temperature during calibration period-1965-1995

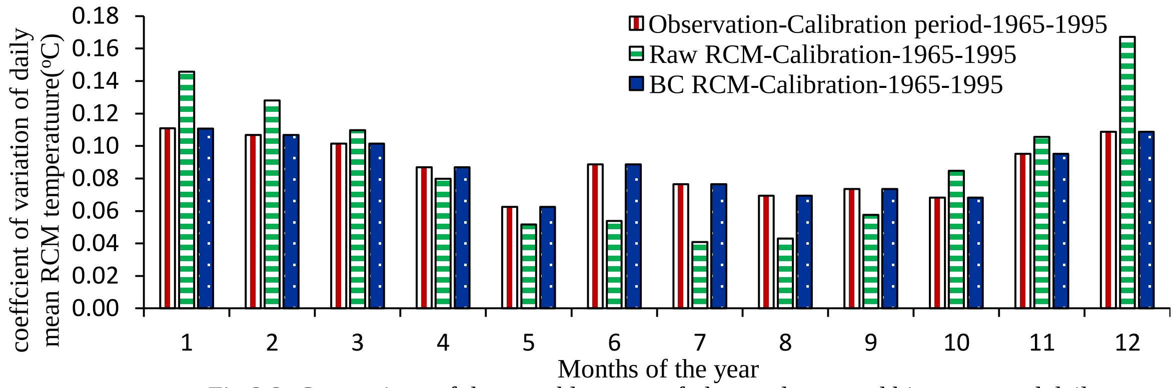

Fig 3.3: Comparison of the monthly mean of observed, raw and bias corrected daily mean temperature during calibration period-1965-1995

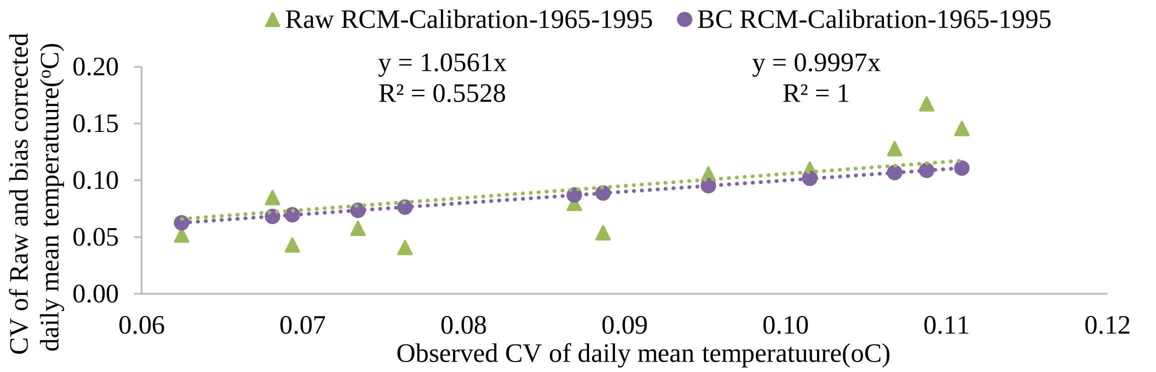

Fig. 3.4: Comparison of the coefficient of variation of observed, raw and bias corrected daily mean temperature during calibration period-1965-1995

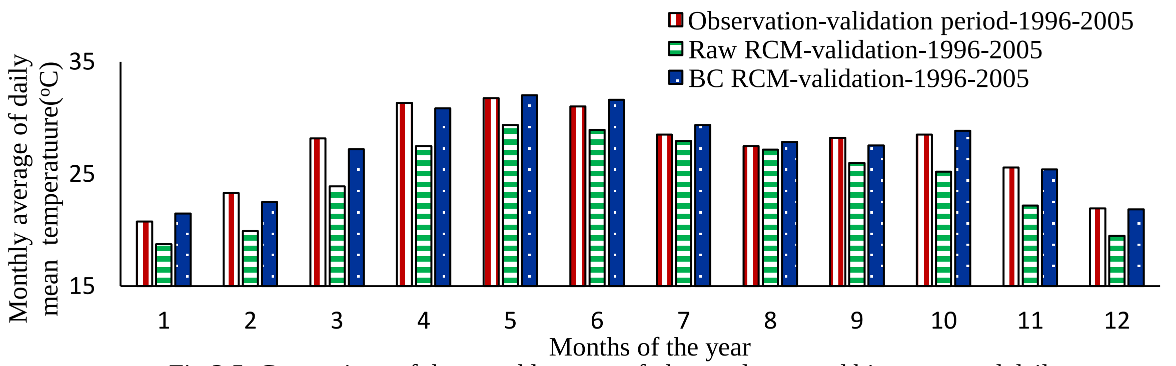

Fig 3.5: Comparison of the monthly mean of observed, raw and bias corrected daily mean temperature during validation period-1996-2005

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

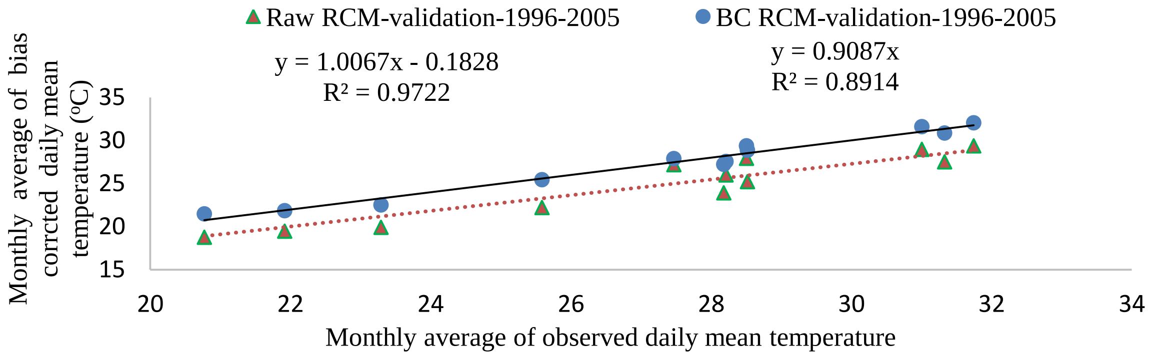

Fig 3.6: Comparison of the monthly mean of observed, raw and bias corrected daily mean temperature during validation period-1996-2005

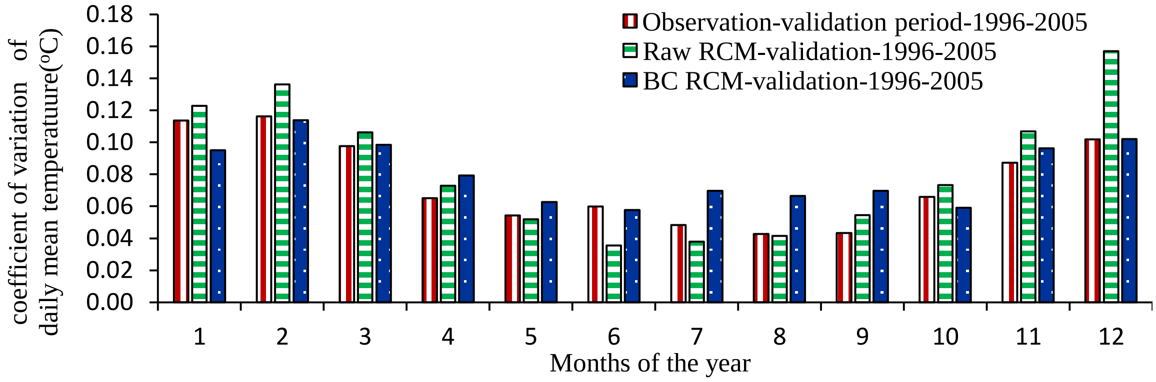

Fig 3.7: Comparison of the coefficient of variation of observed, raw and bias corrected daily mean temperature during validation period-1996-2005

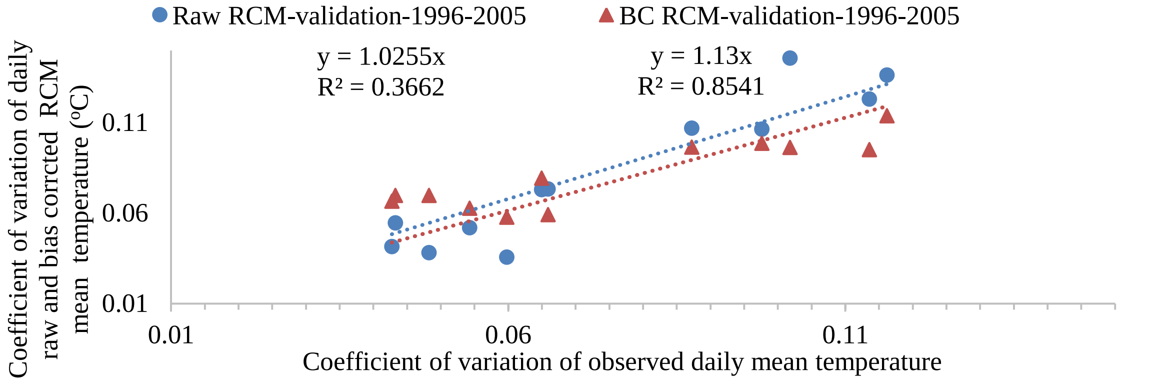

Fig. 3.8: Comparison of the coefficient of variation of observed mean temperature during validation period-1996-2005

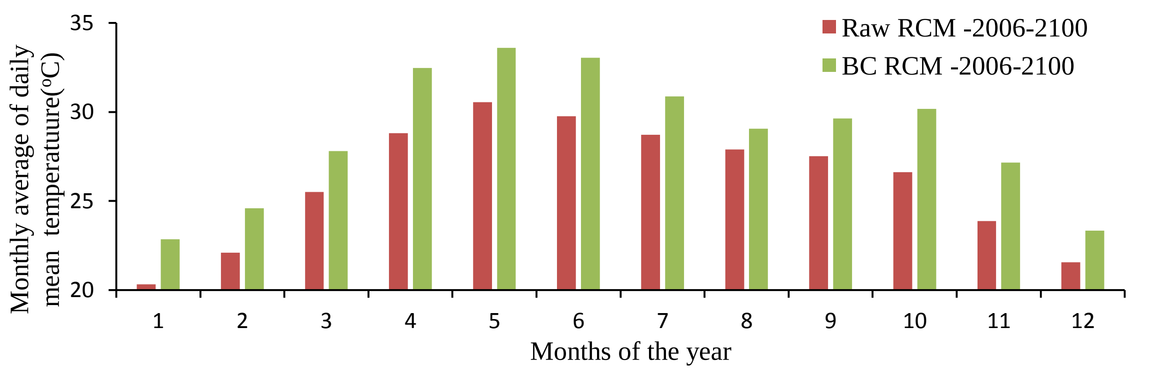

Fig. 3.9: Comparison of monthly mean of raw and bias corrected RCM simulated daily mean temperature during future scenario-2006-2100

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

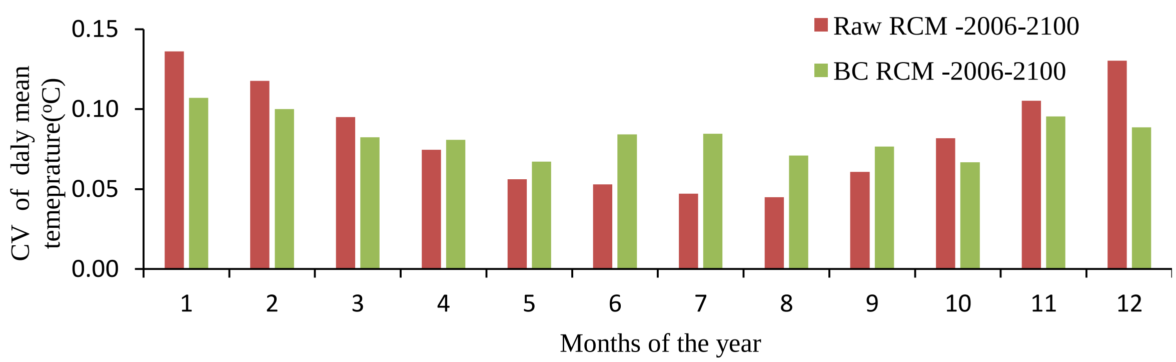

Fig. 3.10: Comparison of CV of monthly mean of raw and bias corrected RCM simulated daily mean temperature during future scenario-2006-2100

VI. CONCLUSION

An approach was adopted as The Gaussian distribution mapping to correct the biases in the simulation of temperature data by RCA4 RCM. The statistical properties like skewness coefficient (Cs) and kurtosis coefficient (Ck) were not altered because of using normal distribution for bias correction of temperature for calibration, validation and future scenario. The Gaussian distribution mapping approach was found very effective tool for the bias correction of the RCA4 RCM simulated temperature.

ACKNOWLEDGEMENTS

The authors are grateful to the Directorate of Water Management, ICAR, Bhubaneswar for the financial and technical supports for the study under NICRA project. Authors are highly thankful for Center for climate change research (CCCR), Indian institute of Tropical management (IITM) and Junagadh Agricultural University, Junagadh for providing the Regional climate Model (RCM) data and climate data.

VII. REFERENCES

[1] Caretta, M.A., A. Mukherji, M. Arfanuzzaman, R.A. Betts, A. Gelfan, Y. Hirabayashi, T.K. Lissner, J. Liu, E. Lopez Gunn, R. Morgan, S. Mwanga, and S. Supratid. (2022). Water. In: H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (Eds.) Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. (pp. 551–712) Cambridge University Press. doi:10.1017/9781009325844.006.

[2] Hazeleger, W., Wang, X., Severijns, C. et al. Clim Dyn (2012) 39: 2611. https://doi.org/10.1007/s00382-011-1228-5.

[3] Meinshausen, M. , S. J. Smith, K. V. Calvin, J. S. Daniel, M. Kainuma, J.-F. Lamarque, K. Matsumoto, S. A. Montzka, S. C. B. Raper, K. Riahi, A. M. Thomson, G. J. M. Velders and D. van Vuuren. The RCP Greenhouse Gas Concentrations and their Extension from 1765 to 2300. Climate Change 109:213-241.

[4] Patel, R.J., Rank, H.D., Ajudiya, B.H. and Dhanani, N.V., 2014. An assessment of ground water recharge potential through tube well. International Journal of Engineering Research & Technology (IJERT), 3(10), pp.155-160.

[5] Rank, P.H. and Satasiya, R.M. (2022). Sweet corn crop (Zea mays L.) performance under various irrigation water management strategies. The Pharma Innovation Journal. 11(6): 1525-1531.

[6] Rank, P.H. and Vishnu, B. (2021a). Design concept of pulse drip irrigation, International Research Journal of Modernization in Engineering Technology. 03(12): 414-420.

[7] Rank, P.H. and Vishnu, B. (2021b). Pulse drip irrigation: A review. Journal of Pharmacognosy and Phytochemistry. 10(1): 125-130.

[8] Rank, P.H. and Vishnu, B. (2022). Validation of Models for Simulating the Soil Moisture Characteristics. Agricultural Science Digest. Accepted on 22.06.2022.

[9] Rank, P.H., Satasiya, R.M., Patel, D.V., Shitap, M. (2022a). Cost economics of irrigation water management strategies for Sweet Corn (Zea mays L.), Multi-Logic in Science. VOL. XII, ISSUE XXXXIII, pp. ISSN 2277-7601.

[10] Rank, P.H., Satasiya, R.M., Vekariya, P B, Limbasiya, B B, Sardhara, V K, Patel, R J, Pandya P A and Mashru H H (2022b). Simulating the Water Footprints of Sweet Corn (Zea Mays L.) Under Various Irrigation Water Management Strategies Using AquCrop Model. International Journal of Modernization in Engineering Technology and Science, 04(08): 1572-1581.

[11] Rank, P.H., Unjia, Y.B., Kunapara, A.N. (2019). Soil wetting pattern under point and line source of trickle irrigation. International Journal of Current Microbiology and Applied Science. 8(07): 785-792.

[12] Rank, P.H., Vekariya, P.B. and Rank, H.D. (2020). Climate change impact on hydrologic system in Aji River Basin. Research Biotica. 2(2): 30-39.

[13] Rank, P.H., Vishnu, B. (2019). Automation of pulsed drip irrigation. International Journal of Engineering Science and Computing. 9(7): 23265-23276.

[14] Taylor, R.G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J.S., Edmunds, M. and Konikow, L., 2013. Ground water and climate change. Nature climate change, 3(4), pp.322-329.