



(RESEARCH ARTICLE)



Comparative study between observed and numerical downscaled data of surface air temperature

Imran Hussain Mahdy ^{1,*}, Mujibur Rahman ¹, Fatema Islam Meem ² and Partha Protim Roy ³

¹ Department of Agricultural Construction and Environmental Engineering, Sylhet Agricultural University, Alurtol Road, Sylhet-3100, Bangladesh.

² Department of Computer Science, Brac University, Badda, Dhaka-1212, Bangladesh.

³ Department of Irrigation and Water Management, Sylhet Agricultural University, Alurtol Road, Sylhet-3100, Bangladesh.

World Journal of Advanced Research and Reviews, 2024, 23(01), 2019–2034

Publication history: Received on 11 June 2024; revised on 18 July 2024; accepted on 20 July 2024

Article DOI: <https://doi.org/10.30574/wjarr.2024.23.1.2175>

Abstract

Surface Air temperature, being one of the key parameters of climate, plays an important role in occurrence severe environmental issues like droughts, floods, rate of evaporation etc. In this study, an endeavor has been made to investigate the experiments available in Educational Global Climate Model (EdGCM) at Sylhet Agricultural University for recognizing best suited experiment to predict the changing pattern of surface air temperature at Sylhet region. Downscaling is a cutting-edge procedure to produce high-goals atmosphere change expectation from coarse to fine goals of worldwide atmosphere model outcomes and a conspicuous device for estimating future atmosphere situation at the local scale for some information alarm zone like Bangladesh. Maps are generated from EdGCM simulation run to collect data and depict global temperature variations. Transform software have been connected to downscale the outcomes of temperature data by Doubled_CO₂, Global_Warming_01, Ice_Age_21kya, IPCC_A1F1_CO₂, Modern_PredictedSST and Modern_SpecifiedSST. The trend analysis was performed using the Mann-Kendall Trend test and Sen-slope estimator. Temperature changes are significant for observed results, Doubled_CO₂ and IPCC_A1F1_CO₂ results where p-value is less than alpha 0.05. Doubled_CO₂ results are more suited for dry season and IPCC_A1F1_CO₂ provides better results for monsoon. The investigation could have been unquestionably progressively broad in the event that more situations of EdGCM information were utilized, and local boundary conditions were used.

Keywords: Surface Air temperature; Environment; Climate Analysis; Global Climate

1. Introduction

Climate is defined as a measure of the average pattern of variation of meteorological parameters (precipitation, humidity, temperature and others) in a given region over a long period. Similarly, Climate change refers to significant changes in global temperature, precipitation, wind patterns and other measures of climate that occur over several decades or longer (Kalhapure et al. 2019). In a study conducted by Azad (2015) signifies the vulnerability of climate change in Bangladesh. The morphological and topological set of Bangladesh creates it at risk of the impact of climate change thus water level rise and different climate anomaly like monsoon transferring and changing intensity of precipitation. In another study, Dastagir (2015) stated the climatic condition of Bangladesh. The effects of natural calamities such as cyclones, tidal surges, floods, salinity intrusions, droughts etc. and damaged causes of them due to global warming and climate change, their frequency and intensity have been increasing over recent decades also discussed. The study was conducted by climate modelling data, where it showed significant trends due to climate change in Bangladesh.

* Corresponding author: Imran Hussain Mahdy

Surface Air temperature is one of the key parameters of climate and variations in the pattern of the variable can affect human health, economic growth and development. An increase or decrease in temperature pattern can result in an increase in the frequency of droughts, instances of floods and the impact on water quality, increase in Earth's temperature results in an increase in evaporation. Cloud formation also to occur, which increases precipitation, indicating that temperature and precipitation are interconnected. Therefore, it is necessary to carry out statistical analysis to find the trend for this important climatic parameter, i.e. temperature. The statistical analyses used in the present study are correlation co-efficient to find out the relation of various global climatic models with local observed data. Mann Kendall Test (Mann 1945, Kendall 1975) and Sen's Slope estimator (Sen, 1968). The Mann Kendall test has been used to detect trends in the time series of the precipitation, and Sen's slope estimator has been used to find out the magnitude of the detected trend. Islam (2009) studied rainfall projection using the regional climate model (RCM) called PRECIS (Providing Regional Climates for Impact Studies) for Bangladesh. The model control run (1961-1990) was completed in 50 km horizontal grid resolution and model generated rainfall was calibrated with ground-based rainfall measurement at 27 observational sites throughout Bangladesh. The model is again run for 2000-2020 to carry out validation and forecast of rainfall. It found that PRECIS over-performed by about 4.47% during 2000-2006 in estimating rainfall over Bangladesh with R2 is 0.81, and the correlation coefficient is 0.90. This admirable performance of PRECIS encourages using it for the projection of rainfall as well as surface water in the country. Kumar et al. (2006) used PRECIS to develop high-resolution climate change scenarios. Xu C Y (1999) discussed the advantages and disadvantages of different methods for the assessment of climate change impacts. Also discussed the gaps between the GCMs ability and requirement of the hydrological models for impact assessment. Xu C Y (1999) studied the existing gap and the methodologies for narrowing the gap between GCMs' ability and the need for hydrological modelling.

Azad (2015) studied the coastal region of Bangladesh, which is vulnerable to climate change due to its flat topography and dense population and poverty. the Global Climate Model (GCM) provides climate change predictions in coarse resolution (>100km), which often not sufficient for the need for high-resolution information for the impact investigations. Downscaling provides a way to generate high-resolution climate change predictions from the coarse resolution GCM output. Dibike and Coulibaly (2005) studied the comparative advantages and disadvantages of the two downscaling techniques, i.e. SDSM and LARS-WG model, used to downscale GCMs into catchment scale. As GCMs do not provide a direct assessment of the regional hydrologic changes, downscaling is required. Fowler et al. (2007) studied the current developments in the real advances and new concepts of downscaling methods for evaluating the uncertainties concerned with hydrological impacts. They suggested a comparison of various downscaling methods, results from multiple GCMs, and multiple emission scenarios for the planning and management should be used in the estimation of climate change impacts. Karl et al. (1990) proved that the regression-based downscaling techniques also help from the standardization of the predictor variables so that the corresponding distributions of observed and present-day GCM predictors are in close agreement. Arora et al. (2009) studied the trends in temperature time series of 125 stations distributed over the whole of India. They used the non-parametric Mann-Kendall test for detecting the monotonic trends in annual average and seasonal temperatures. Chakraborty et al. (2013) showed Mann Kendall and Spearman correlation trend detection tests for rainfall analysis over the Seonath basin during 1960 - 2008.

Nowadays for climate analysis, Computer-driven global climate models (GCMs) are one of the most common tools used to improve the quality of climate-change science advising and to learn through broader access to GCMs and to help through supplying the correct support, technology, and materials to use these models efficiently. In order to fulfill the required goal Educational Global Climate Model, the software was developed. As per the guidelines set by Columbia University, the creator of EdGCM software, the GCM at running smoothly and the core of EdGCM were promoted at NASA which is presently utilized by researchers to investigate climates of the past, present, and future. EdGCM itself incorporates a user-pleasant interface that simplifies the control of climate simulations. In a study by Hansen et al. (1983), they found that the experiments were automatically archived in a searchable database, and smooth-to-use utilities for mapping, plotting and information analyses are integrated.

Educational Global Climate Model (EdGCM) provides six different options to perform simulation run and collect data on global a scale. The experiments are

- Doubled_CO₂
- Global_Warming_01
- Ice_Age_21kya
- IPCC_A1F1_CO₂
- Modern_PredictedSST
- Modern_SpecifiedSST

EdGCM provides global data from various simulation model depending on various boundary conditions. Transform software is a compelling visualizing image software package application that supports view graphically and analyzes the data. It upholds a continuous relationship between various types of graphs on the screen. This software was designed to support in analyzing two-dimensional data, which has two independent variables (such as latitude and longitude) and one dependent variable such as temperature. The primary goal of this study is to provide a suitable scenario for the finer-resolution Sylhet district in Bangladesh. So, the global climate change impacts can be quantified at a local scale. In this study, the outputs from all available EdGCM simulations by are downscaled by transform software for predicting the most suitable experiment of surface air temperature. The objectives of the research includes calculating global climate data using different simulation methods of EdGCM software, to downscale global climate data through transform software, and to identify the most suitable data comparing the variation between local and downscaled data.

2. Methodology

Sylhet is selected as the location of the study located at 24.8917°N 91.8833°E in the northeast part of the country. It is circumscribed by Khasia, Jaintia Hills of India, Maulvi Bazar district on the south, India's Cachar and Karimganj districts (Assam state of India), and Sunamganj and Habiganj districts on the west. The total area of Sylhet district is 3,452.07 sq. Km or 1332.00 square miles with a population of total 3,957,000 (Sylhet • Population, 2016).

Three types of data were collected (global data, downscaled data, observed data) that had been used in this study, collected from the Global Climate Model EdGCM over a period of 50 years (January 1969 to December 2018). For downscaling, transform software was used. The observed data were collected from Bangladesh Meteorological Department (BMD).

The following flow chart indicating the working procedure followed in the study.

Numerical Analysis using EdGCM → Formation of simulation → Collection of global data → Downscaling EdGCM data → Data Analysis.

The process was repeated to collect data and analyze them for Doubled_CO₂, Global_Warming_01, Ice_Age_21kya, IPCC_A1F1_CO₂, Modern_PredictedSST and Modern_SpecifiedSST experiments.

The Mann-Kendall method is used to determine the upward or downward trend of a time series. It does not require that the data be normally distributed or linear. It does require that there is no autocorrelation.

The null hypothesis for this test is that there is no trend, and the alternative hypothesis is that there is a trend in the two-sided test or that there is an upward trend (or downward trend) in the one-sided test. For the time series x_1, \dots, x_n , the MK Test uses the following statistic:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i)$$

Note that if $S > 0$ then later observations in the time series tend to be larger than those that appear earlier in the time series, while the reverse is true if $S < 0$.

The variance of S is given by

$$\text{var} = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_t f_t(f_t-1)(2f_t+5) \right]$$

where t varies over the set of tied ranks and f_t is the number of times (i.e. frequency) that the rank t appears.

The MK Test uses the following test statistic:

$$z = \begin{cases} (S - 1)/se, & S > 0 \\ 0, & S = 0 \\ (S + 1)/se, & S < 0 \end{cases}$$

where se = the square root of var. If there is no monotonic trend (the null hypothesis), then for time series with more than 10 elements, $z \sim N(0, 1)$, i.e. z has a standard normal distribution (URL 1)

3. Results and discussion

3.1. Doubled_CO₂ model simulation and temperature scenario

The run started from December 01, 1968 for Doubled_CO₂ simulation to 31st December, 2018. Output was analyzed to predict surface air temperature for Sylhet district for a 50-year period. EdGCM provides data on global maps, zonal averages, time series plots and diagnostics tables for a wide range of climatic variables. After the simulation run, precipitation and surface air temperature were collected for the required latitude and longitude. Figure 1 shows the average scenario of annual surface air temperature between 1968 and 2018. The global surface air temperature is 16.86 °C with a maximum of 31.22 °C and minimum value is -41.80 °C. Figure 2 depicts the temperature scenario for Bangladesh. For Sylhet the depicted temperature is 19.76 °C.

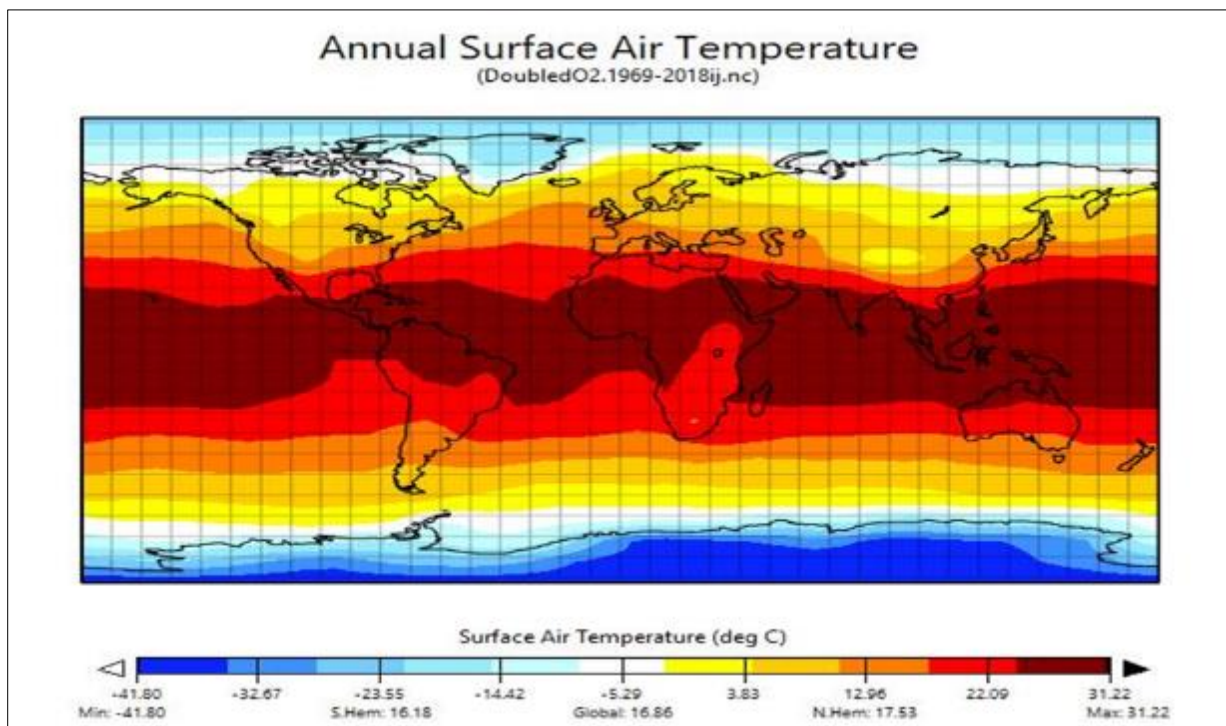


Figure 1 Temperature Change for Doubled_CO₂ scenario from 1969 to 2018

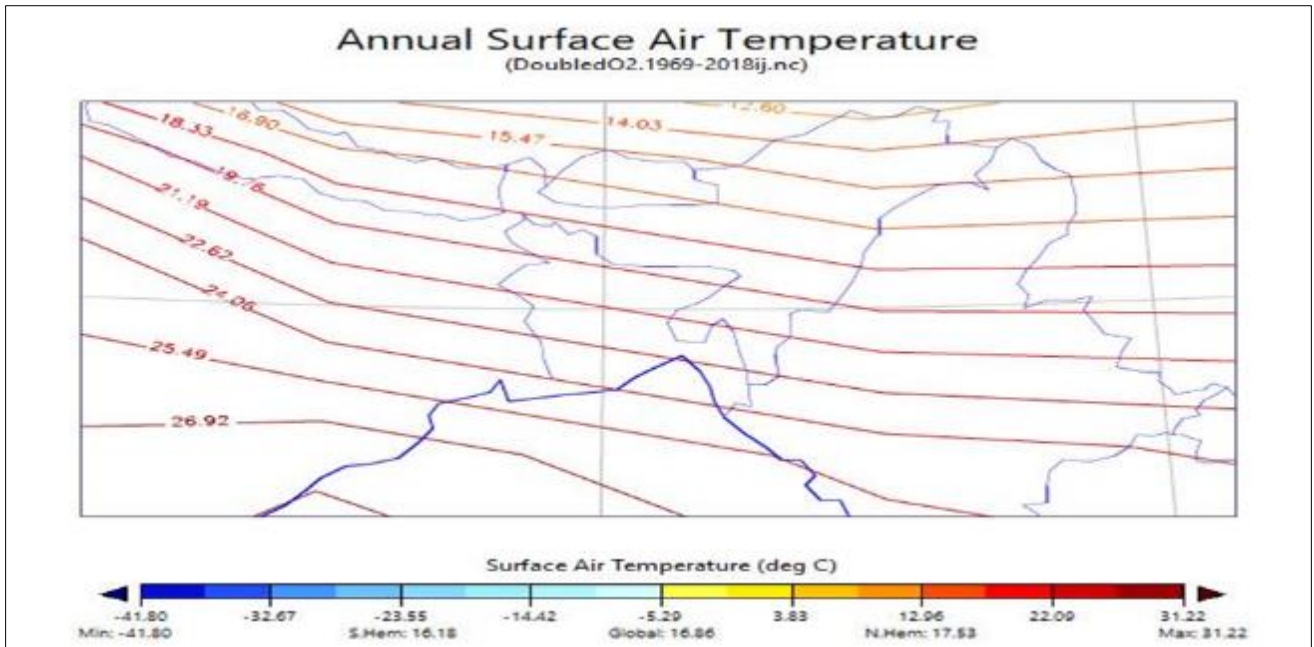


Figure 2 Temperature change for Doubled_CO₂ scenario for Bangladesh

3.2. Temperature change scenario from different model simulation

Temperature scenario was deduced similarly from EdGCM simulation run for Global_warming_01, Ice_Age_21kya, IPCC_A1F1_CO₂, Modern_Predicted and Modern_Specified experiments. The following figures shows the temperature change from above mentioned experiments with global data and maximum and minimum surface air temperature.

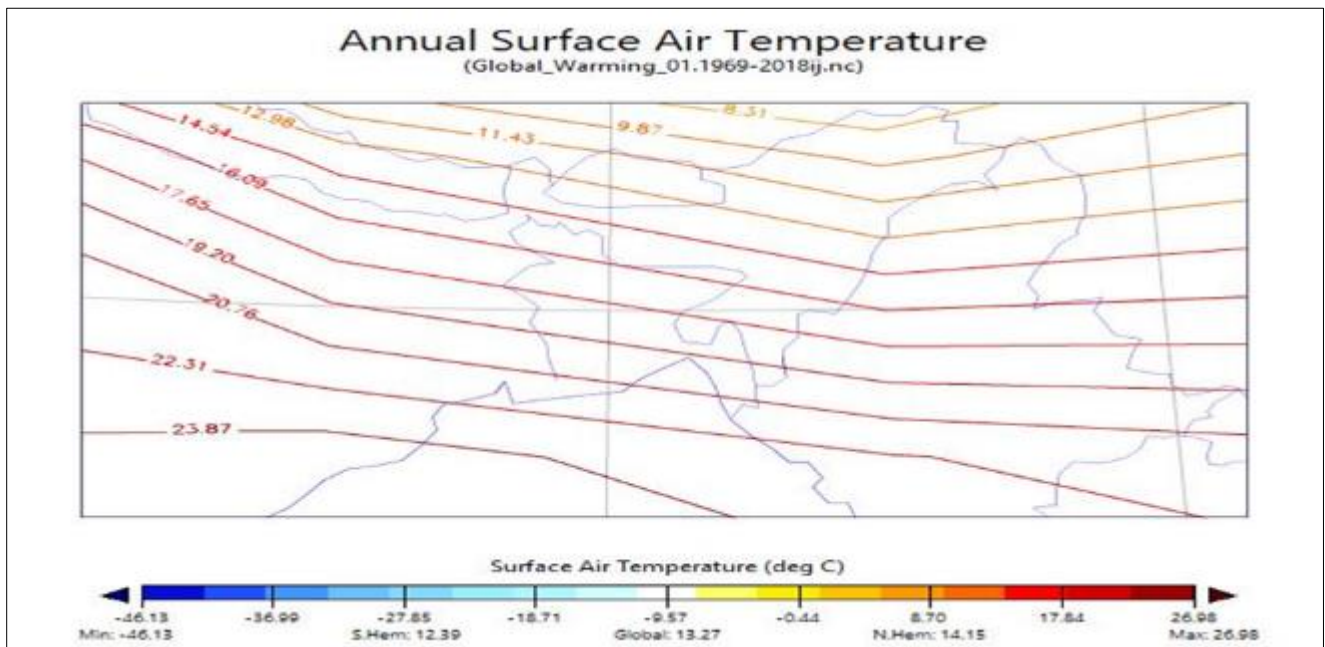


Figure 3 Temperature change for IPCC_A1F1_CO₂ scenario from 1969 to 2018

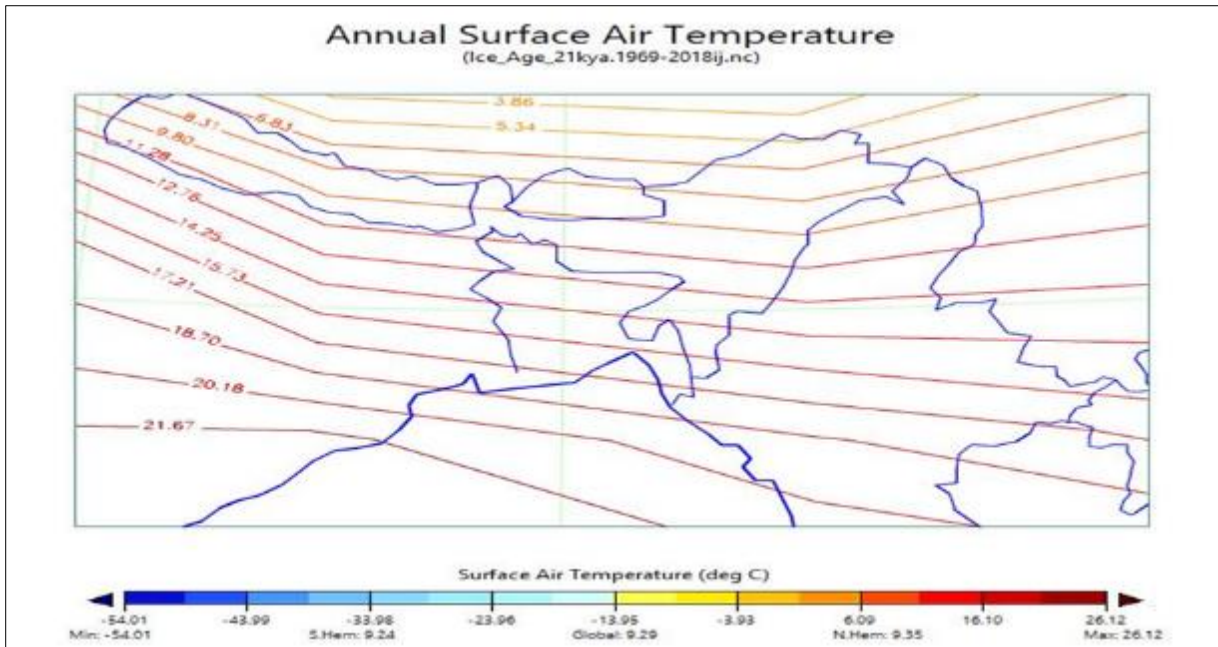


Figure 4 Temperature change for Ice_Age_21kya scenario from 1969 to 2018

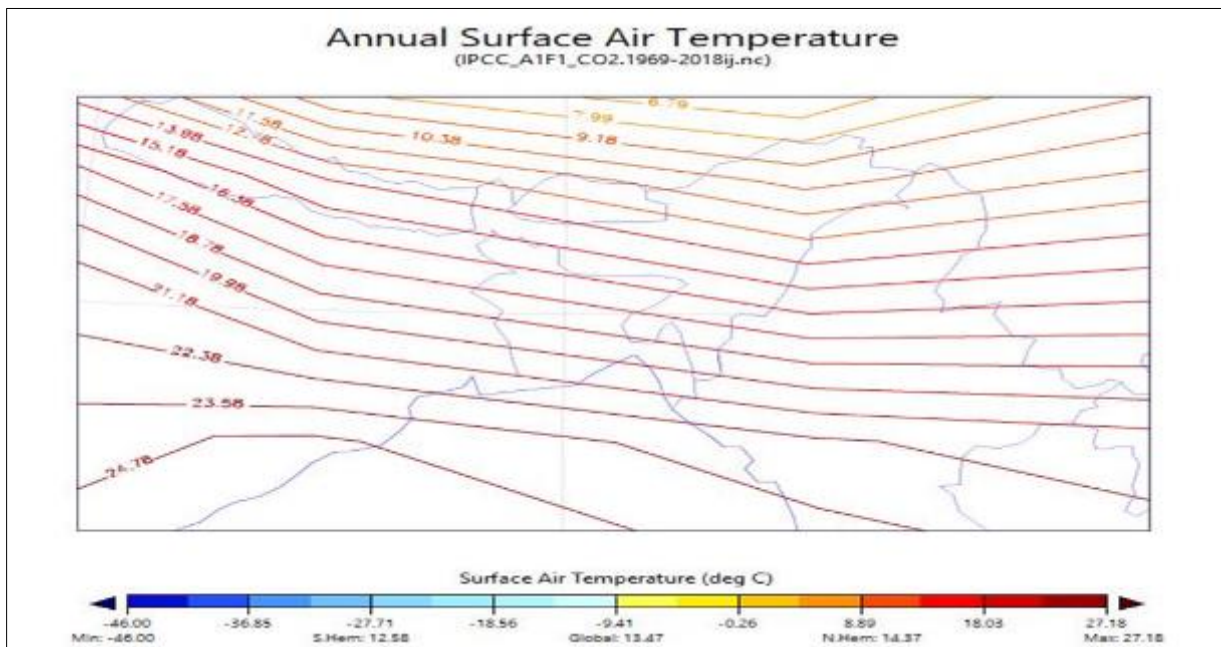


Figure 5 Temperature change for IPCC_A1F1_CO₂ scenario from 1969 to 2018

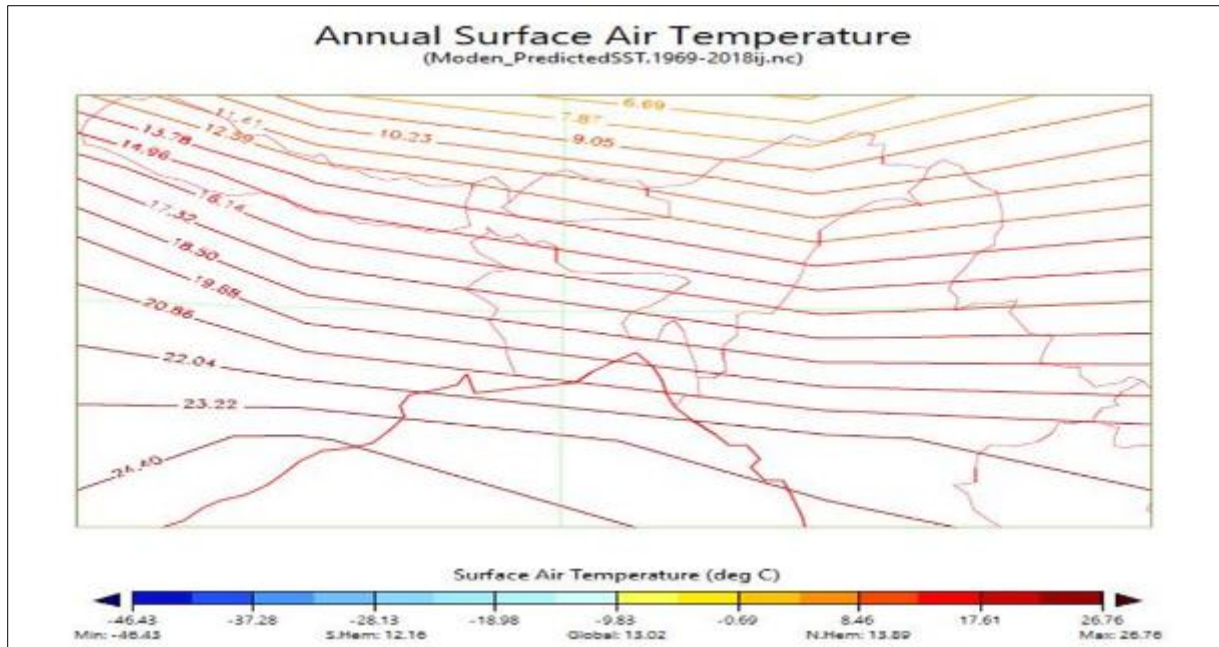


Figure 6 Temperature change for Modern_PredictedSST scenario from 1969 to 2018

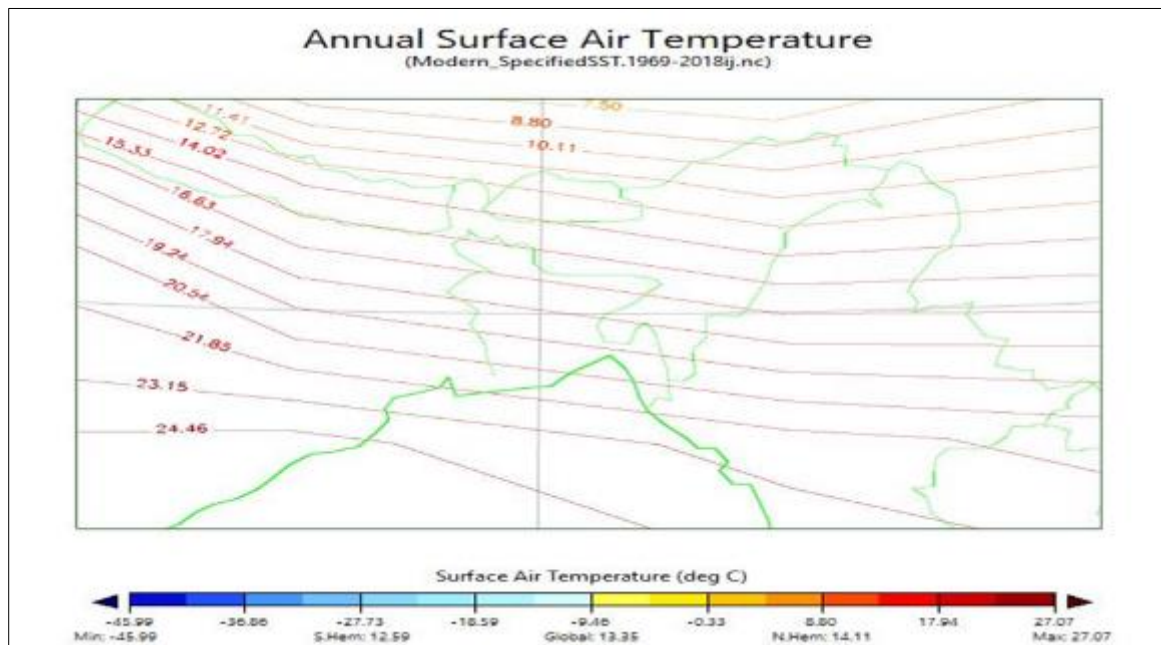


Figure 7 Temperature change for Modern_SpecifiedSST scenario from 1969 to 2018

3.3. Comparison of observed and downscaled mean monthly temperature

For Sylhet district, the trend of downscaled and observed data depicts a similar type of variation which indicates a better correlation between the predictor and predictand variables which is showed in figure 8. The performance of the downscaled temperature is more satisfying in May, June, August, September and October for the period 1969 to 2018. The downscaled and observed values are more matching in this case. For the month January, April, July, November, and December the downscaled does not show well performance and temperature decreasing in this case shown in figure 8. Similar result was found for rainfall where model failed to match the observed data because of poor correlation between predictor and predictand Azad (2015).

Similarly, monthly mean downscaled temperature data from each of the EdGCM model was compared with local data and described below

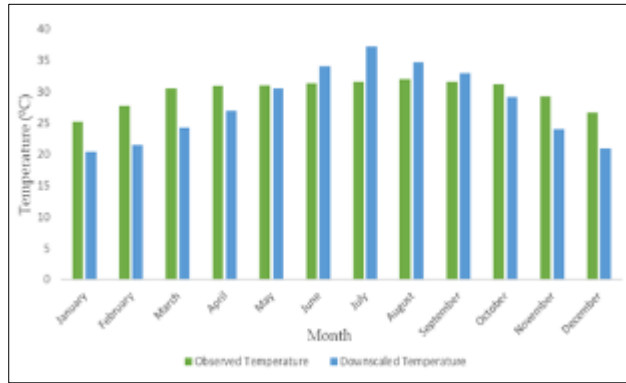


Figure 8 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for Doubled_CO₂ experiment

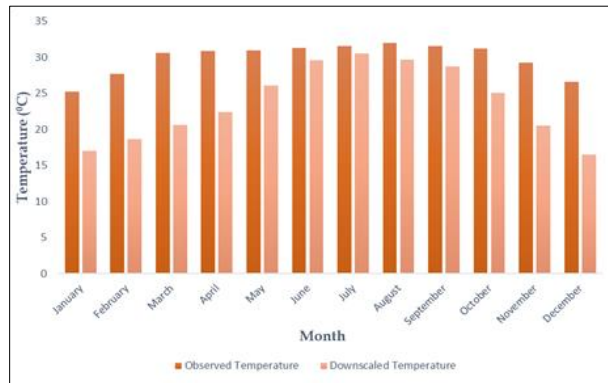


Figure 9 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for Global_Warming_01 experiment

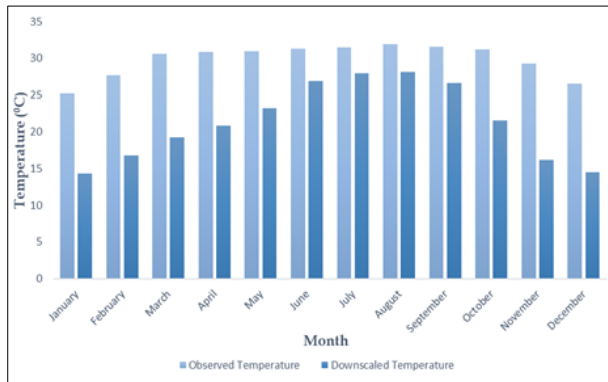


Figure 10 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for Ice_Age_21kya experiment

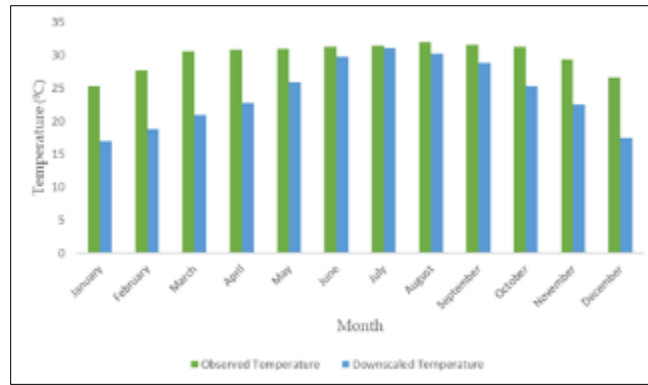


Figure 11 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for IPCC_A1F1_CO₂ experiment

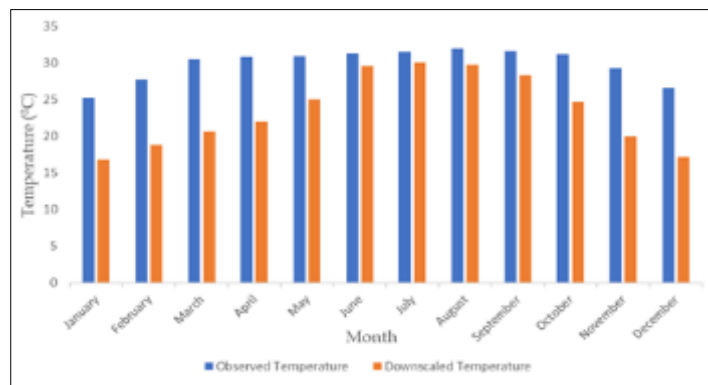


Figure 12 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for Modern_PredictedSST experiment

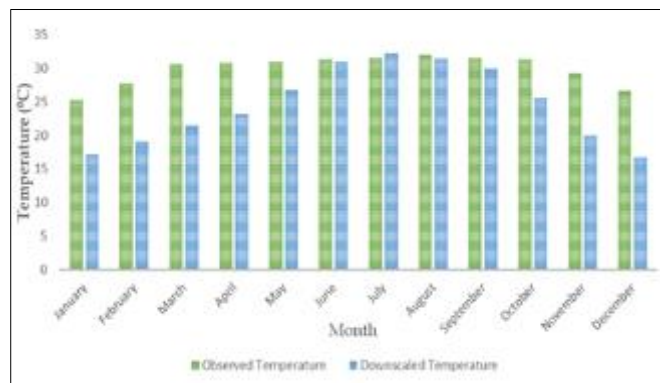


Figure 13 Comparison of observed and downscaled mean monthly temperature (°C) for a 50-year period (1950-1999) for Modern_SpecifiedSST experiment

Comparing downscaled monthly mean temperature extracted from different simulations available with observed data, IPCC_A1F1_CO₂, Modern_SpecifiedSST values shows the perfect correlation for the months of June, July and August. Doubled_CO₂ model data provide the best values for the months January, February, September, November and December. Among six models Ice_Age_21kya shows the greater variations.

3.4. Statistical summary of average annual mean temperature

The analyzed temperature recorded data and the employed descriptive statistics which are the mean, standard deviation (SD), minimum, maximum temperature and correlation co-efficient are calculated for all experiments and given below

Table 1 Summary of average annual mean temperature for Doubled_CO₂ experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	28.06
Annual minimum	27.56	22.64
Annual maximum	31.45	32.08
Std. deviation	0.841	2.59
Correlation co-efficient	0.849	

Table 2 Summary of average annual mean temperature for Global_Warming_01 experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	23.79
Annual minimum	27.56	22.24
Annual maximum	31.45	26.44
Std. deviation	0.841	0.874
Correlation co-efficient	0.869	

Table 3 Summary of average annual mean temperature for Ice_Age_21kya experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	21.35
Annual minimum	27.56	19.05
Annual maximum	31.45	23.84
Std. deviation	0.841	1.021
Correlation co-efficient	0.866	

Table 4 Summary of average annual mean temperature for IPCC_A1F1_CO₂ experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	24.03
Annual minimum	27.56	21.67
Annual maximum	31.45	26.07
Std. deviation	0.841	0.922
Correlation co-efficient	0.872	

Table 5 Summary of average annual mean temperature for Modern_PredictedSST experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	23.57
Annual minimum	27.56	21.81
Annual maximum	31.45	25.61
Std. deviation	0.841	0.949
Correlation co-efficient	0.858	

Table 6 Summary of average annual mean temperature for Modern_SpecifiedSST experiment

Variables	Observed Temperature (°C)	Downscaled Temperature (°C)
Annual Mean	29.90	24.52
Annual minimum	27.56	22.71
Annual maximum	31.45	26.53
Std. deviation	0.841	0.832
Correlation co-efficient	0.863	

3.5. Mann-Kendall trend test for observed temperature

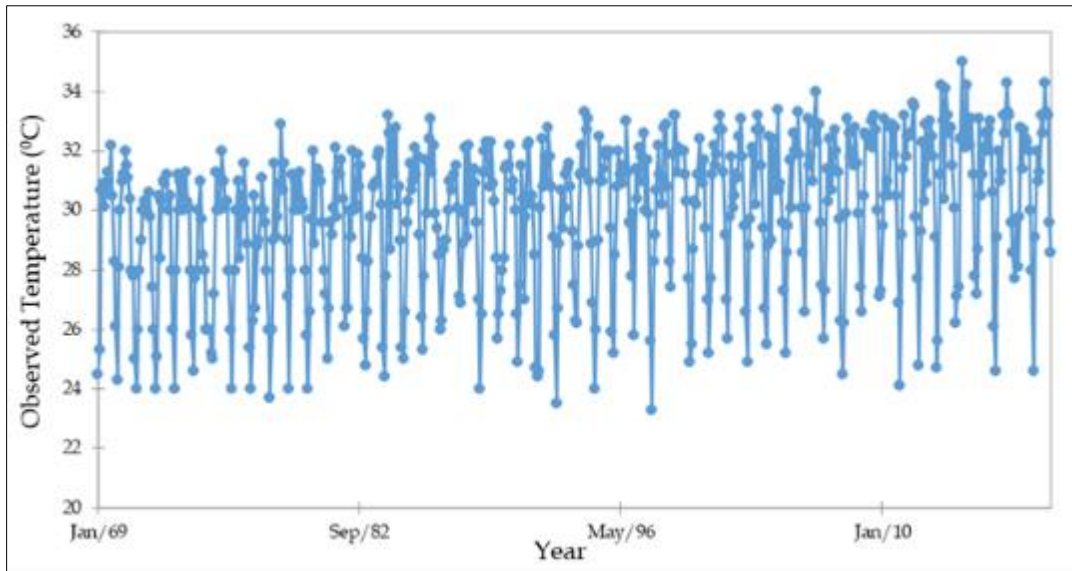


Figure 14 Observed monthly mean temperature for a 50-year period (1969-2018)

Table 7 Summary statistics of Mann-Kendall trend test for monthly observed temperature

Variables	Downscaled Temperature (°C)
Observations	600
Obs. with missing data	0
Obs. without missing data	600
Minimum	23.30
Maximum	35.00
Mean	29.896
Std. Deviation	2.479

Table 8 Mann-Kendall (two-tailed test) trend test (Observed Temperature)

Kendall's tau	0.424
S'	6138.000
Var(S')	522291.667
p-value (Two-tailed)	< 0.0001
alpha	0.05
Sen's slope	0.049

3.6. Test interpretation

- H_0 : There is no trend in the series
- H_a : There is a trend in the series

As the computed p-value is lower than the significance level $\alpha=0.05$, one should reject the null hypothesis H_0 , and accept the alternative hypothesis, H_a . There is a significant trend in the time series of observed data. A positive value of S' shows an upward trend. From table 8, a positive value of Sen's slope refers to an increasing trend in the time series.

Mann-Kendall trend test for downscaled temperature

Mann-Kendall trend was performed for downscaled data from six different simulation experiments.

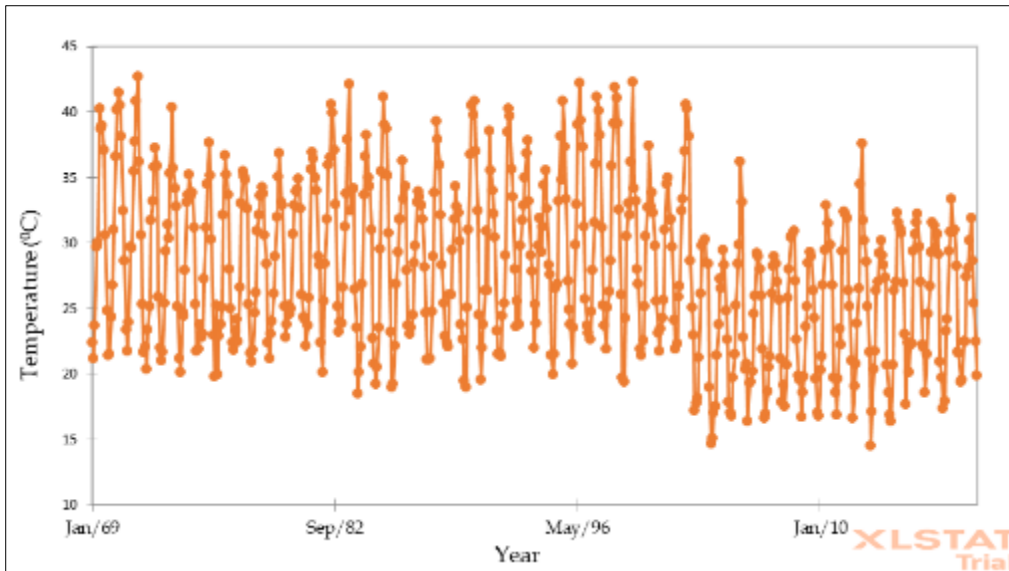


Figure 15 Downscaled monthly mean temperature from Doubled_CO₂ experiment (1969-2018)

Table 9 Summary statistics of Mann-Kendall trend test for monthly downscaled temperature from Doubled_CO₂ experiment

Variables	Downscaled Temperature (°C)
Observations	600
Obs. with missing data	0
Obs. without missing data	600
Minimum	14.54
Maximum	42.71
Mean	27.92
Std. Deviation	6.267

Table 10 Mann-Kendall (two-tailed test) trend test (Doubled_CO₂)

Kendall's tau	-0.332
S'	-4881.000
Var(S')	741254.000
p-value (Two-tailed)	< 0.0001
alpha	0.05
Sen's slope	-0.1

Test interpretation:

- H₀: There is no trend in the series
- H_a: There is a trend in the series

As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H₀, and accept the alternative hypothesis, H_a. There is a significant trend in the time series of downscaled data. A positive value

of *S'* shows an upward trend. From table 10, a positive value of Sen’s slope refers to an increasing trend in the time series.

Mann-Kendall trend test shows a significant trend in downscaled temperature data from Doubled_CO₂ and IPCC_A1F1_CO₂ simulation. No significant trend was found from Global_Warming_01, Ice_Age_21kya, Modern_PredictedSST and Modern_SpecifiedSST model data.

Table 11 Comparison of observed monthly mean temperature (°C) with downscaled temperature from six different simulation for the period 1969-2018

Month	Observed temperature	Downscaled temperature					
		Doubled_CO ₂	Global_Warming	Ice_Age_21kya	IPCC_A1F1_CO ₂	Modern_PredictedSST	Modern_SpecifiedSST
January	25.25	20.45	17.01	14.33	17	16.77	17.12
February	27.73	21.53	18.66	16.79	18.78	18.7	19.07
March	30.58	24.23	20.62	19.22	20.91	20.68	21.43
April	30.84	26.9	22.45	20.8	22.72	21.96	23.23
May	30.94	30.55	26.1	23.22	25.88	25.11	26.69
June	31.31	34.05	29.62	26.86	29.74	29.6	30.92
July	31.5	37.22	30.57	27.96	31.03	30.07	32.22
August	31.96	34.75	29.65	28.15	30.24	29.76	31.43
September	31.56	32.98	28.75	26.66	28.83	28.29	29.88
October	31.25	29.13	25.1	21.57	25.25	24.65	25.57
November	29.29	24.03	20.5	16.18	20.51	19.93	20.01
December	26.59	20.95	16.51	14.5	17.47	17.22	16.7

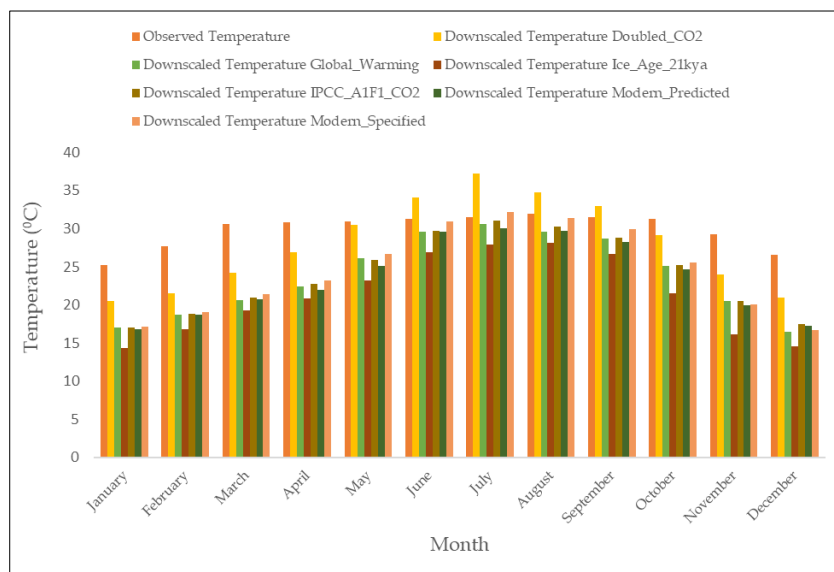


Figure 16 Comparison of monthly mean temperature (°C)

3.7. Discussion between observed and downscaled temperature

In almost all model simulation, the downscaled and observed temperature for month (June-September) from 1969 to 2018 shows a similar pattern that indicates a good correlation between the observed and downscaled data. Doubled_CO₂ is most suitable for dry season while IPCC_A1F1_CO₂ provides the best result for monsoon season compared with observed local data. Mann-Kendall trend test provides there's a significant trend in two of the models downscaled data.

4. Conclusion

EdGCM output scenario produce global data on surface air temperature from Doubled_CO₂, Global_Warmin_01, Ice_Age_21kya, IPCC_A1F1_CO₂, Modern_PredictedSST, Modern_SpecifiedSST simulation. This study used transform software for downscaling global data from EdGCM simulation. Missing data was filled using kriging method.

The downscaled temperature from each of the six available experiments were compared with observed local data collected from BMD. The downscaled and observed temperature values are more accurate for monsoon season (June-September). IPCC_A1F1_CO₂ simulation run provides nearly perfect downscaled data for the month of June, July and August. Ice_Age_21Kya simulation data shows the most variation with local observed data. For Sylhet, IPCC_A1F1_CO₂ simulation run shows the greatest correlation between observed and downscaled monthly mean data. Observed average annual temperature increased gradually where downscaled temperature experienced fluctuations over the 50-year time period.

Mann-Kendall trend test was used for all models. As per Mann-Kendall test there is a significant trend for downscaled temperature obtained from Doubled_CO₂ and IPCC_A1F1_CO₂ simulation. No significant trend in temperature was detected from Global_Warming_01, Ice_Age_21kya, Modern_Predicted and Modern_Specified simulation run.

In view of the present analysis, the accompanying criteria have been distinguished as confinements and recommendations for further research work:

The analysis could have been unmistakably broad if more global weather data were used from EdGCM. More statistical downscaling techniques could be tested to find out the most suited technique and their performance. Availability of large amount of historical climate data will enhance the performance of the model. In future EdGCM model simulation can be performed by changing existing boundary conditions i.e. CFC11, CFC12, N₂O etc. of respected local area for better outcomes.

Compliance with ethical standards

Disclosure of conflict of interest

Authors declare that they have no conflicts of interest or financial conflicts to disclose.

References

- [1] Kalhapure AH, Gaikwad DD, Sah D, Tripathi A 2019: Climate change: Causes, impacts and combat with special reference to agriculture-A review. *Current Advances in Agricultural Sciences (An International Journal)*, 11(1) 1-10.
- [2] Azad S 2015: Comparison of statistical downscaling techniques for development of future climate change scenarios for the coastal areas of Bangladesh.
- [3] Dastagir MR 2015: Modeling recent climate change induced extreme events in Bangladesh: A review. *Weather and Climate Extremes*, 7 49-60.
- [4] Mann HB 1945: Non-parametric test against trend, *Econometrica*13, 245–259.
- [5] Kendall MG 1975: *Rank Correlation Methods*, 4th edition. Charles Griffin, London, U.K.
- [6] Sen PK 1968: Estimates of the regression coefficient based on Kendall 's tau, *Journal of American Statistical Association* 39 1379–1389.

- [7] Islam MN 2009: Rainfall and Temperature Scenario for Bangladesh. *The Open Atmospheric Science Journal*, 3(1) 93–103.
- [8] Kumar KR, Sahai AK, Kumar KK, Patwardhan SK, Mishra PK, Revadekar, Kamala K, Pant GB 2006: High-resolution climate change scenarios for India for the 21st century *Current Science*, 90 no. 3.
- [9] Xu CY 1999: Climate change and hydrologic models: a review of existing gaps and recent research developments||, *Water Resources Management* 13(5) 369–382.
- [10] Dibike YB, Coulibaly P 2005: Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. *Journal of hydrology*, 307(1-4) 145-163.
- [11] Fowler HJ, Blenkinsop S, Tebaldi C 2007: Linking climate change modelling to impact studies: Recent advances in downscaling techniques for hydrological modelling. *Int. J. Climatol.*, 27 1547–1578.
- [12] Karl TR, Wang WC, Schlesinger ME, Knight RW, Portman D 1990: A method of relating general circulation model simulated climate to the observed local climate. Part I. Seasonal statistics. *J. Climate*, 3 1053-79.
- [13] Arora M, Goel NK, Pratap Singh 2009: Evaluation of temperature trends over India, *Hydrol. Sci. J.*, 2005 50 81–93.
- [14] Chakraborty S, Pandey RP, Chaube UC, Mishra SK 2013: Trend and variability analysis of rainfall series at Seonath River Basin, Chhattisgarh (India). *International Journal of Applied Sciences and Engineering Research*, 2(4) 425-434.
- [15] Hansen J, Russell G, Rind D, Stone P, Lacis A, Lebedeff S, Travis L 1983: Efficient three-dimensional global models for climate studies: Models I and II. *Monthly Weather Review*, 111(4) 609-662.
- [16] URL 1: <https://www.real-statistics.com/time-series-analysis/time-series-miscellaneous/mann-kendall-test/>