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Research

Evaluation of weather generator tools to estimate climate conditions in different agro ecological zones of North Shewa, Ethiopia

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Abstract

The information on climatic condition is difficult to obtain, expensive, and time-consuming so as to make timely decision on agricultural activities. As a scientific effort, this study was conducted to assess the temporal changes and trends of rainfall and temperature, to know the performance of weather generator (WG) tools in capturing the temporal and spatial distribution of rainfall, maximum temperature (Tmax) and minimum temperature (Tmin) and to evaluate the performance of WG in simulating the observed rainfall, Tmax and Tmin by using statistical methods. Mann–Kendall's trend analysis revealed that rainfall had non-significant ($P < 0.05$) decreasing trends, while Tmax and Tmin had an increasing significant ($P < 0.05$) trends at all stations. NASA POWER data followed by NewlocClim exactly capture the temporal changes of rainfall, Tmax, and Tmin in all stations except Debre Birhan and Mehal Meda. NewlocClim well captures rainfall at Alem ketema, while NASA well simulates rainfall at Debre Birhan and Majete stations. However Had-GEM2-ES, MRI-CGCM3, and CSIRO-Mk3.6.0 were not handling the spatial variability of observed rainfall at all stations. Similarly, some WGs showed moderate to good performance in capturing the spatial distributions of Tmax and Tmin. The smallest RMSE and CV, the highest R and d values were observed in NASA POWER and NewlocClim for rainfall, Tmax and Tmin. Therefore, NASA and NewlocClim are more accurate with goodness of fit to estimate rainfall, Tmax and Tmin in most of the stations to access weather data for ungagged stations for timely and reasonable decision-making on agriculture.

Highlights

- Climate variability in Ethiopia
- Temporal and spatial variability of temperature and rainfall
- North Shewa
- Weather generators tools

Keywords Climate · North Shewa · Trend · Validation · Weather generators

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1 Introduction

Climate change is the front line of agriculture as it has a pronounced impact on the hydrology, cropping pattern, water resource system, and agro-pastoral systems. However, the assessment of climate change and its impact in absence of climatic data is impossible [1]. Climate-smart agriculture majorly depends on the availability of correct weather information to simulate water and crop models. The major climate-smart agriculture including agro-forestry, soil and water conservations, and climate information services should be practiced to cope with the current climate change and take mitigation and adaptation measures [2]. Farmers must practice climate-resilient agriculture to improve agricultural productivity and to adapt to climate variability like erratic rainfall patterns, decreased rainfall, and temperature increases, leading to crop productivity decline and increased livestock mortality [3]. Similarly the provision of important guidance for improving the identification of causes, minimizing the impacts, and enhancing the resilience to droughts in East Africa [4].

The adaptations of stochastic WGs, describing daily weather variations in the current climate at particular locations, to generate synthetic daily time series consistent with assumed future climates [5]. The choice of a WGs in the downscaling process may have a higher impact on crop yield than the climate scenario adopted [6]. The major weather elements that have high impacts on agriculture are temperature and rainfall [7]. The higher variability of these parameters has a significant impact on crop evapotranspiration and water management [8]. The use of well-validated WGs to access these parameters in stations that couldn't have observed data or lack quality data is mandatory. The right selection of WGs to downscale climate data which has a higher impact on crop yield should be adopted [6].

The major weather-generating models included in this study were NASA, ClimaGen, Marksim DSSAT, and NewlocClim. From 17 global climate models (GCM) in MarkSim DSSAT, gfdlCM2.16, csiroMK3.0, and ukmoHADCM3 have good trends of temperature [9]. It is widely used to generate climate data for modeling the impact of climate change on the yield and performance of different crops and the incidence of pests, insects, and diseases. For instance, for the modeling of wheat by the DSSAT-CERES wheat model [10, 11], rice DSSAT-CERES RICE model [12, 13], maize by DSSAT-CERES MAIZE model [14], sesame by DSSAT-CERES Sesame model [15], sorghum by using DSSAT-CERES Sorghum model [16], to know spatio-temporal existence of insect on mango [17]. MarkSim GCM well generates daily climatic data for future climate conditions which affect the agriculture and impact modeling [18]. LARS-WG performed better than MarkSim in generating daily weather parameters [19]. The NASA POWER reanalysis datasets are one of the most important data types that could help to overcome the scarcity of observed weather data [20].

The selection of finest model contributes to the development of a reliable climate service assessment and facilitates decision making for climate adaptation, ultimately leading to optimal benefits in mitigating the impacts of climate change [9]. Anybody can get time series data sets of long term climate data from anywhere by providing latitude and longitude coordinates. There is hardly little information about the evaluation of these WGs in the peer-reviewed journals. The availability climate data in conducting future climate impact analyses by globally validated models to the observed datasets [9]. In areas of the Free State Province without meteorological measurements, it is advised to use NASA satellite and modeled data [21]. On a daily and monthly time scale, altitude does not significantly impact the Tmin data, but on an annual scale, NASA POWER products perform better at low-land stations [17]. The required historical input data for WGs to simulate the observed data sets should be at least 15 years [22].

In developing countries, the availability of weather data hardly exists because it is time-consuming and so expensive to establish metrological stations for all places. The evaluation of well-validated climatic data sources is an important issue in replicating past rainfall and temperature. In this study, the evaluation of different WGs provides valuable information for selecting the best models that aim to make informed decisions on water resource systems and climate change adaptation strategies in North Shewa. Therefore, this study is designed to achieve (a) to describe the variability and trends of temperature and rainfall over the three AEZs of North Shewa and (b) assess the performance of various WGs in capturing the temporal extent and spatial variability in related to the observed data (c) to evaluate the statistical performance of each WGs and recommend the best models for various adaptation and mitigation strategies.

2 Materials and methods

2.1 Description of the study area

The study was conducted at North Shewa, which exhibited the three major AEZs. The study area included Shewarobit (SW) and Majete (MJ) from the low-land, Arerti (AR) and Alem Ketema (from the mid-land, and Debre Birhan and Mehal Meda from the high-land, and the geographical location of the area is presented in Fig. 1. The overall area is covered by 45% high-land, 23% mid-land, and 32% low-land [23]. In the area, agriculture is the mainstay of the economy including crop production, agro-pasture, and livestock production.

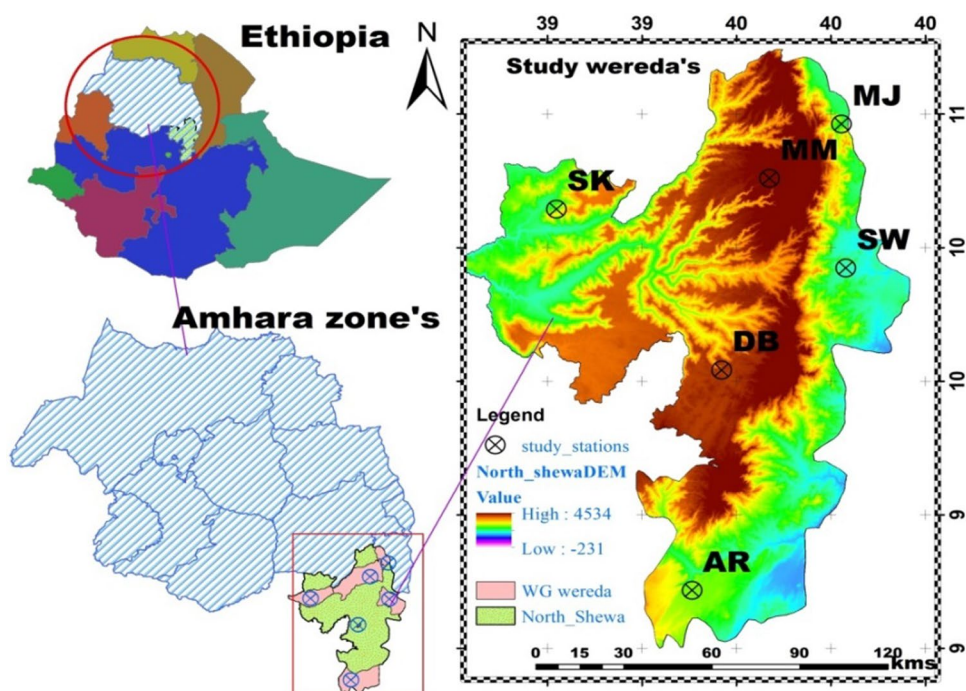
The major crops produced in low-land areas including teff, mango, papaya, banana, orange, onion, tomato, cabbage, potato, wheat, sorghum, maize, and mung bean. The major crops in the high-land are wheat, barley, faba bean, chickpea, garlic, and apple. The major constraints of agricultural productivity are soil salinity problems and droughts in the low-land, soil acidity, and water logging problems in the high-land. The monthly Tmax happened from February to June and the declined nearly in all stations. The maximum rainfall for all stations was found in the months from half of June to half of September. The rainfall pattern of the areas is uni-modal in nature. The long-term metrological data showed that the averaged highest Tmax and Tmin for stations are on the order of Shewarobit, Majete, Arerti, Alem Ketema, Debre Birhan, and Mehal Meda stations (Fig. 2).

2.2 Observed and modeled data sets

2.2.1 Observed climate data

Long-term daily climatic data (1991–2020) were collected from Ethiopia National Metrological Agency (ENMA). The required data quality management like outlier detection and filling missing data were conducted. The parameters were Tmax and Tmin and rainfall. Outliers in the data set were checked in R software. The normal ratio method was used to fill the missing data. The consistency and homogeneity data was adjusted by double mass curve method on excel worksheet. The geographical information and data range of the dataset is presented in Table 1.

Fig. 1 The geographical location of the study areas



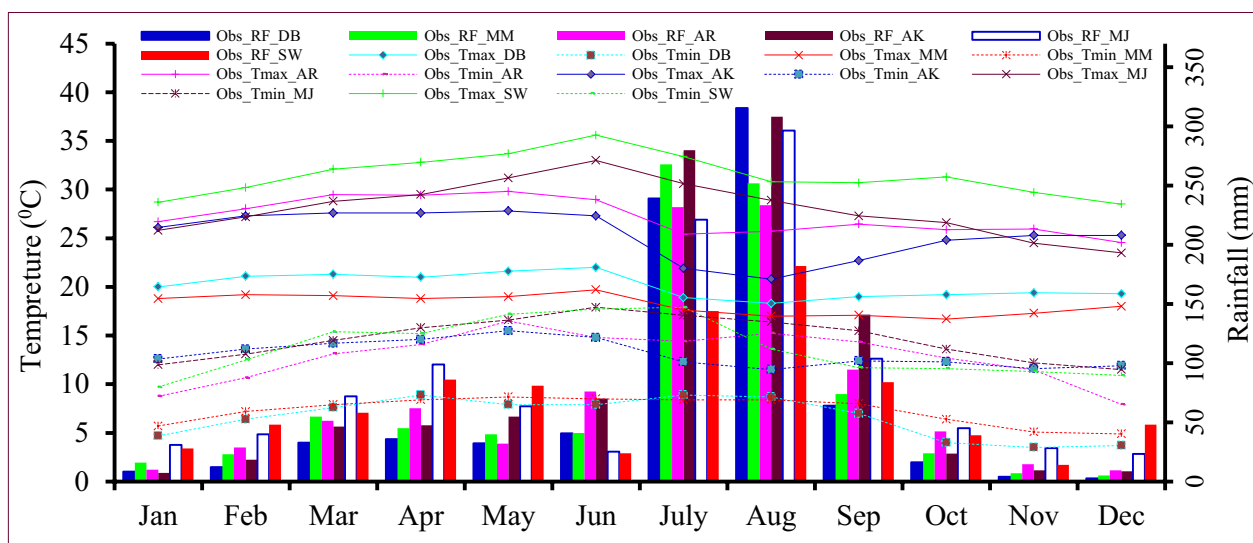


Fig. 2 The long-term monthly rainfall, maximum and minimum temperature (1991–2020)

Table 1 The geographical location and information climate data

Stations	Northing	Easting	Altitude	Data range	Numbers of missing data
Debre Birhan	556,263.7	1,068,985	3206	1991–2020	34
Mehal Meda	572,291.2	1,140,275	3084	1991–2020	15
Alem Ketema	500,760.6	1,128,702	2572	1991–2020	37
Arerti	546,509.2	987,017	1777	1991–2020	–
Shewarobit	598,017.9	1,106,958	1277	1991–2020	47
Majete	596,340	1,160,483	1573	1991–2020	56

Table 2 The GCMs downscaled in Marksim DSSAT web applications, Source [29]

No.	Model	Institution	Resolution
1	MIROC5	Japan Agency for marine-earth science & technology, atmosphere and ocean research institute	1.41 × 1.41
2	MRI-CGCM3	Meteorological Research Institute	1.13 × 1.13
3	HadGEM2-ES	Met Office Hadley Centre	1.24 × 1.88
4	CSIRO-Mk3.6.0	Commonwealth scientific & industrial research organization and the queens land cc center of excellence	1.88 × 1.88

2.2.2 Modeled data sets

2.2.2.1 MarkSim DSSAT weather file generator It is a WGs of an online web platform that reproduces daily Tmax and Tmin, rainfall, and solar radiation [24]. The data generation is based on daily either based on a single year or an average of more than two years based on the replications number provided. It works based on the process of third third-order Markov chain [25]. It includes about 17 downscaled global climate models (GCM) with a spatial resolution of 18 km [26]. The input data to access the climatic data are the GPS data, number of years, model name, and the number of replications. In this study, only four GCMs (Had-GEM2-ES, MRI-CGCM3, MIROC5, and CSIRO-Mk3.6.0) that had the best spatial resolution were included in Table 2 [27].

Several studies have been conducted to assess the ability of various GCMs to reproduce the statistical characteristics of observed weather data. Additionally, under the three scenarios RCP2.6, RCP4.5, and RCP8.5, daily weather data for the period 2021–2030 were downscaled using the MarkSim DSSAT [28]. Temperature change is more significant than rainfall changes in major studied stations [9]. It is used to downscale general circulation models to produce daily weather [18].

2.2.2.2 NewlocClim It is first developed by the German Weather Service and Global Precipitation Climatology Center (GPCC). It is used to simulate long-term daily weather data sets and employed in hydrological and agricultural modeling to generate synthetic weather series data for specific locations. The database is extended by the data described in the previous section and the data are stored in the binary format [30]. It used interpolation techniques to determine whether parameters especially for stations with no metrological services [31]. The inverse distance weighted average (IDWA) method was employed for the interpolation of Tmax, Tmin and rainfall. After importing the GPS data, making on best estimates and 99% confidence interval and then running allows to access the required data.

2.2.2.3 NASA POWER product The NASA Climate Data Portal provides access to a variety of historical climate datasets, tools, and resources for researchers and the general public [32]. Climatological data was obtained from the National Aeronautics and Space Administration Prediction of Worldwide Energy Resource (NASA POWER) project with the website <https://power.larc.nasa.gov> and accessed in October 2021. The data products are based on satellite observations and models and provide accurate metrological data also procedure of analysis is not limited to specific geographical locations [33]. It gives an estimation of certain climatological parameters with a spatial resolution of 0.5° with 0.5°. This is the limitation of NASA POWER data. The input data includes GPS data, fixing temporal extent, select parameters and output file formats.

2.2.2.4 ClimaGen This was created using SIMMETEO, which was created by [34]. It creates weather parameters for newly provided user stations or for weather stations that already exist. The WG requires the following inputs to function: the name of station, latitude, longitude, altitude, number of years, means temperature change, and percentage change in rainfall. According to the given column order, it produces the following outputs: wind speed (m/s), vapor pressure (kPa), total monthly rainfall (mm), number of rainy days, Tmax (°C), Tmin (°C), and solar radiation (MJ/m²/day).

2.3 Trend analysis of observed data

In this study, trend analysis was carried out using the non-parametric Mann–Kendall test (MK) to identify the significant changes in environmental datasets [35]. To determine the trend analysis, the MK test was employed and Sen's slope was used to determine the magnitude of change as computed from Eqs. 1–3. The Sen's slope estimator was employed after MK statistics to determine the change in rainfall and temperature trends through time series [36]. The null hypothesis (Ho) of the MK test indicates that there is no trend and this is tested against the alternative hypothesis (H1), which shows the existence of a trend. The test statistic (S) for the MK test is computed by the formula [37] (Eq. 1).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad (1)$$

where, X_i and X_j are data values of the time series in the years j and i ($j > i$) and n is the length of the time series. If 'S' is positive, it shows an increasing trend. But, if it is negative, it shows a decreasing trend. It attains a normal distribution in the conditions of Ho [38]. It is possible to determine the variance of test statistics as Eq. 2.

$$\text{Var}(S) = \frac{1}{18} \left[N(N-1)(2N+5) - \sum_{i=1}^m ti(ti-1)(2ti+5) \right] \quad (2)$$

whereas, N is the number of data points, m is the number of tied groups in the data set and tie is the number of data points in the i^{th} tied group. For larger 'n' larger than 10, Z_m estimates the standard normal distribution [39] (Eq. 3).

$$Z_m = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}}, & S > 1 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{var}(S)}}, & S < 1 \end{cases} \quad (3)$$

In a two-sided test, H_0 is accepted if $|Z_m| < |Z_{1-\alpha/2}|$, $Z_{1-\alpha/2}$ is the critical value of Z_m at $(P < 0.05)$.

2.4 Temporal and spatial variability of climatic variables

2.4.1 Monthly variations of temperature and rainfall under each weather generators

The collected observed and modeled daily minimum temperature, maximum temperature, and rainfall were summarized monthly. The temporal scale variation of monthly temperature and rainfall over stations was plotted on a bar graph. The deviation of model output with the observed was assessed and quantified to know the accurate models over stations. The temporal variation of climatic parameters had a significant impact on agricultural activities.

2.4.2 Capability of WGs for capturing spatial variability

The spatial map of the annual rainfall, T_{max} , and T_{min} was determined by inverse distance weighted (IDW) interpolation methods in Arc GIS 10.5 software environment. It is a local intermediate value estimation method as it estimates from neighboring points. The weight of a data point is inversely proportional to the square of its distance from the grid cell [40]. Since North Shewa has a diverse climate with temperature and rainfall variability, the ability of WGs to handle the spatial variability in contrast to the observed value was studied.

3 Evaluation of weather generators models

The models' output was compared with the observed climatic data by these statistical indicators including root mean square error (RMSE), coefficient of variation (CV), Correlation analysis (R), Coefficient of determination (R^2), and Willmott index of agreement (d). These indicators were conducted on Microsoft Excel software. RMSE measures the average magnitude of error, calculated as the square root of the average of squared differences between model output and the observed data (Eq. 4). RMSE represents the mean standard deviation of model prediction concerning the observation. A lower RMSE indicates that better performance of the model and a higher RMSE shows a poor performance of the model.

The coefficient of variation (CV) value as generated from Eq. 5 is considered as excellent if smaller than 10%, good if between 10 and 20%, fair if between 20 and 30%, and poor if larger than 30%. Correlation analysis (R) was computed following Eq. 6 to determine the association between the observed and generated values of these WGs. It is used to quantify the relation between observed and modeled output data. The coefficient of determination (R^2) is defined as the squared value of the Pearson correlation coefficient (Eq. 7). It ranges from zero to one; values close to 1 indicate a good agreement. The value of index of agreement as calculated following Eq. 8 varies between 0 and 1; in which 0 indicates no agreement between model output and observed data, and 1 indicates a perfect agreement of the model and the observed value. It was developed by [28] to avoid insensitivity of Nash–Sutcliffe efficiency and coefficient of determination. The index of agreement was proposed to measure the degree to which the observed data are approached to the predicted data.

$$RMSE = \left[\frac{1}{n} \sum_{i=0}^n (p_i - o_i)^2 \right]^{0.5} \quad (4)$$

where, p_i = model generated value; o_i = observed value; n = number of observations.

$$CV = \frac{1}{O_i} * \sqrt{\frac{\sum (p_i - O_i)^2}{N}} * 100 \quad (5)$$

$$R = \left[\frac{\sum (O_i - O_i^-)(p_i - p_i^-)}{(\sum (O_i - O_i^-)^2)(\sum (p_i - p_i^-)^2)} \right] \quad (6)$$

$$R^2 = \left[\frac{\sum (O_i - O_i^-)(p_i - p_i^-)}{(\sum (O_i - O_i^-)^2)(\sum (p_i - p_i^-)^2)} \right]^2 \quad (7)$$

p_i = generated value, O_i = observed value, O_i^- = mean of O_i and p_i^- = mean of P

$$d = 1 - \frac{\sum (P_i - O_i)^2}{\sum ((P_i - O_i) + (O_i - O_i^-))^2} \quad (8)$$

where: d is Willmott's index of agreement, p_i is predicted value, O_i is the individual observed, O_i^- is the mean of observed value.

4 Results and discussions

4.1 Climate variability and trends

As the MK trend test shows the change on monthly rainfall was on decreasing trend in all station except AK station. However, the changes were found as statistically non-significant. On the other hand, the change on rainfall pattern showed statistically significant decreasing in January, February & September [39]. This shows that higher rainfall variations at spaces over the years, erratic and uneven distribution. This result is aligned with [28], who founds that insignificant changes of rainfall at all stations.

The change in T_{max} showed a significant increasing trends at all stations. For instance, the changes found with in the range from 0.12 °C/year at MJ to 0.37 °C/year at AR. Similarly the changes of T_{min} were found as significant increasing trends at DB, MM and AK stations. However, the changes in T_{min} were found as non-significant increasing at AR, MJ and SW stations. The changes found were with in the range of 0.01 °C/year at MJ and 0.2°C/year at AK. In general, the rainfall was on an insignificant decreasing rate and T_{max} & T_{min} were at significantly increasing rate at most of stations (Table 3). The result is similar with [41], the long-term T_{min} and T_{max} have a significant increasing trend over the studied stations.

4.2 Monthly distribution of temperature and rainfall for the WG models

Figures 3, 4, and 5 illustrate the performance of WG models in simulating monthly T_{max} , T_{min} and rainfall (1991–2020) for all stations. Some models overestimate the temperature and rainfall, while others models underestimate them. The performance of the models in simulating monthly values of parameters also varies under wet and dry seasons. Newloc-Clim performed well in simulating T_{max} at DB, AK, AR, and MJ stations (Fig. 3). There was a strong correlation between the recorded weather data and data from NASA satellites. Nonetheless, in comparison to data gathered at weather stations, NASA T_{min} tended to overestimate measured values while NASA T_{max} tended to underestimate values [21]. On high-land stations, ClimaGen underestimates T_{max} , and others overestimate. But on mid-land and low-land, some models well simulate, and some models underestimate T_{max} . The four GCMs downscaled under MarkSim DSSAT (Had-GEM2-ES,

Table 3 The MK's trend test value, Sen's slope and P-values

Metrological stations	RF			T_{max}			T_{min}		
	Zm	Sen's slope	P-value	Zm	Sen's slope	P-value	Zm	Sen's slope	P-value
Debre Birhan	0.35	− 0.007	0.79 ns	0.24	0.168	**	0.19	0.2	**
Mehal Meda	0.03	0	0.41 ns	0.31	0.199	**	0.2	0.146	**
Arerti	0.01	0	0.89 ns	0.42	0.37	**	0.09	0.131	0.45 ns
Alem Ketema	0.03	0.11	0.42 ns	0.28	0.277	**	0.23	0.202	**
Shewarobit	0.01	0	0.84 ns	0.15	0.184	*	0.03	0.042	0.64 ns
Majete	0.03	− 2.66	0.367 ns	0.1	0.121	*	0.05	0.01	0.26 ns

Zm is MK trend test, Sen's slope is the change in RF, T_{max} or T_{min}

**, * is significant at 0.05 and 0.1 probability level; ns is non-significant

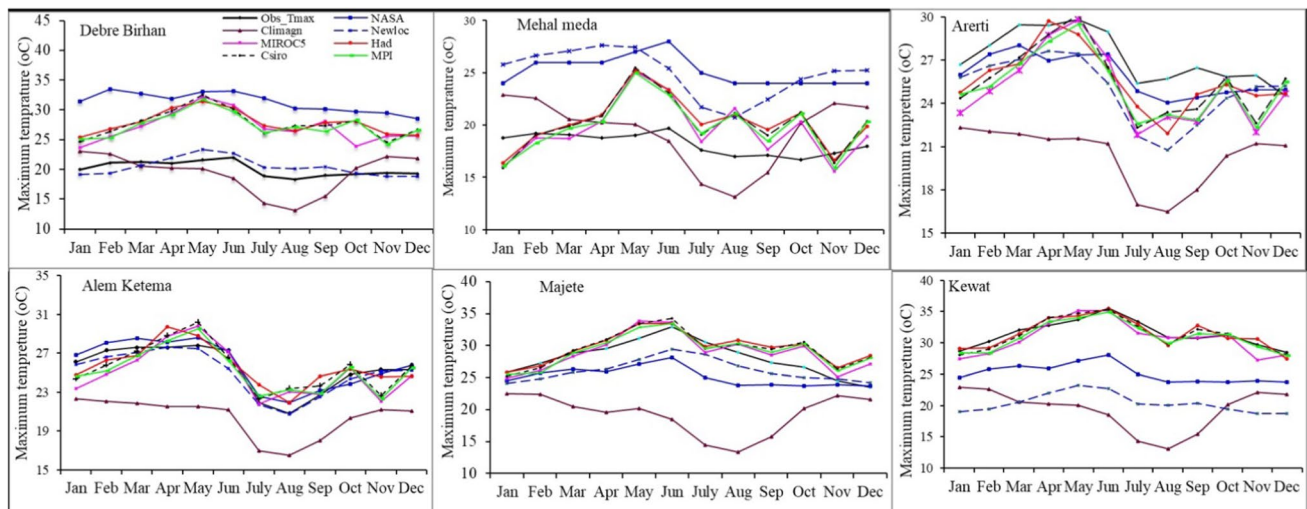


Fig. 3 Monthly distribution of maximum temperature under each WG

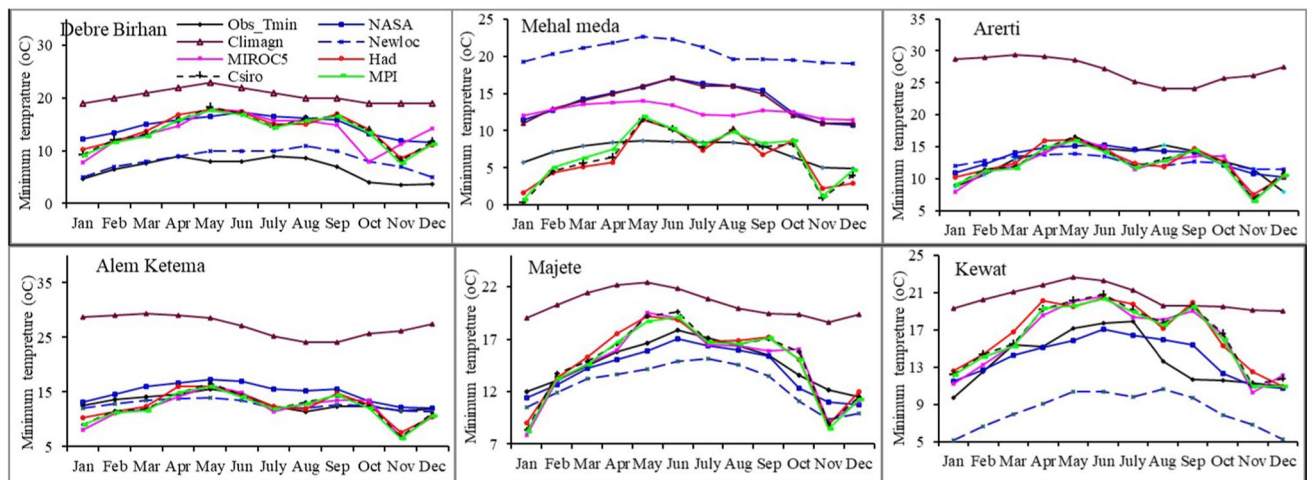


Fig. 4 Monthly distribution of minimum temperature under each WG

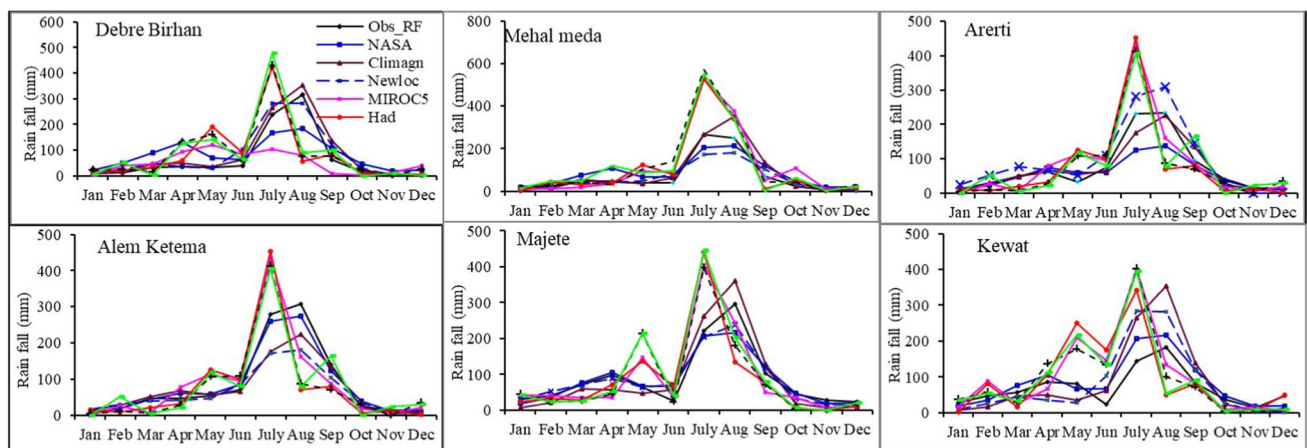


Fig. 5 The monthly distribution of rainfall under each WG

MRI-CGCM3, MRIOC5, and CSIRO-Mk3.6.0) well simulate Tmax at AK, AR, MJ, and SW stations. In general, all models showed variable Tmax patterns at each station and season. This showed that the variation in Tmax would imply a significant variation in crop production, water resources, land use systems, forest systems, and livestock production. The accuracy of NASA POWER data is higher at Tmax than at Tmin [42].

As shown in Fig. 4, NewlocClim very well reproduces monthly Tmin, and other models overestimate at the DB station. On the contrary, at MM station NewlocClim, NASA and MRIOC5 overestimate Tmin and Had-GEM2-ES, MRI-CGCM3, and CSIRO-Mk3.6.0 well reproduce Tmin. The NASA POWER Tmin values are higher than the observed Tmin in the high-land station and perfectly fit in mid and low-land areas. This is supported by another research conducted in Egypt [43]. Thus, NASA POWER simulates Tmax and Tmin at lower elevated areas with better accuracy. At the stations of AK, AR, MJ, and SW, nearly all models well performed in simulation Tmin except ClimaGen (over-estimates). However, relative to others NASA showed a better capability of estimating the observed monthly Tmin. It well reproduces Tmin, especially in mid and low-land than in high-land. This result is in line with that of [42], who found better simulation of NASA POWER. Therefore, it can be recommended to access weather data from ungagged stations for timely and reasonable decision-making on agriculture, climate change impact, and hydrological modeling purposes.

4.3 Spatial capabilities of weather generators in capturing the observed data sets

The capability of WG in capturing the spatial variability of Tmin varies from station to station and model to model (Fig. 6). For instance, NewlocClim well reproduce the observed spatial variability of Tmin over DB and AK stations. The NASA POWER product is not well capturing the spatial distributions of Tmin. The three GCMs under MarkSim DSSAT (Had-GEM2-ES, MRI-CGCM3, and CSIRO-Mk3.6.0) well capture the spatial variability of Tmin on stations of MM, AR, and SW. None of the WGs cannot able to simulate the spatial distribution of Tmin except at MM station. In general, WGs showed moderate to good performance in capturing the spatial distributions of Tmin.

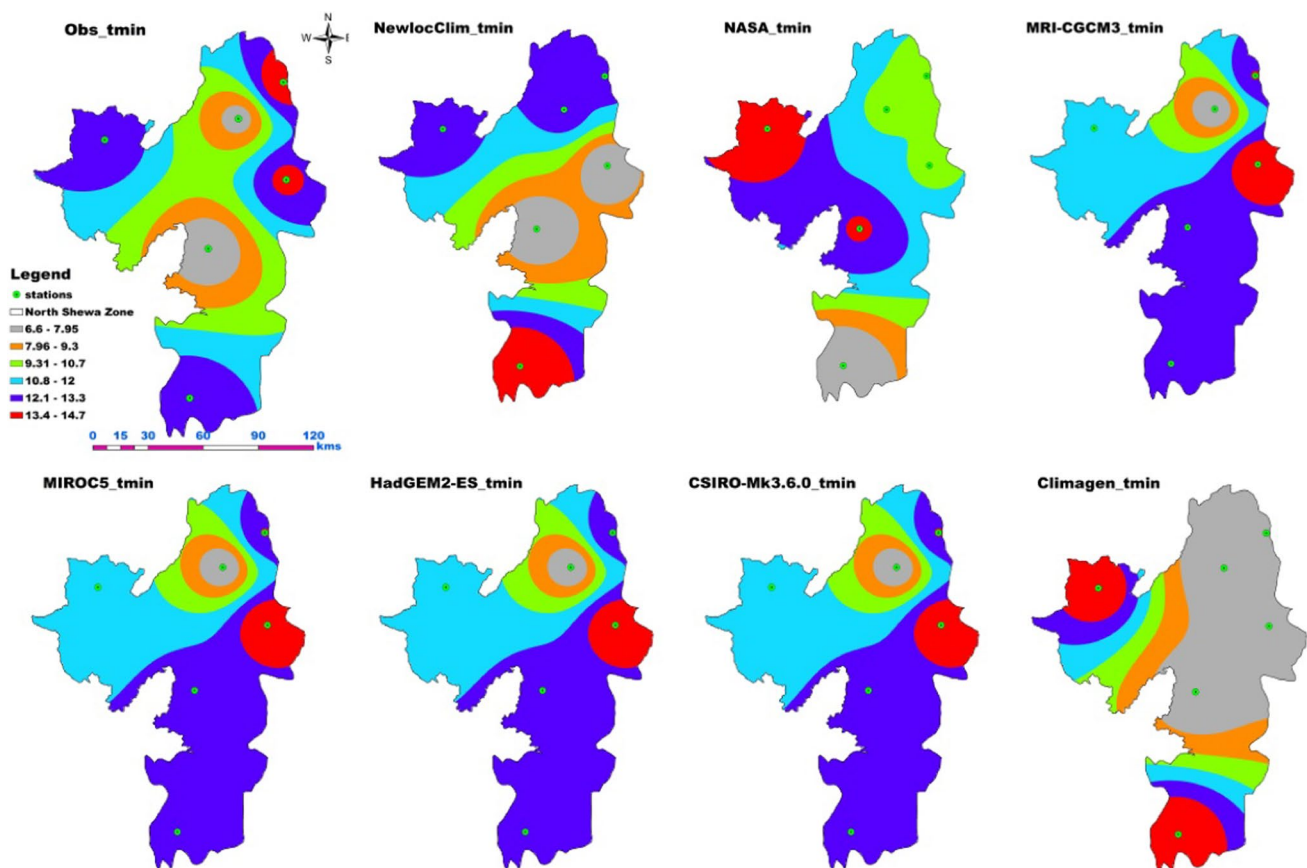


Fig. 6 The spatial variability of minimum temperature under each WG

The spatial variability of WGs in simulating monthly Tmax is shown in Fig. 7. ClimaGen, NewlocClim, and NASA POWER products well handle the spatial variability of Tmax at high-land stations (MM & DB) and poorly perform on other stations. Had-GEM2-ES, MRI-CGCM3, and CSIRO-Mk3.6.0 well capture the spatial variability of Tmax at the stations of MM, MJ, SW and AR stations. This indicates that the recommended WGs can be used to access the weather data in areas that haven't metrological stations.

The spatial distribution of rainfall for various WGs showed fair to moderate performance in handling the spatial variability of observed rainfall. This means the spatial map for rainfall indicates that the spatially interpolated value of distributed rainfall from the gauging stations of the WGs across locations was variable from the observed values (Fig. 8). NewlocClim well captures rainfall distributions at AK, while NASA well simulates rainfall distributions at DB and MJ. Similarly, MIROC5 and ClimaGen showed better performance at DB and MJ respectively. However Had-GEM2-ES, MRI-CGCM3, and CSIRO-Mk3.6.0 were not handling the spatial variability of observed rainfall at all stations.

4.4 Evaluation of the statistical performance of weather generator models

The observed data were compared with the generated data from the WGs. The degree to which the RMSE is lower and the estimations are closer to historical values in a given time series determines the applicability of WGs. In the majority of the stations, the minimum RMSE for Tmax and Tmin was recorded by NewlocClim; however, for rainfall, the minimum RMSE was recorded by NASA except for AR station. The RMSE for NASA POWER products for the study stations ranges from 1.5 °C to 6.8 °C for Tmax, 2.2 °C to 4.1 °C for Tmin, and 48mm to 86 mm for rainfall. This result is aligned with the result obtained by [42], who found RMSE values of less than 5 °C for temperature. The Tmax and Tmin as well as the patterns of rainfall are reasonably captured by NASA POWER and ERA5-Land [44]. The Tmin values in the cooler times of the year

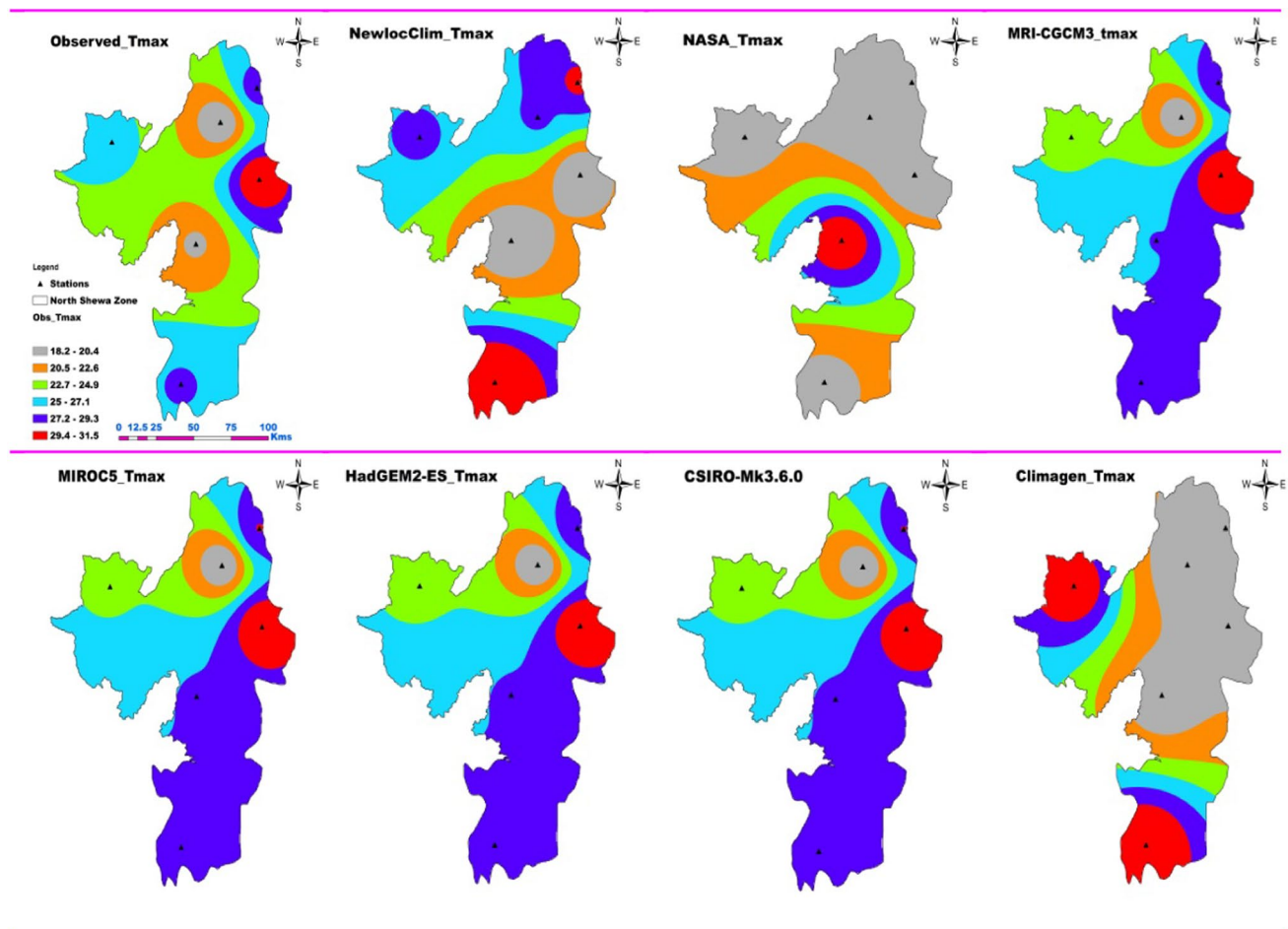


Fig. 7 The spatial variability of maximum temperature under each WG

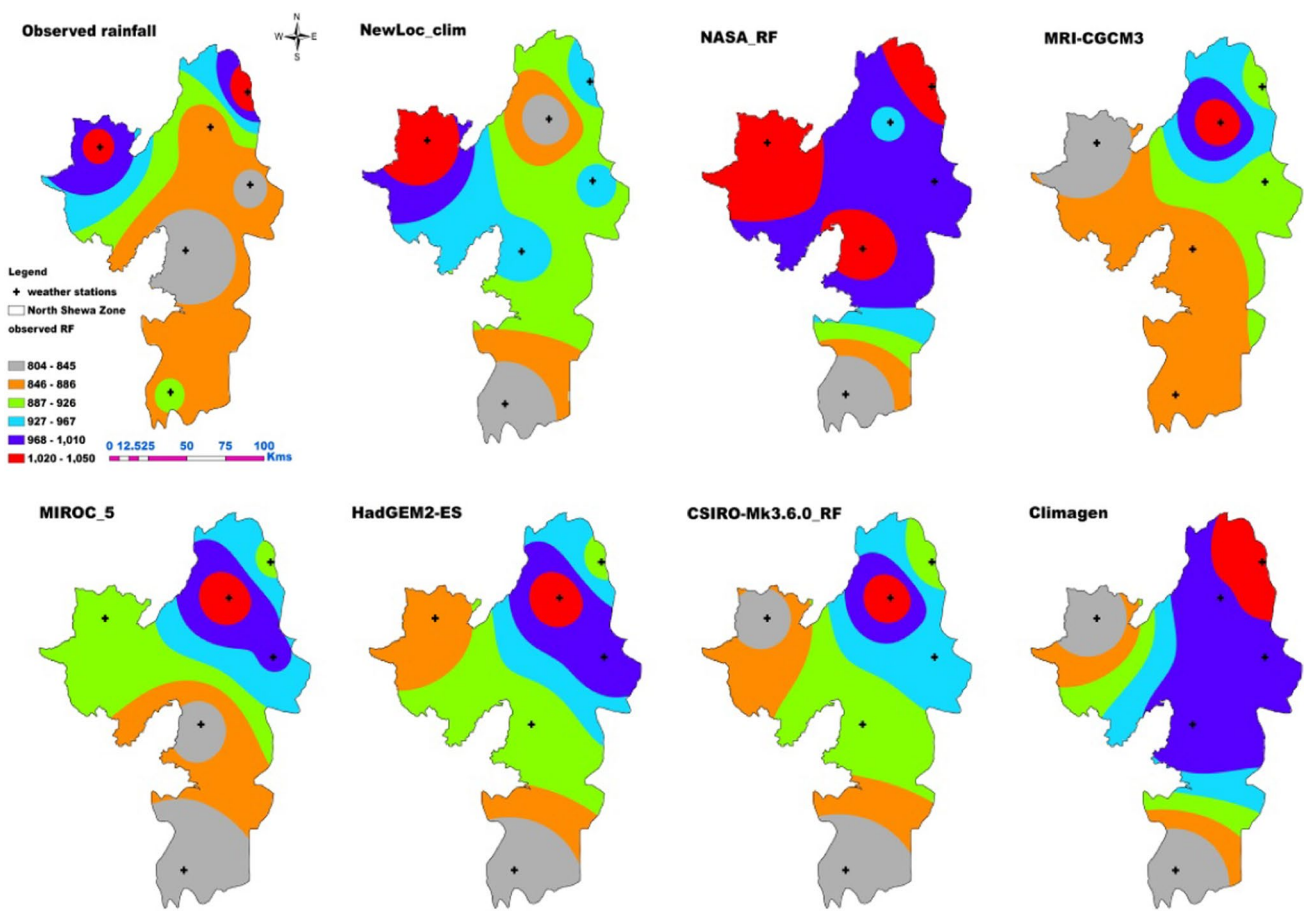


Fig. 8 The spatial variability of rainfall under each WG

was between 6.26 and 7.48 °C, which is a substantial difference from the RMSE values in the hotter months of the year, which ranged from 2.64 to 2.81 °C nationwide. It was also demonstrated by the research that NASA POWER data are less accurate at T_{min} in cold climates and more accurate at T_{max} than at T_{min} [42].

When comparing the data to the observed data, there is little need for bias adjustment and a high degree of accuracy, agreement, and goodness of variable fit [20]. According to [42], NASA POWER had a good agreement with RMSE of 4.1 °C for T_{max} and 3.7 °C for T_{min} in the USA. Similarly, there was a match of NASA POWER and the observed data with RMSE of 4.0 °C for T_{max} and 3.2 °C for T_{min} in China [45]. Another study conducted by [46], found that local bias correction of NASA POWER T_{max}, and T_{min} with RMSE values from 1.91 °C, 2.01 °C to 1.59 °C and 1.58 °C respectively indicating that can simulate T_{max}, T_{min} and solar radiation with a high goodness of fit and agreement.

The range of T_{min} and T_{max} that deviates (either underestimates or overestimates) from the average observed values for most of the stations are 1.1 °C to 7.6 °C under the given WGs. According to [21], the NASA T_{min} had overestimations of observed monthly T_{min} of 1.4 °C to 4.1 °C. ClimaGen has the greater RMSE for both the T_{min} and T_{max}. For the majority of WGs, the RMSE for T_{min} in areas of low land is comparatively smaller than that of high-land and mid-land. In the majority of the tools, the RMSE of rainfall for low-land is greater than that of mid and high-land. This indicates low-land have more variability of rainfall. NASA data on low-land reveals low RMSE for temperatures and high RMSE for rainfall (Fig. 9).

Figure 10 presents the CV values of all-weather generator tools in six weather stations. The CV for T_{max} and RF were found as in the acceptable range, where the CV for T_{min} was highest at DB and MM stations. The lowest CV for T_{max} was obtained by NewlocClim (6.8%) at DB, MRI-CGCM3 (11.6%) at MM, NewlocClim (7.7%) at AR, NASA (6.4%) at AK, MRI-CGCM3 (7.0%) at SW and NewlocClim (8.9%) at MJ station. Whereas, the lowest CV for T_{min} was obtained with NewlocClim (33.1) at DB, MIROC5 (34.4) at MM, NASA (13.8) at AR, NewlocClim (8.7) at AK, NASA (18.4) at SW, NASA (14.9) at MJ station. Nearly at all stations, all WGs have higher CV values for T_{min} at DB and MM. The CV values for rainfall in NASA, HadGEM2-ES, CSIRO-MK3.6.0, and NewlocClim are less for all stations except SW. The highest CV for temperature and

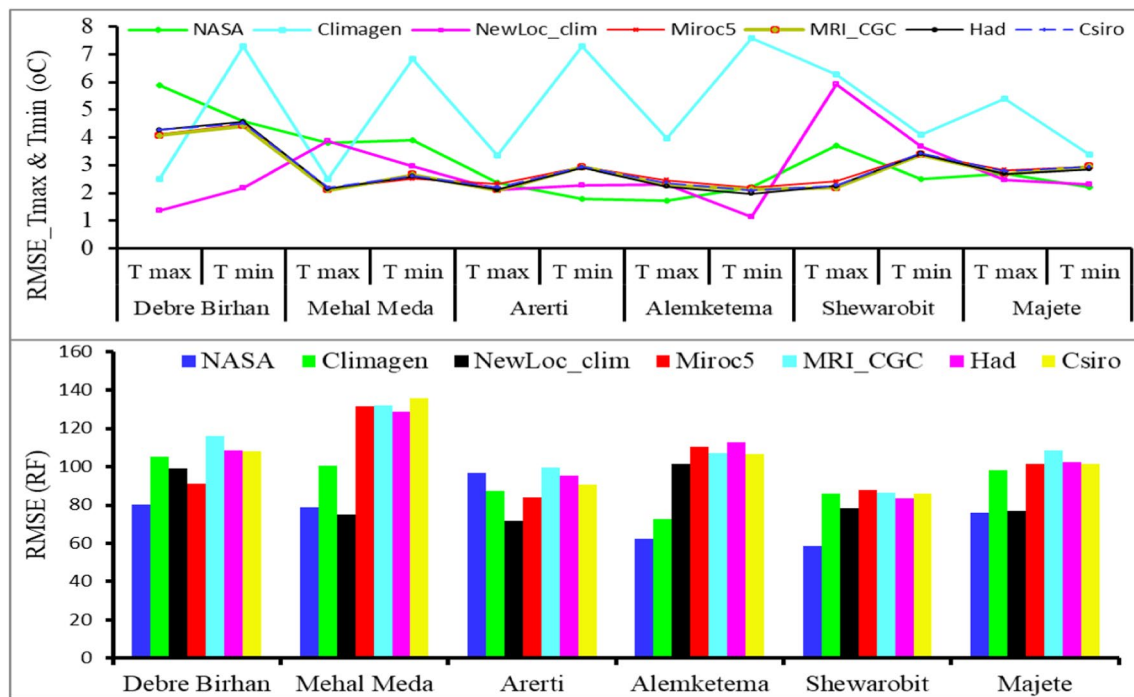


Fig. 9 The root mean square error values for each weather generator over stations

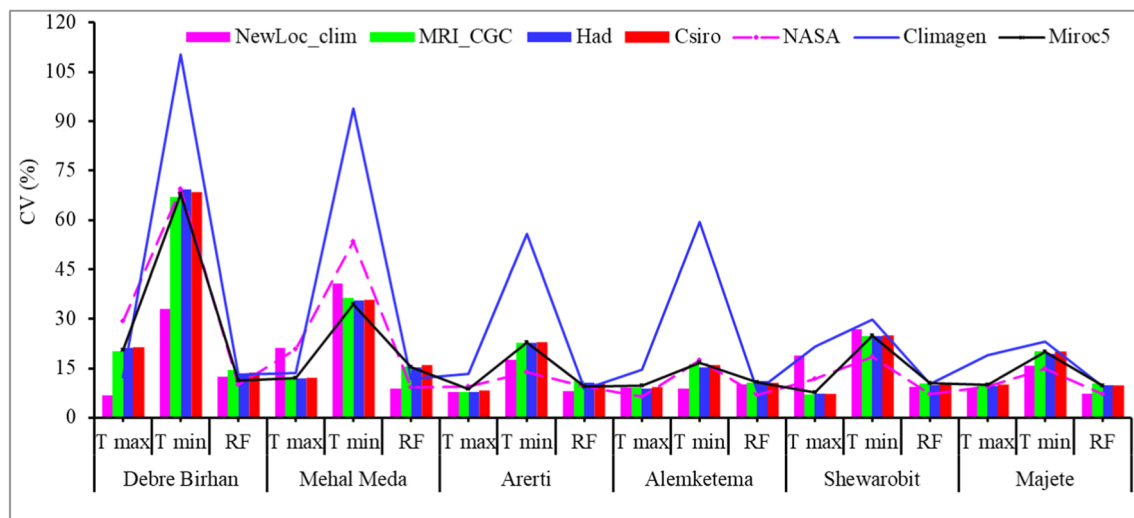


Fig. 10 The Coefficient of variation values for each weather generator over stations

rainfall was discovered in ClimaGen models. The Tmin variability reduced substantially for HadGEM2-ES, CSIRO-MK3.6.0, from high-land to low-land. NewlocClim and NASA are better WGs when it comes to CV; this is because the temperature and rainfall variability are smaller.

The degree of correlation between estimation and observation is indicated by the correlation coefficient. At every station, the R between the Tmax and Tmin in NASA and NewlocClim was found to be greater (> 80%) (Fig. 11). The highest R-value for Tmax was obtained by NASA (0.8) at DB, NASA (0.9) at MM, NASA (0.97) at AR, NASA & NewlocClim (0.9 & 0.98) at AK, NewlocClim & MarkSim GCM (0.8 & 0.9) at SW, and NASA & NewlocClim (0.9 & 0.98) at MJ station. The lowest R-value for Tmax found by ClimaGen (0.5) at DB, MRI-CGCM3 (0.2) at MM, at the four MarkSim GCM (0.7) at AR, ClimaGen (0.5) at AK, ClimaGen (0.4) at SW, and ClimaGen (0.5) at MJ. Whereas, the highest R-value for Tmin was obtained by NASA

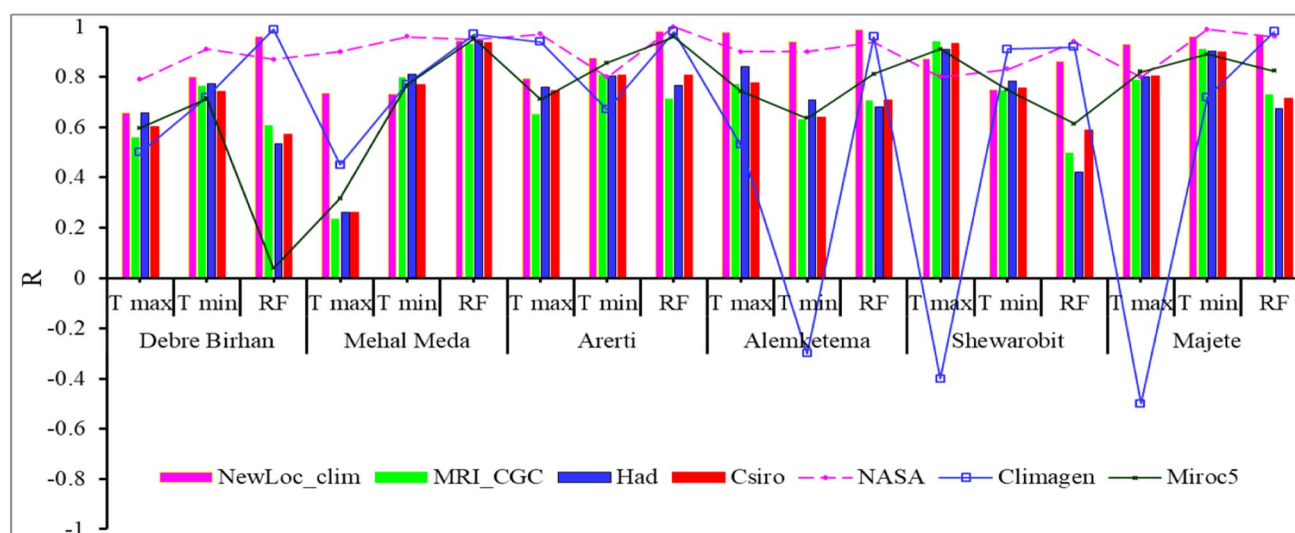


Fig. 11 The values of correlation coefficient (R) for each weather generator over stations

(0.9) at DB, NASA (0.96) at MM, NewlocClim (0.9) at AR, NASA & NewlocClim (0.9 & 0.9) at AK, NASA (0.83) at SW, and NASA & NewlocClim (0.99 & 1.0) at MJ station.

Thus, NASA and NewlocClim estimate Tmax and Tmin for the three AEZ more accurately than any of the other models. The R -value for rainfall under all WGs ranges from 0.9 to 1.0, indicating that the model output rainfall has a high relationship with the observed value. Relatively, NASA and NewlocClim's rainfall distribution over stations was accurately predicted. Nevertheless, ClimaGen does a poor performance of predicting rainfall and temperature for every station. As a result, NASA and NewlocClim are more accurate with goodness of fit to estimate temperature and rainfall in most of the stations. A better correlation and goodness of fit was obtained between the NASA POWER products and the observed historical data in Egypt [43].

Based on validation of NASA POWER data at four stations over four years indicated that the air temperature obtained from NASA was enough accurate and could be used for any local assessment of warming and agriculture [33]. They found the R^2 of 0.75 for temperature simulation. The results of this parameter also agreed tangentially, similar to RMSE, for all but ClimaGen. The R for rainfall, Tmax and Tmin and all tools are generally good for the majority of stations. Figure 12

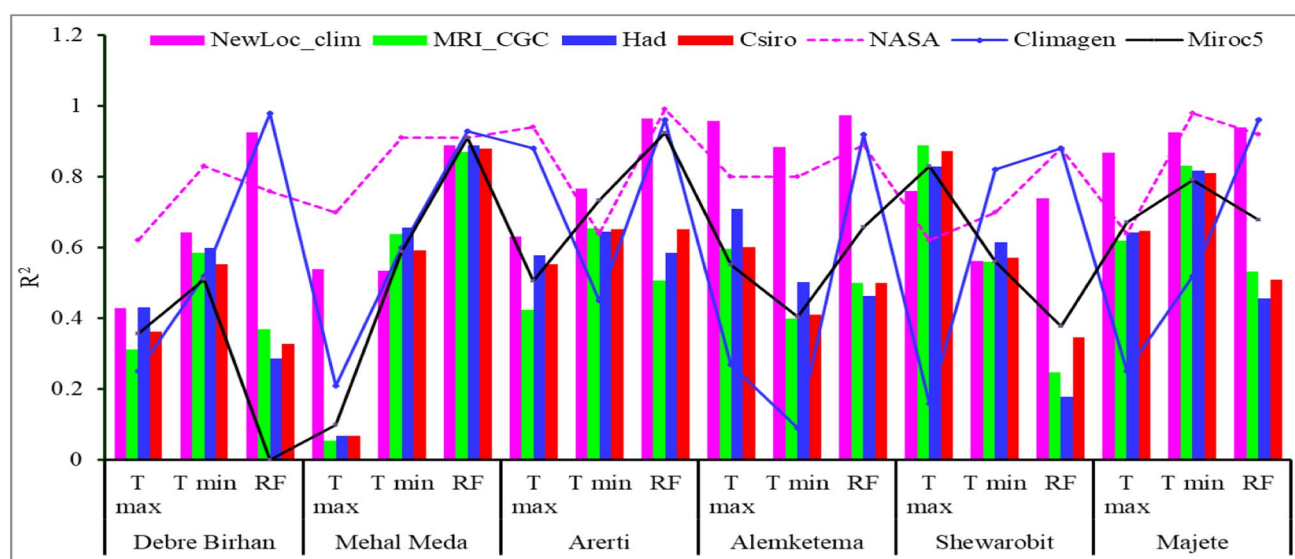


Fig. 12 The values of coefficient of determination for each weather generator over stations

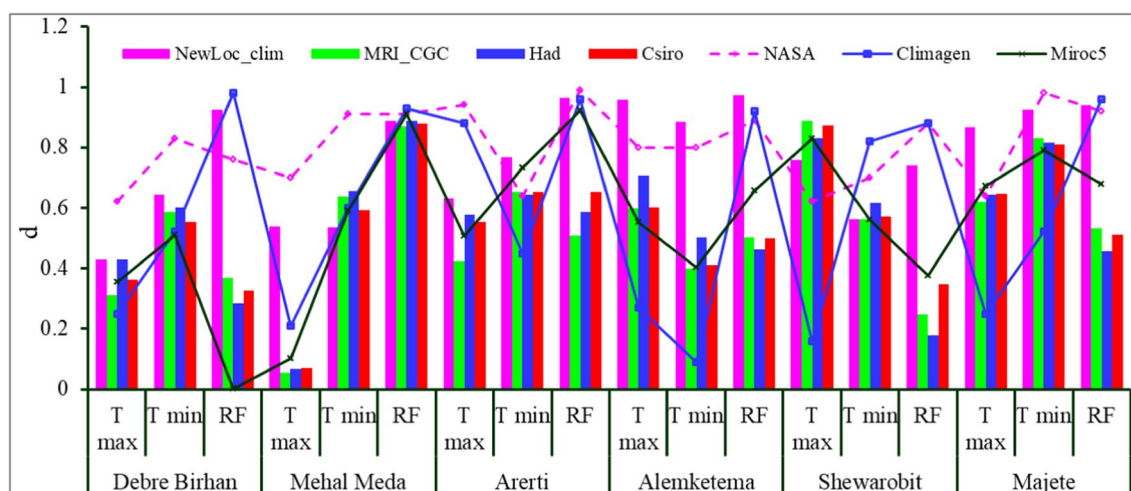


Fig. 13 The Willmot index of agreement values for each weather generator over stations

shows that, for all NASA stations with the exception of AK, the R^2 for the Tmax and Tmin are higher. With the exception of SW, rainfall was highly predicted by NewLocClim, with R^2 of nearly 90%.

Figure 13 shows the evaluation of the monthly average of different WGs output agreement with the observed Tmin, Tmax, and rainfall at the six stations. For all stations, there is sufficient consistency between the rainfall generated by all WGs and what is seen. It is unlikely that the highest and lowest temperatures in NewLocClim, which is followed by NASA, have better agreement indicators at high and mid-land. The index of agreement for temperature was found 0.7 to 0.9 for NewlocClim and 0.6 to 0.9 for NASA. This result is supported by [42], who found an index of agreement of 0.9. However, NASA's index of agreement for low-land is higher than NewLocClim.

At all stations, Climagen's performance complies poorly with the recorded Tmax and Tmin (Fig. 13). For the most part, NASA and NewlocClim could agree on temperature and rainfall. The observations over Egypt and the NASA POWER reanalysis datasets showed a higher degree of consistency [42]. When producing meteorological data sets, NASA POWER can be a helpful alternative for observations in cases where data from weather stations is inadequate or unavailable [43, 46]. NASA POWER and FAO NewlocClim data source well simulated the observed rainfall and temperature in North Shewa [47]. Given the bias in the data, it is advised in the Free State Province to use NASA temperature data to power models that are crucial for decision-making, particularly in situations where there are no climate records or missing values [21].

5 Conclusion and recommendation

The use of well-validated WGs is required for the agriculture as it is directly impacted by climatic variability, including the observed fluctuation in temperature and rainfall. This study examined the long term changes and trends of rainfall and temperature of North Shewa by using some statistical indicators. The performance of WG tools in capturing the temporal and spatial distributions of rainfall, Tmax and Tmin were assessed. Moreover, validation of weather generator tools including NASA POWER data sources, MarkSim DSSAT, ClimaGen and NewlocClim over a range of AEZs were conducted by statistical methods. The Mann–Kendall trend test revealed that there were no statistically significant ($P < 0.05$) changes of rainfall trends at all stations. However the overall trends of rainfall had a decreasing trend, and the maximum amount of changes was happened at Majete and Alem Ketema stations.

This erratic and uneven distribution and trends might be caused by the significant variations in the region's climate change and anthropogenic factors. There were statistically significant ($P < 0.05$) increasing changes of both Tmin and Tmax at all stations. NASA POWER data followed by NewlocClim exactly capture the temporal changes of both rainfall and temperature except high-land AEZs. None of the WGs able to simulate the spatial distribution of temperature and rainfall at each station. Some models well capture the spatial variability at some stations while others are not. However, overall WGs showed moderate to good performance in capturing the spatial distributions of temperature and rainfall. For instance, NewlocClim well captures rainfall distributions at AK, while NASA well simulates rainfall distributions at DB and MJ stations. Thus, they are the recommended WGs that can be used to access the weather data in areas that

haven't metrological stations. With regard to statistical indicators, WGs that exhibit minimum CV and RMSE, and highest R^2 and index of agreement are the best fit to the observed and can be used in ungagged weather stations. For most of the stations, NewlocClim and NASA had the lowest RMSE and CV for both temperature and rainfall. Similarly, a stronger correlation and index of agreement were noted in NewlocClim and NASA almost for all stations. As a result, NASA and NewlocClim are more accurate with goodness of fit to estimate temperature and rainfall in most of the stations. They can be recommended to access weather data for ungagged stations for timely and reasonable decision-making on agriculture, climate change impact, hydrological modeling purposes, crop modeling, soil erosion and water management systems. From this study, we can draw that NASA and NewlocClim provide better reproduction of rainfall, Tmax and Tmin over North Shewa areas. Moreover, further research using a larger number of meteorological stations and additional WGs is needed to obtain accurate weather data source for the required stations.

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Data availability Data will be made available on request.

Declarations

Competing interests The authors declare no competing interests.

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