Research in: Agricultural & Veterinary Sciences
Vol.5, No.3, 2021, pp.128-141

VALIDATION OF DIFFERENT WEATHER GENERATOR TOOLS UNDER VARIOUS CLIMATIC CONDITION OF NORTH SHEWA, AMHARA REGION, ETHIOPIA

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Abstract. Weather data is profoundly an important input for crop simulation models and soil and water management models. However, the metrological data cannot be easily accessed and sometimes it may be time consuming and costly. Validated climate models are needed to produces meteorological information for a given locations and altitudes. This study is designed to describe the temporal trends and spatial distribution of long-term weather data, to validate and test the performance of different weather generator tools, and to select the best-fit weather generator tools. Long-term climatic data (1990-2020) from the three agro ecologies of North Shewa was collected. In validation procedures, statistical indicators like mean, RMSE, CV, Correlation, and Regression analysis was done. The spatial Variability of Rainfall and minimum temperature is higher, having a coefficient of variability of nearly above 30%. As the analysis of PCI, the rainfall distribution shows a bimodal nature from March to May and July to September in all stations. From Man Kendall trend analysis, rainfall has decreasing trends, while maximum and minimum temperatures have increasing trends. The correlation coefficient for maximum temperature and minimum temperature in NASA and NewlocClim was found to be higher (> 80 %) at all stations. In general, the best-fit tools for temperature and rainfall data generations are NewLocClim and NASA. Therefore, from this study for rainfall data generation one may use NASA and NewLocClim for reproducing maximum and minimum reproducing over location.

Keywords: *North Shewa, AEZ, climate variability, trend analysis, WG, validation.*

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Received: *7 October 2021;* ***Accepted****: 21 November 2021;* ***Published:*** *14 December 2021.*

1. Introduction

Climate variability affects the overall environment (Agriculture, health, construction, education…. etc.). Weather is a major influencing factor in agricultural production and management systems like hydrologic system, cropping system, and environmental effects in the World and the same is true in Ethiopia also. According to (Chinnachodteeranun *et al*, 2016), climate data is used to simulate crop growth, planning agricultural management and farm decisions. Now a day, weather information is playing a great role in precise climate smart agricultural activities. The users can use the data to fill out missed data; to assess the impact of climate change like droughts, rainfall pattern changes and extreme temperature (Wilks & Wilby, 1999). As per the investigation of (Chena *et al*, 2014), the generation of precipitation and temperature are the two main components for most stochastic weather generators, especially for climate change impact studies. Similarly, these parameters are widely used by researchers in their impact models and standard component of decision support systems in agriculture, environmental management, and hydrology (Tingem *et al*. 2010).

At present time, the output from global climate models is of a poor spatial and temporal resolution and less reliable to be used directly in different models. Weather generators are necessarily in climate change-related studies and are essential tools for temporal downscaling of weather variables (Tseng *et al*, 2012). The variability in monthly means of precipitation and maximum temperature in the generated data by ClimGen and observed for all the sites was nearly smaller (Tingem *et al*, 2010). ClimGen is a stochastic weather generator that generates daily precipitation, minimum and maximum temperature, solar radiation, humidity, and wind speed data series with similar statistics to that of the historical weather data (Gayatri *et al*, 2014). The MarkSim DSSAT weather file generator web application was used to acquire downscaled future climate data on a daily time step. For instance, only 6 out of 17 projections were significant trends over Metehara, namely: csiroMK3.0 (for 2030s in both scenarios), gfdlCM2.1 (B1 2030's) and ukmoHADCM3 (except A2 for 2050s) (Mequanint *et al*, 2016).

To get a metrological data, most of the times users are refer to the national metrological service agency. However, this takes a too long time and sometimes it may costly. The option to address this problem is accessing WG platforms that offer Spatial and temporal climate data on a global basis. Well-validated climate models are needed to produces meteorological information for the given locations and altitudes. However, limited information exists in the peer-reviewed literature regarding testing and validation of these tools. A rapid method of obtaining downscaled future climate data by using globally validated models to the observed datasets would therefore greatly expand the availability of such data to scientists and policy planners wishing to conduct future climate impact analyses (Trotochaud *et al*., 2016). Therefore, this proposal was initiated to the objectives of: - to describe the temporal trends and spatial distribution of long-term weather data in the three agro ecological zones, to validate and test the performance of different weather generator tools across different locations, to select the best fit weather generator tools for each parameter.

2. Materials and methods

Description of the study area

The study was conducted in three agro-ecological zones of North Shewa; shewarobit and Antsokia Gemza, Minjar Shenkora and Merhabete, Basona werena and mehalmeda wereda from low lands, mid-altitude, and high altitudes respectively

Figure 1). Actual observed daily weather data was collected from these weather stations from the National metrology service agency. Long-term climatic data (1990-2020) collected and data arrangement was done accordingly. Data quality management like outlier detection and handling of missing data was done. It was filled with interquartile range test on excel sheet and treated as a missing values and filled by normal ratio methods.

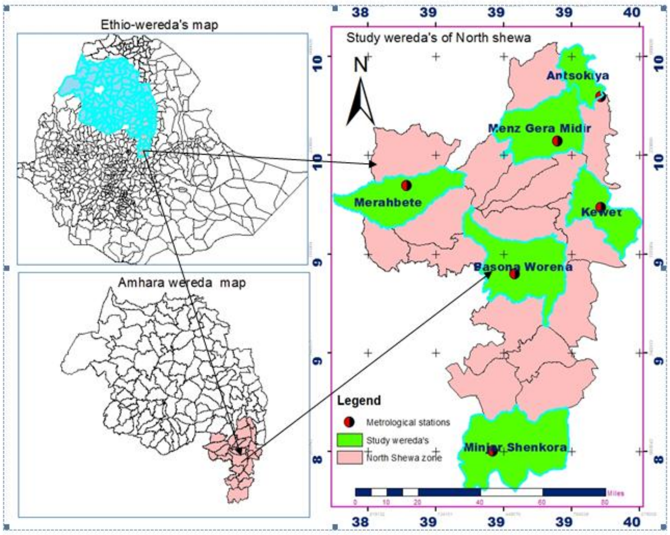


Figure 1. Geographical location of the study areas

Weather generator's description

Marksim DSSAT weather file generator

It is an easy-to-use online web application (http://gismap.ciat.cgiar.org/MarkSimGCM), and a valid weather simulator model that produces rainfall, temperature, and solar radiation, soil type information for other model applications. It produces either continuous daily data in single year segments or the assembles of more than two years data depending on the replication fields. It follows the procedures of global climate models (GCM) sequence by requesting the geographical location data. MarkSim DSSAT is a weather generator that works on the principle of a third order Markov chain process (Jones & Thornton, 2000).

Marksim DSSAT was downscaled about 17 GCM with a resolution of 18km *18km; among these, four of them are validated in this study (Table 1).

According to (Dhakal *et al*, 2018), the four models of GCMs; Had-GEM2-ES, MRI-CGCM3, MRIOC5, and CSIRO-Mk3.6.0 were specifically chosen as they had the finest spatial resolution.

Table 1. The global climatic models tested in this study

No	Model abbreviation	Institution	Resolution
1	CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization and the Queens land Climate Change Centre of Excellence	1.875 x 1.875
2	HadGEM2-ES	Met Office Hadley Centre, UK	1.2414 x 1.875
3	MIROC5	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute	1.4063 x 1.4063
4	MRI-CGCM3	Meteorological Research Institute	1.125 x 1.125

New_LocClim V 1.10

It is a new version of LocClim, developed in collaboration with the Deutscher wetterdienst (German weather service) and the Global precipitation Climatology center (GPCC). The users make it at single point mode and fed the geographical co-ordinates of the points.

It allows all the interpolation methods (Nearest neighbor, IDW, kriging, modified IDW, polynomials methods) to determines the desired variables like, Maximum and Minimum Temperature, Precipitations, Wind speed, Sunshine hours (Gommes *et al.*, 2004).

NASA data source

Climatological data, from 1983 onwards can be obtained from NASA at the following link:
http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi?email=agroclim@larc.nasa.gov

The NASA Prediction of Worldwide Energy Resource (POWER) gives an estimation of certain climatological parameters, based primarily upon solar radiation derived from satellite observations and meteorological data from assimilation models. In other words, they are not "recorded" values, but are derived from satellite imagery.

A detailed description of the methodology, including an accuracy assessment is found at http://power.larc.nasa.gov/documents/Agroclimatology_Methodology.pdf

ClimaGen weather generators

It is a weather generator based on SIMMETEO, as developed by (Geng *et al.*, 1988). It needs an input of name of weather station, Latitude, longitude, altitude, number of years to be generated and gives an output of solar radiation (MJ/m2/day), maximum temperature (ºC), minimum temperature (ºC), total monthly rainfall (mm), number of rainy days, wind speed (m/s), vapor pressure (kPa). It also makes a summary of descriptive statistics.

Spatial and temporal distributions of observed data

Precipitation concentration index (PCI) was determined for each agro-ecological zone by dividing the square of the monthly rainfall amount to the square of the yearly rainfall. The PCI value less than 10 % indicates uniform rainfall distribution (low rainfall concentration),values between 11% and 15% a moderate rainfall concentration; values between 16% and 20% an irregular rainfall distribution, and greater than 20% shows highly irregularity of rainfall distribution (i.e. high rainfall concentration) of rainfall distribution (De Luis *et al.*, 2011). The coefficient of variability was also determined to determine the rainfall pattern and temperature variation in each agro-ecological zone. It is the ratio of standard deviation to the mean values for each parameter. ArcGIS was used to map the distributions of extreme climate trends across the study area by using inverse distance weighted interpolation methods.

Trend analysis of observed data

To determine the trend analysis of observed maximum temperature, minimum temperature and rainfall over the three agro-ecologies, Sen's slope method and Mann-Kendall's trend test (non-parametric method) was used. The Sen's slope estimator was employed after Mann-Kendal test statistics in order to determine the change and variability of rainfall and temperature trends through time series (Worku *et al.*, 2018). The equation of test statistic is given by -

$$T_s = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sign}(X_j - x_i)$$

where T_s is the Mann-Kendal's test statistics; x_i and x_j are the sequential data values of the time series in the years j and I (j > i) and N is the length of the time series. A positive S value indicates an increasing trend and a negative value indicates a decreasing trend in the data series. The variance of S, for the situation where there may be ties;

$$\operatorname{Var}(T_s) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i - 1)(2t_i + 5)\right]$$

where, 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 the values of 'n' larger than 10, Z_{mk} approximates the standard normal distribution (Kahya, 2006).

$$Z_{mk} = \begin{cases} \dfrac{T_s - 1}{\sqrt{\operatorname{var}(T_s)}}, & T_s > 1 \\ 0, & \text{if } T_s = 0 \\ \dfrac{T_s + 1}{\sqrt{\operatorname{var}(T_s)}}, & T_s < 1 \end{cases}$$

In a two-sided test for trend, the null hypothesis Ho should be accepted if $|Z_{mk}| < |Z_{1-a/2}|$ at a given level of significance. $Z_{1-\alpha/2}$ is the critical value of Z_{mk} from the standard normal table.

Validation criterion

The outputs from each generator compared with the observed climatic data with statistical methods to select the best-fit models. To check the predicted climatic parameters: - a statistical procedure (mean, RMSE, CV, R^2 and Correlation analysis) was employed. Among Descriptive Statistics of Error or deviation between actual value and estimate, Error Mean is the representative value of the error. The SD of Error indicates the deviation from mean values. The coefficient of determination R^2 is defined as the squared value of the Pearson correlation coefficient. It ranges from zero to one; values close to 1 indicating a good agreement.

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

g_i -generated value, O_ii -observed value, O_i^- -mean of O_i and g_i^--mean of P_i.

RMSE measures the average magnitude of error, calculated as the square root of the average of squared differences between prediction and observation data. A lower RMSE indicates that better performance of the model.

$$\text{RMSE} = \left[\frac{1}{n}\sum_{i=0}^{n}(g_i - O_i)^2\right]^{0.5}$$

where, g_i -model generated value; O_i -observed value; n -number of observations.

$$\text{NRMSE} = \frac{1}{O_i^-} * \sqrt{\frac{\sum(g_i - O_i)^2}{N}} * 100$$

NRMSE (C.V) generated value 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%.

The index of agreement was proposed to measure the degree to which the observed data are approached by the predicted data (Willmott, 1982). It ranges between 0 and 1, with "0" indicating no agreement and "1" a perfect agreement between the predicted and observed data.

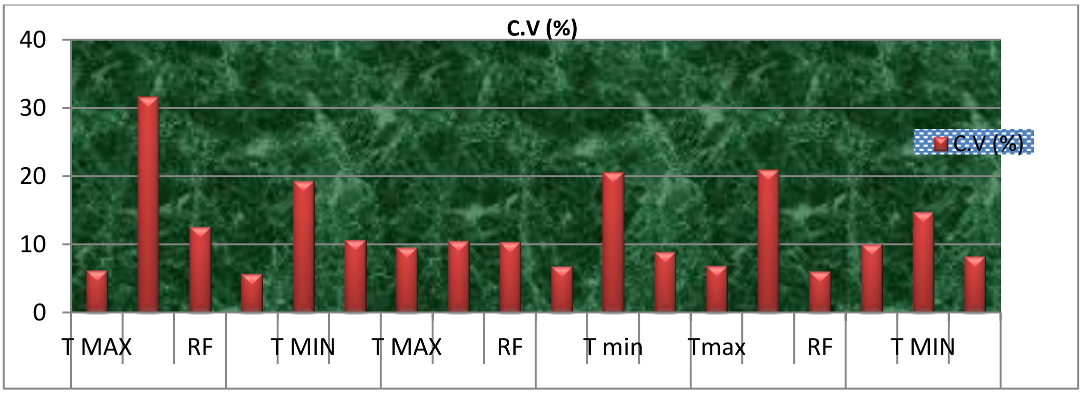
$$d = 1 - \frac{\sum(P_i - O_i)^2}{\sum(|P_i - O_i^-| + |O_i - O_i^-|)}$$

where, d = Willmott's index of agreement, P_i - predicted value O_i -observed value, O_i^- -mean of O_i correlation analysis was done for the observed and generated value of each weather generator.

3. Result and discussions

Spatial and temporal variaiation of parameters

The temporal variation for monthly rainfall distribution over stations is enough good, having a coefficient of variability of fewer than 10%, indicates that the rainfall amount distributed uniformly over years. This implies well impacts on agricultural activities of the community and hence assures the well-being of the community. The coefficient of variations for maximum temperature and rainfall nearly for each stations is in acceptable range, which is 6^0C (Mehal Meda) to 10^0C (Minjar Shenkora) and 7 mm (Kewat) to 13 mm (Debre Birhan) respectively. The higher rainfall variability was observed in the low lands areas. Minimum temperature for all stations is highly variable except Alem ketema. In general, the temporal variability of maximum temperature is smaller (C.V<10%), uniform distributions over stations. Whereas, the coefficient of variability for minimum temperature over stations is range from 15-33, indicates that satisfactorily distributions (Fig. 2)



DB-Debre birhan, MM-Mehal meda, AK-Alem Ketema, MS-Minjar shenkora, KW-Kewat, MJ-Majete.

Figure 2. The temporal variability of rainfall and temperatures over stations

The coefficient of variation nearly in all stations shows that rainfall in North Shewa has high inter-annual variability. The result indicated that annual rainfall and temperature over stations are highly variable. The spatial Variability of Rainfall and minimum temperature is higher, having a coefficient of variability of nearly above 30%. However, the coefficient of variability for maximum temperature is 15-25%, which indicates that satisfactorily distributions over seasons (
Figure 3). This primarily influences all the agricultural activities either positively or negatively. The map of the annual rainfall, maximum temperature, and minimum temperature across the study location were determined by inverse distance weighted interpolation methods. It revealed that the rainfall distributions over high land areas (900-1050mm), mid lands (850-1000mm), and low lands (1000-1100mm). Similarly, the

maximum temperature and the minimum temperature ranged from 17-39 ^{0}C and 3-20 ^{0}C respectively shown in the figure below (Figure 3, 4)

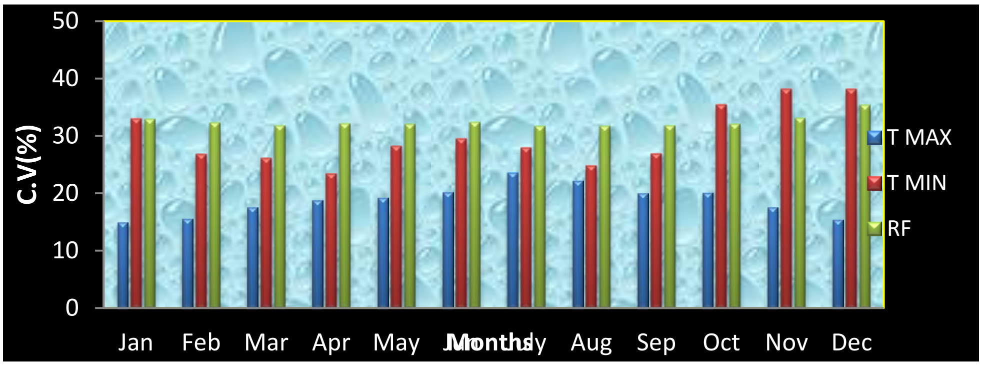


Figure 3. The spatial variation of rainfall and temperatures over seasons

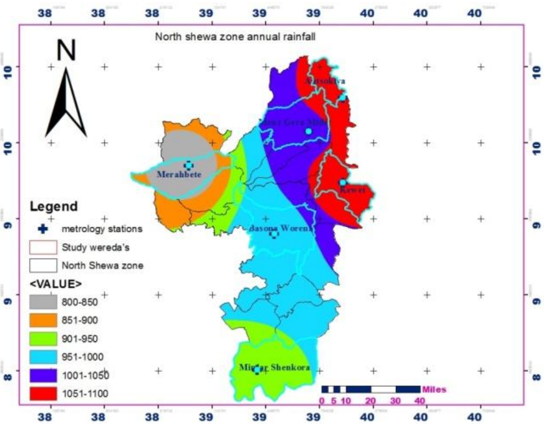


Figure 4. The map of rainfall extremes distribution across locations

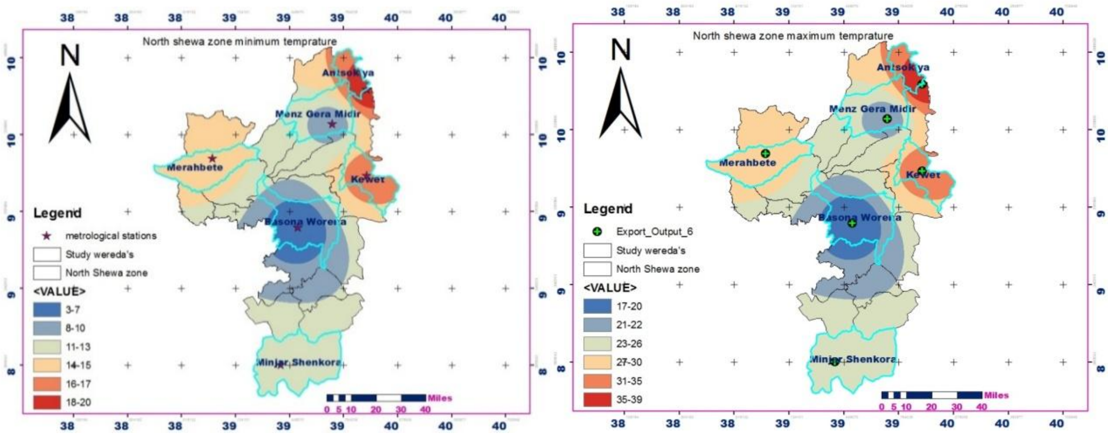


Figure 5. The map of minimum and maximum temperature distribution across locations

As the analysis of PCI, the rainfall distribution shows a bimodal nature from March to May and July to September in all stations. The PCI value across the stations for kiremt season rainfall is ranged from 5 to 15, indicates that there were moderate rainfall distributions (higher rainfall concentration). While, on other months the value of PCI is nearly 0 and 1, indicates the more uniformity of rainfall (no rainfall, or small amount of rainfall concentration) over the three-agro ecological zones of North Shewa (Table 2).

Table 2. The PCI (%) values for each month over stations

Stations		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
DB	Ave	9	12	33	36	32	41	239	316	64	16	4	3
	PCI	0	0	0	0	0	0	9	15	1	0	0	0
MM	Ave	16	23	45	55	40	41	268	252	74	24	7	5
	PCI	0	0	0	0	0	0	10	9	1	0	0	0
AK	Ave	7	19	46	48	55	70	280	308	141	24	10	9
	PCI	0	0	0	0	0	0	8	9	2	0	0	0
MS	Ave	10	29	51	62	32	76	232	233	94	42	15	9
	PCI	0	0	0	0	0	1	7	7	1	0	0	0
KW	Ave	28	48	58	86	81	24	144	182	84	39	14	48
	PCI	0	0	0	1	1	0	3	5	1	0	0	0
MJ	Ave	31	40	72	99	64	25	221	297	104	45	28	23
		0	0	0	1	0	0	4	8	1	0	0	0

DB-Debre Birhan, MM-Mehal Meda, AK-Alem Ketema, MS-Minjar Shenkora, KW-Kewat, MJ-Majete, PCI----precipitation concentration index, Ave-----average.

Trend Analysis of parameters

Seasonal rainfall trends: The Mann–Kendall trend test shows a decreasing trend on monthly and annual rainfall in the three agro ecologies of North Shewa except in Alemketema stations, but the trends were found to be statistically non-significant in both decreasing and no trends. This could be due to higher variability of rainfall in the areas over years, eratic availaaablity and uneve distribution.This similar with that of (Gebre *et al.*, 2013), the trends were found to be statistically non-significant (P>0.05) at most of the stations where they were studied.

Maximum temperature and minimum temperature: There was highly significant increasing trend of maximum tempreture in highlands and mid lands and significantly increasing trends at low lands, which ranges from 0.12 °C/year at Majete to 0.37 ^{0}C/year at Arerti; and for minimum temprature the increase rate ranged at low lands (Majete) 0.01 °C and mid lands (Alemketem) 0.2^{0}C respectively.

Table 3. Trends of Rainfall, maximum and minimum temperature over stations from 1981-2020

Stations	Rain fall			Maximum Temperature			Minimum Temperature		
	Z_{mk}	Sen's slope	P-value	Z_{mk}	Sen's slope	P-value	Z_{mk}	Sen's slope	P-value
DB	0.35	-0.007	0.79ns	0.24	0.168	**	0.19	0.2	**
MM	0.03	0	0.41ns	0.31	0.199	**	0.2	0.146	**
AR	0.01	0	0.89ns	0.42	0.37	**	0.09	0.131	0.45ns
AK	0.03	0.11	0.42ns	0.28	0.277	**	0.23	0.202	**
KW	0.01	0	0.84ns	0.15	0.184	*	0.03	0.042	0.64ns
MJ	0.03	-2.66	0.367ns	0.1	0.121	*	0.05	0.01	0.26ns

*ZMK is Mann–Kendall trend test, Slope (Sen's slope) is the change in mm per annual; **,* is statistically significant at 0.05 and 0.1 probability level; ns is non-significant trend at 0.1;*

There was a significantly increasing trend of minimum temperature at highland areas and Alem ketema stations. Whereas, at Arerti from mid lands and at low lands there were statistically insignificant increasing trends. Generally, Maximum temperature and Minimum temperature at highlands, mid lands and low lands shows an increasing trend (выше 3). This results agreed to (Worku *et al*., 2018), the long-term minimum and maximum temprature have significant increasing trend over the stations.

Validation of weather generators

The generated data from the weather generators were compared with the historical records of weather data in the three agro-ecological conditions of North Shewa. The suitability of weather generators is decided by how the RME is as much to be smaller and close the estimates to historical values are in a given time series. The minimum error mean square error was observed for NewlocClim in most of the stations for maximum and minimum temperature, whereas for rainfall the minimum root mean square error observed with NASA and followed by NewlocClim except station Arerti (Minjar Shenkora). The higher RME for minimum and maximum temperature were observed in Climagen. The RMSE for minimum temperature in low lands are relatively smallest than that of the highlands and mid altitude agro ecologies for most of the weather generators. The RMSE of Rain fall for lowlands is largest than mid and high lands agro ecologies in most of the tools. That means, there is greater rainfall variability in the lowland's areas. Lowland agro ecology shows high RMSE for rainfall and low RMSE for temperature in NASA (Figure 6).

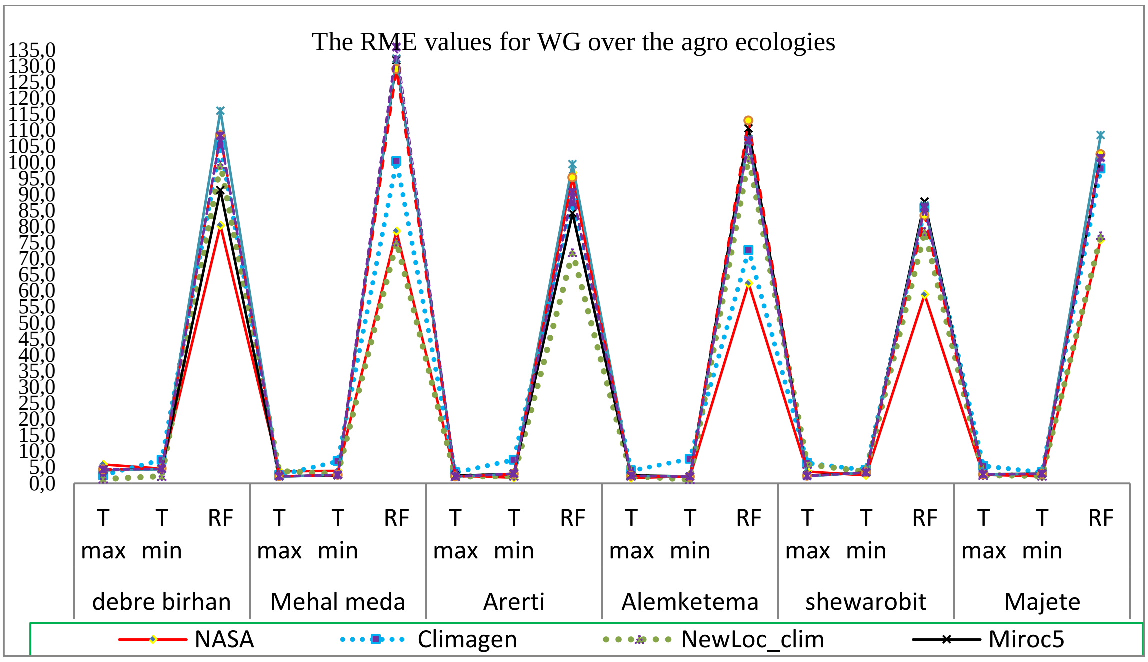


Figure 6. The root mean square error values for each weather generator over stations

The coefficient of variation for maximum temperature and minimum temperature in NewlocClim was found to be minimum at all stations except Mehal Meda and Shewarobit stations (Figure 7). However, the C.V values of minimum temperatures for all weather generators tools are higher. The C.V values for rainfall in all station except Shewarobit are smaller in NewlocClim, followed by NASA, HadGEM2-ES CSIRO-MK3.6.0. The maximum C.v found in ClimaGen models for both temperature and rain fall. For HadGEM2-ES, CSIRO-MK3.6.0, the variability of minimum temperature decreased tangentially from highlands to lowlands. In general, the best-fit tools are NewLocClim for temperature and NASA for rainfall (the variability in temperatures and rainfall is smaller in NewLocClim and NASA). Nextly, Had-GEM2-ES and MIROC-5 best fit for maximum temperature and minimum temperature.

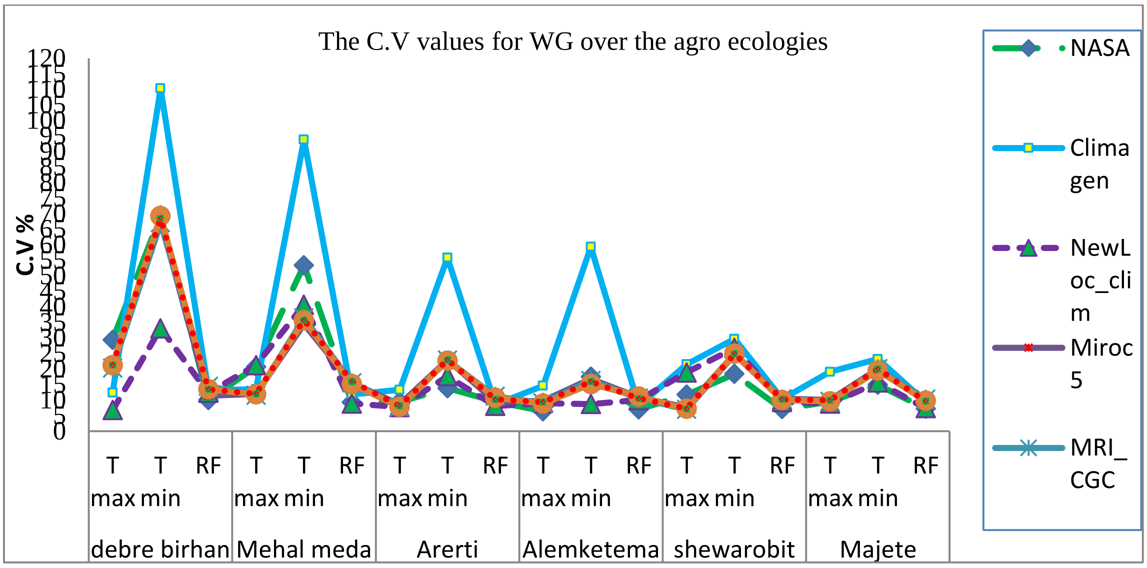


Figure 7. The Coefficient of variations values for each weather generator over stations

Correlation Coefficient is an indicator for the strength of the relationship between observations and estimates. Higher correlation coefficients indicate that the generated data is high or low when observed data is high or low respectively giving evidence about the suitability of the generator tools. The correlation coefficient for maximum temperature and minimum temperature in NASA and NewlocClim was found to be higher (> 80 %) at all stations (Figure 8).

The coefficient of determination r^2 is the squared value of the Pearson correlation coefficient. For the three agro ecologies, NASA and NewLocClim well predicts for maximum tempratures and minimum tempratures better than others do. Similarly, the rainfall distribution over stations well predicted by NASA and NewlocClim. However, ClimaGen poorly predicts both temperature and rainfall for all stations. Therefore, NewLocClim and NASA are alternatively predicts temperature and rainfall. Similar to RMSE, the results of this parameter also agreed tangentially for most of the tools except ClimaGen. Generally, for most station the correlation coefficient for rainfall, maximum and minimum temperature has good correlation for all tools. From the (Figure 9) the coefficient of determinations is higher for maximum and minimum temperature in NASA at all stations except Alemketema. Rainfall highly predicted with NewLocClim over stations except Shewarobit, nearly 90% coefficient of determinations.

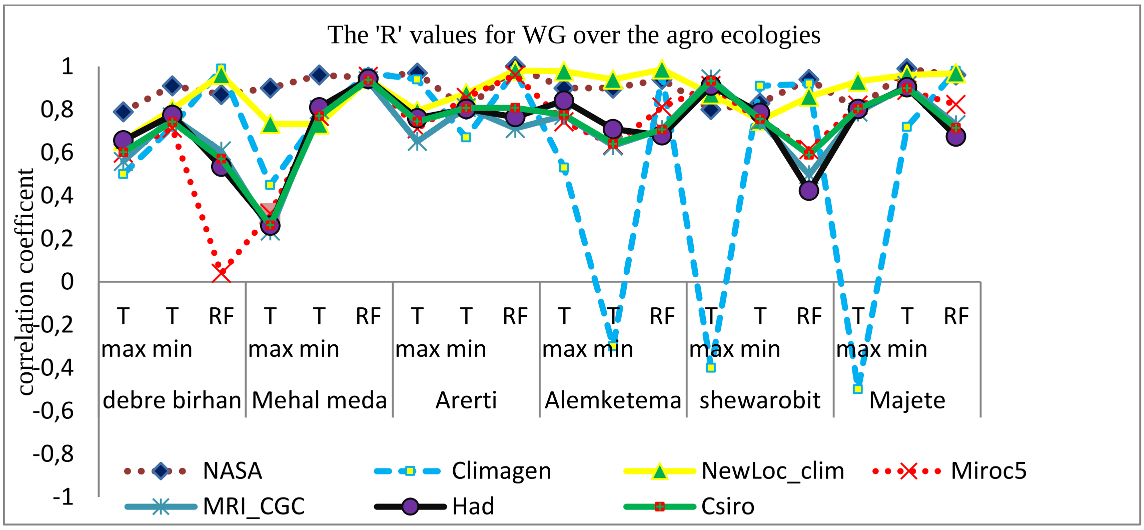


Figure 8. The values correlation coefficient for each weather generator over stations

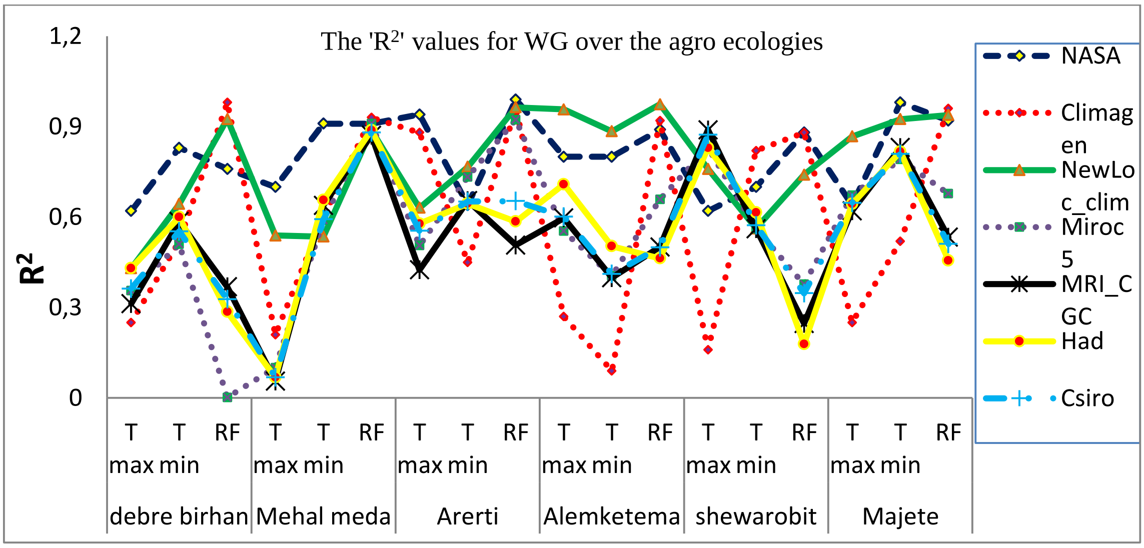


Figure 9. The values coefficient of determinations for each weather generator over stations

The observed and generated rainfall from all-weather generators is in enough agreement for all stations. Unlikely, maximum and minimum temperature have higher index of agreement at high lands and mid lands in NewLocClim, and followed by NASA. However, for low lands the index of agreement for NASA is higher than NewLocClim. Climagen performs poor agreement to the observed maximum and minimum temperature at all stations (Figure 20). According to (Bal *et al.*, 2008), there was good agreement between observed and generated weather data for monthly period parameters in majority of the weather parameters for study areas. In general, there was enough agreement for rainfall and temperature for NewlocClim and NASA.

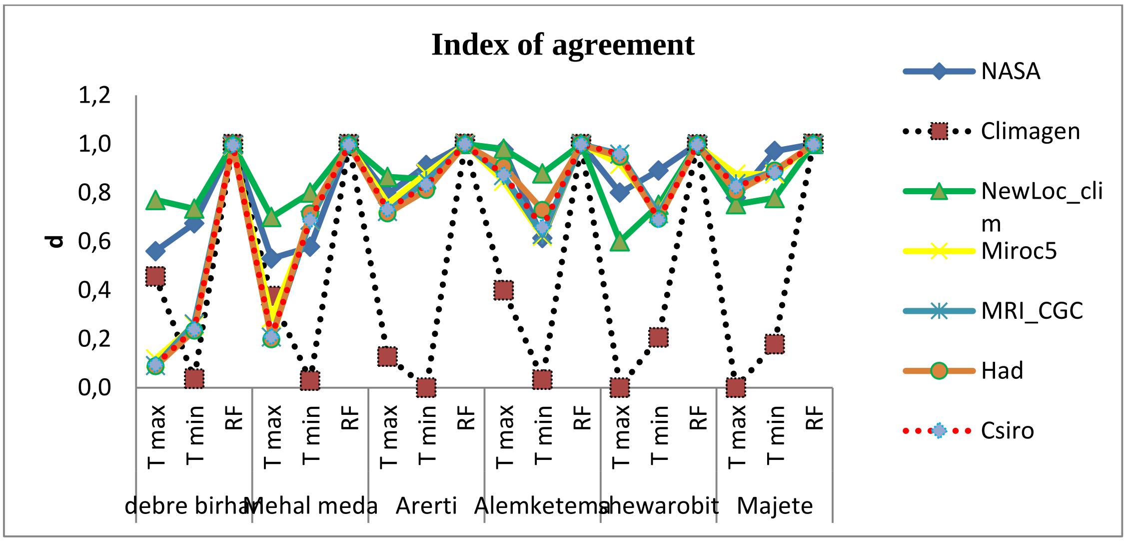


Figure 20. The willmot index of agreement values for each weather generator over stations

4. Conclusion and recommendation

The Mann–Kendall trend test shows a decreasing trend of monthly rainfall in the three agro ecologies in some of stations and no trends in some of stations except Alem ketema. This might be due to large variation of rainfall in the area over years. The rainfall event was not having a significant trend. There was variability in maximum temperature, having significant increasing trends in the three agro ecologies, while the variability in minimum temperature at highland areas, but at mid and low lands variation in minimum temperature and have not significant increasing trends in the three agro ecologies. Both NASA and NewLocClim well performed with respect to representing the statistical characteristics of observed precipitation and minimum and maximum temperatures. Since agriculture is directly related to climatic variability; this actual observed increasing temperature and rainfall variability, well-validated weather generators are needed. This works provide an input climatic data for crop simulation models, soil erosion models , and water management system models where no actual weather stations are present. Therefore, from this study for rainfall data generation one may use NASA and NewLocClim for reproducing maximum and minimum reproducing over location. Furthermore, to get precise results others similar studies should be conducted with a greater number of metrological stations and others more weather generators tools.

Acknowledgment

The authors would like to acknowledge the ARARI, Debre Birhan Agricultural Research Center for the financial support. Moreover, the authors also acknowledged the National Metrological Agency of Ethiopia for providing the necessary data.

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