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Effects of Droughts on Rain-Fed Agriculture in a Changing Climate: Case Study of Arba Minch Zuriya District, Ethiopia

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Abstract: *This study assesses effects of drought on agriculture in a changing climate using maize and cotton. Two Atmosphere-Ocean General Circulation model (AOGCM) outputs were downscaled using statistical downscaling model (SDSM). It revealed that average annual rainfall will increase by 1.6% and 2.6% for HadCM3 B2a and A2a scenarios respectively while maximum temperature will increase by* 0.4^0c *for A2a and* 0.9^0c *for B2a and minimum temperature will increase by* 1.8^0c *for B2a and 1.9* ^0c *for A2a scenarios. Drought years were identified using standardized methods and droughts will become more frequent and severe for A2a than B2a scenarios relative to baseline (1981-2010). Upper limits of yield losses for Maize is 100 % for all scenarios while for cotton 100, 83 and 8% for baseline, B2a and A2a scenarios respectively. To mitigate and adapt these adverse impacts community cooperation in tackling emissions should be strengthened and important to have new crop varieties and technologies.*

Key words: *Drought, Arba Minch Zuriya, scenarios, HadCM3 A2a, HadCM3 B2a.*

1. Introduction

Climate is constantly changing, and the signals indicating the changes can be evaluated over a range of temporal and spatial scales. Climate change as a term in common usage over much of the world is now taken to mean anthropogenically driven change in climate [23].

[14] indicated that rising temperatures, droughts, floods, desertification and weather extremes will severely affect agriculture, especially in the developing world for three reasons: (i) climate change will have its most negative effects in tropical and subtropical regions; (ii) most of the predicted population growth till 2030 will occur in the developing world; and (iii) more than half of the overall work force in the developing world is involved in agriculture.

Agricultural crop production might be negatively affected under the scenarios of future climate Change. Many studies have indicated that elevated atmospheric CO_2 will tend to increase crop growth rates and harvest yields globally. However, the increases in temperature and changes in precipitation associated with global warming may either increase or decrease crop production in the future, depending on local conditions [16]. The impacts of climate change on agriculture are expected to be widespread across the globe, although studies suggest that African agriculture is likely to be most affected due to heavy reliance on low-input rain-fed agriculture and due to its low adaptive capacity [14].

The definition of drought has continually been a stumbling block for drought monitoring and analysis. It can be characterized as a deviation from normal conditions in the physical system (climate and hydrology), which is reflected in variables such as precipitation, soil water, groundwater and stream flow [8]. Different literatures proposed different definitions for drought. However, all points of view seem to agree that drought is a condition of insufficient moisture caused by a deficit in precipitation over some time period. Difficulties are primarily related to the time period over which deficits accumulate and to the connection of the deficit in precipitation to deficits in usable water sources and the impacts that ensue[9].

The definition of drought proposed for this study is based on standardized precipitation. Standardized precipitation is simply the difference of precipitation from the mean for a specified time period divided by the standard deviation where the mean and standard deviation are determined from past records. The basic approach is to use standardized precipitation for a set of time scales which together represent water sources of several types. [9].

Droughts are commonly classified under meteorological, agricultural, hydrological and socioeconomic factors. Meteorological drought is usually defined by a precipitation deficiency threshold over a predetermined period of time.

Agricultural drought is defined more commonly by the availability of soil moisture to support crop and forage growth than by the departure of normal precipitation over some specified period of time. Hydrological drought is defined as the departure of surface and subsurface water supplies from some average condition at various points of time. Socio-economic drought reflects the relationship between the supply and demand for some commodity or economic good [22].

According to [12] a year is said to be drought year when the monthly rainfall is less than that of minimum rainfall amount expected at 80% probability level for two or more months along the monthly rainfall less than potential evapotranspiration (PET) for all months starting from March to October.

The risk associated with drought for any region is a product of both the region's exposure to the event i.e. probability of occurrence at various severity levels and the vulnerability of society to the event (for example, dependency on rain-fed small holder farming). Drought severity is dependent on the duration, intensity, spatial extent of a specific drought episode and the demands made by human activities and vegetation on a region's water supplies. The characteristics of drought, along with its far reaching impacts make its effects on society, economy, and environment difficult to identify and quantify. This continues to represent a formidable challenge to scientists involved in operational climate assessments [21].

Effective drought monitoring requires the integration of a variety of indices and indicators. Indices commonly used to monitor drought and rainfall conditions include the Standardized Precipitation Index (SPI), deciles, percentile of normal rainfall/precipitation, the Palmer Drought Severity Index, the Surface Water Supply Index, and the Vegetation Condition Index, Water Satisfaction Index (WSI), NDVI, aridity anomaly index (AI), Water Requirement Index etc. [17].

There are strong indications that developing countries will bear the brunt of adverse consequences. This is largely because of high poverty rates, high vulnerability levels, and low adaptation capacities in the developing world. Furthermore, the rural population of developing countries (like Ethiopia) for whom the agricultural production is the primary source of direct and indirect employment and income will be most affected because of agriculture's direct exposure to climate change [15].

Research on changes of extreme events specific to Africa, through either models or observations, is limited. However, little can be said about changes in climate variability or extreme events especially in Ethiopia. Most climate models simulate drier conditions during the 21st century in eastern Sudan and in Ethiopia and this drying were prevalent during the last decades of the 20th century in these regions [19].

Over the past 50 years, the mean annual temperature rose by 1.3^{0}C or by 0.28^{0}C per decade during 1960-2006 and the strong inter-annual and inter-decadal variability in rainfall makes difficult to detect long term trends in the country [1]. This trend of increasing temperature, variability in precipitation and increasingly frequent drought is predicted to continue in the tropics through the future [2].

The drought probability map of Ethiopia presented by [12] showed that some areas of the Gamo Gofa zone, in which Arba Minch Zuriya district found, is drought prone area with high drought probability. This shows that drought is a common event in the study area, as well in the case of other drought prone areas in the country.

2. Statements of problems

It is widely recognized that climate change associated with increased concentration of greenhouse gases in the atmosphere will have local implications. Ethiopia is highly vulnerable to drought, which is the most important climate related natural hazard affecting the country. The 2000 and 2002-03 El Niño cases resulted starvation of people of 10.5 and 13 million respectively and led to emergency food assistance as reported in Climate Change National Adaptation Programme of Action [11]. Rain-fed agriculture is the main livelihood source for the society in the study area. It is common that droughts are recurrent phenomena and affect the food security and results in asset depreciation. Although droughts result in huge losses of agricultural production, the current adaptation measures for rain-fed agriculture do not consider the characteristics of the droughts in relation to climate change. Future aspects of drought effects on rain-fed agriculture are not well studied based on the projected future climate scenarios following the IPCC specified storylines. Since future climate is expected continually to be changed, drought events are expected that their effects on agricultural production are important to device appropriate adaptation and mitigation measures. Thus it is important to examine the effects of droughts on crop production in a changing climate. The effects of droughts on rain-fed agricultural production are needed to explore based on major selected crops (maize and cotton) in the study area. Maize and Cotton are the crops that largely under production in the study area. Maize is used as source of food and income generation in the study area whereas Cotton is for preparation of cultural clothes as well as income generation. The events and severities are expected to be complicated in the future whenever situations of climate change due to increased concentrations of GHGs are continued.

3. Materials and Methods

3.1. Location of the study area

The study was conducted in Gamo Gofa zone of Southern Nations, Nationalities and Peoples Regional state, Southern Ethiopia, about 250 Km from the Regional capital, Hawassa and about 430 km south of Addis Ababa. The study area is geographically located between 5°42'6" to 6°12'38"N and 37°18'59" to 37°40'34"E and 1290 m above sea level which is at western catchments of Abaya and Chamo lakes basin.

3.2. Climate of the study area

The rainfall characteristic of the study area is bi-modal type (double wet and dry season). The first wet season runs from March to May and the second from July to November. The mean annual minimum temperature of Arba Minch area is 17^oC, and the mean annual maximum temperature is 31^oC. The maximum temperature is above 30^0c between January and April and below 30^0C between May and September. Comparing monthly rainfall and potential evapo-transpiration, on average only in April and May the monthly rainfall is more than the monthly evapo-transpiration, which indicates the area is in shortage of moisture for most of the months in the year.

3.3. Methods of the study

Daily observed precipitation (1981-2010) and maximum and minimum temperature (1987-2010) data was obtained from National Meteorology Agency of Ethiopia (NMA). Future climate was generated using the third version of AOGCM outputs from the Hadley center [5]. Crop yield data were obtained from Central Statistical Agency of Ethiopia and Gamo Gofa zone Agriculture department.

Student's t test was employed to test the trends of historical climate data. SDSM version 5.1 [20] was used to build the future scenario (2026-55) for the present study area. This method requires observed daily rainfall, minimum and maximum temperatures and global scale predictors General circulation model outputs. The model provides daily information of the climate of future scenarios at local (site) level.

The yield losses of selected crops against historical and future scenario climates during drought events of the study area were analyzed using Aquacrop model version 3.1 [18] after calibration and validation for maize and cotton using data obtained from Central Statistical Agency of Ethiopia and Gamo Gofa Zone Agriculture department. To run the Aquacrop model, one of the required inputs is reference crop evapo-transpiration (ET0). Observed data of this input is not readily available for the study area. Therefore, it is calculated by cropwat8.0 using baseline and future climate data sets [4].

The two drought indices, the SPI and Standardized Precipitation and Evapotranspiration Index (SPEI) were implemented for the identification of historical droughts. But for the future drought scenarios, only SPI is employed. This is because of inaccessibility of the SPEI software to calculate its value using the historical and future scenario datasets. However, for the historical period the SPEI values are available on Global SPEI database (1901-2010) for any point location on the earth. Therefore, for the study area the SPEI value of the years 1981-2010 was extracted and compared with that of the SPI values calculated from observed datasets. For the years which were identified as the drought years, the percentage yield losses were simulated using the Aquacrop model.

The outputs of the Aquacrop model which are the percentage yield losses of the identified drought years were used to obtain probability/return period of yield losses in percent due to the occurrences of droughts both in the baseline period and future scenarios. CumFreq software available from [7] was used to fit the distribution of the percentage yield losses for all scenarios.

4. Results

4.1. Trends of historical climate

The trends of historical climate of study area have been assessed using a student's t test. Average temperature has shown increasing trend with 99% confidence level. It is increased by 0.016^oc per decade in 1987-2010. The maximum temperature is increased by 0.31^oc whereas the minimum temperature is decreased by 0.27^oc. On average the temperature of study area has experienced increasing trend in the past 3 decades. The annual rainfall has shown an increasing trend with 90% confidence level. It has shown 53mm increment of annual rainfall per decade between 1981 and 2010.

4.2. Downscaling Future Climate

4.2.1. Calibration of SDSM. Calibration is the processes of building multiple regression equation between the site level predictand and global scale selected predictors. Before developing the regression equation the predictor variables that provide physically sensible meaning in terms of their predicting skill were selected. From the selected predictors, it is observed that different atmospheric variables control different local variables (Table 1and 2).

Table 1) Selected Predictors during calibration for rainfall

No	Variable code	Name of variables
1	ncepp_zhaf.dat	surface divergence
2	ncepp5_uaf.dat	500 hpa zonal velocity
3	ncepp500af.dat	500 hpa geo-potential height
4	ncepp8_zaf.dat	850 hpa vorticity
5	ncepp850af.dat	850 hpa geo-potential height
6	ncepr850af.dat	Relative humidity at 850 hpa
7	nceprhumaf.dat	near surface relative humidity

Table 2) Selected Predictors during calibration for Tmax and Tmin

No	Variable Code	Variable name	MaxT	MinT
1	ncepmlpaf.dat	Mean sea level pressure	X	X
2	ncepp_faf.dat	surface air flow strength	X	
3	ncepp_zaf.dat	surface vorticity		X
4	ncepp5_uaf.dat	500 hpa zonal velocity	X	
5	ncepp8_faf.dat	850 hpa air flow strength	X	
6	ncepp8_uaf.dat	850 hpa zonal velocity		X
7	ncepp850af.dat	Geopotential height at 850 hpa	X	X
8	ncepr850af.dat	Relative humidity at 850 hpa	X	X
9	nceprhumaf.dat	Near surface relative humidity	X	X
10	nceptempaf.dat	Mean temperature at 2m	X	X

As illustrated in the Tables rainfall is more sensitive to surface divergence and near surface relative humidity, pressure fields at 500 and 850hpa geo-potential heights, relative humidity at 850 hpa. Mean sea level pressure, surface air flow, zonal velocity at 500 hpa, air flow strength at 850 hpa, pressure fields at 850 hpa geo-potential height, relative humidity at 850 hpa, near surface relative humidity and mean temperature at 2m are responsible for maximum

temperature. Finally, the selected predictor variables are used to derive parameter files that can be used for downscaling after validation with the independent dataset.

4.2.2. Validation of SDSM. The parameters established during the calibration process that explains the statistical agreement between observed and simulated data were used for model validation. For rainfall the 15 years data (1996-2010) was used to validate the performance of the model. The mean daily rain was taken as the statistical performance evaluation criteria. Figure 1 shows the comparison of observed and modeled rainfall during validation period. The observed and modeled results show agreements with coefficient of determination equal to 78% which is considered satisfactory to downscale from AOGCM outputs. For temperature (Tmax and Tmin), the mean and median values are used to evaluate the performance of the model. The results presented in Figures 2 A and B indicate a reasonable agreement between the simulated and observed values for maximum temperature with coefficient of determination for the mean value 90% and for median 93%. Similarly, Figures 3 A and B indicate the modeled and observed Tmin were agreed with coefficient of variations equal to 94% for the mean and 88% for the median.

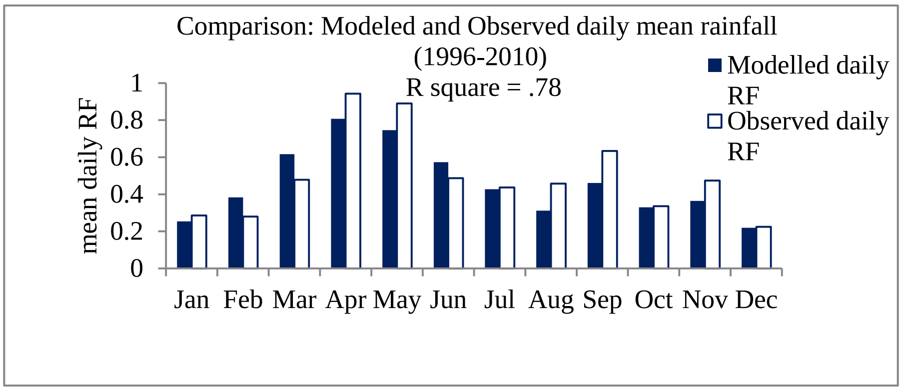


Figure 1) Modeled and Observed daily mean rainfall

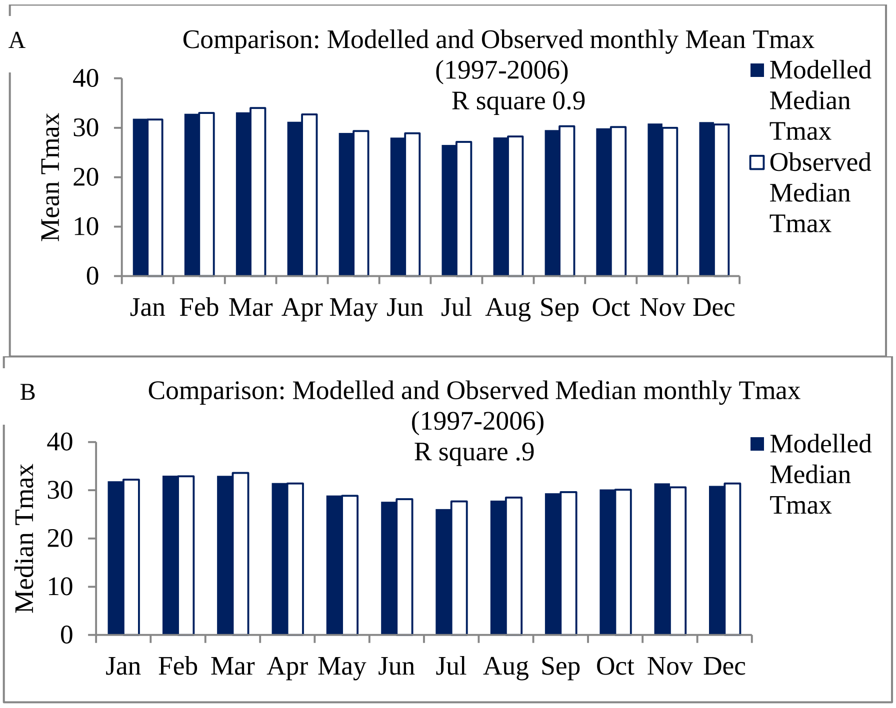
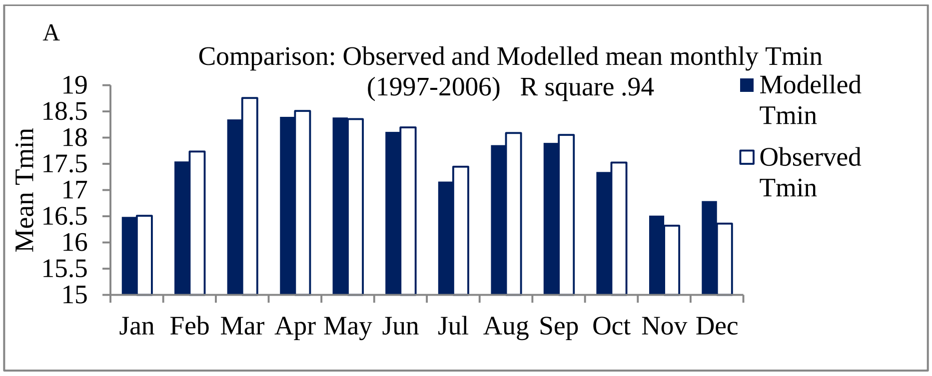


Figure 2) Modeled and Observed A) mean Tmax, B) median Tmax



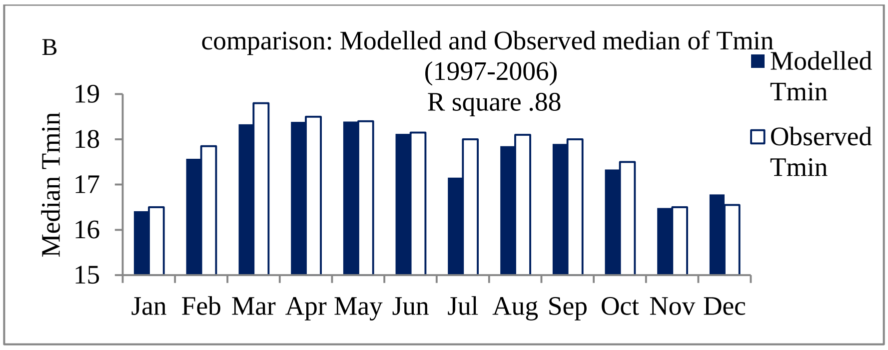


Figure 3) Modeled and Observed A) mean Tmin, B) median Tmin

4.2.3. Generation of Climate Scenarios. A future climate scenario is generated for rainfall, maximum and minimum temperature for the study area. The regression equations established during the calibration process are used to build the scenario data considering two scenario periods, including the base period (1981-2010) and future period (2026-2055). Consequently, the scenario generation operation was implemented to generate future rainfall, maximum and minimum temperature data for the period (2026-2055).

The changes in annual rainfall between observed historical rainfall (1981-2010) and future scenario (2026-2055) have been presented in Table 3. The projected values generally show an increasing trend with respect to the average rainfall of the base period. The results show the average annual rainfall will increase by 1.6% and 2.6% for HADCM3 B2a and A2a scenarios respectively.

The result agrees with that mentioned in [11] of Ethiopia for south central part of Ethiopia, projected 1.4% and 3.1% changes of rainfall in 2030 and 2050 respectively relative to 1960-90.

The projected minimum and maximum changes in rainfall for the two scenarios agreed with that stated by [19] which states in East Africa the MAM and JJA rain will change between -9 % and 20% and -18 and 16% at the end of the 21st century compared with 20th century. The increasing trends of the average rainfall for both scenarios also agreed with that stated by [10].

Similarly, scenario analysis of monthly maximum and minimum temperatures with the model reveal that maximum and minimum temperatures will increase in the next 3-4 decades (Table 4). The maximum temperature will increase by 0.4 for A2a scenario and 0.9^{0}c for B2a scenario while the minimum temperature will increase by 1.8 for B2a scenario and by 1.9^{0}c for A2a scenario.

These results agree well with most of the scenarios constructed for Africa and Ethiopia for the 21st century. Particularly this result coincides with [6], which states that if the recent warming trend continues, most of the Ethiopia will experience more than 1^{0}c increase in air temperature through 2010-2039 compared to the observed data during 1960-2009.

Table 3) changes in observed and generated future scenarios for mean annual rainfall

Model	**Baseline**	**Future scenarios**		
		Min (change)	**Max (change)**	**Average (change)**
hadCM3(A2a)	871.1	779.9(-10%)	975.6 (12%)	893.7(2.6%)
hadCM3(B2a)	871.1	775.7 (11%)	986.6 (13%)	885.4(1.6%)

4.3. Identification of Drought years

SPI and SPEI of 3 months time scale of the six consecutive crop growing months March to August (MAMJJA) of each year was used to differentiate a given crop year is experienced drought or not. Figures 4) A and B show the six months SPI and SPEI graphs respectively for the baseline period. Drought begins when the index value first falls below zero and ends with the positive value. The droughts years of the historical period are identified and presented in Table 5. In this study the drought years are considered as the years which are indicated as drought years by the two indices. The drought intensity is arbitrarily defined for values of the SPI according to [9]. The results indicate that between 1981 and 2010 the study area experienced two severe droughts in 1999 and 2002, four extreme droughts in 1984, 2000, 2004 and 2009, two moderate droughts in 1995 and 2008 and three mild droughts in 1989, 1991 and 1992 during the major crop growing season. Comparing with previous studies, 67% of the identified drought years are coincident with those mentioned by [3] and [11].

Table 4) changes in observed and Future scenarios for mean Monthly average temperatures

Temp	Observed	hadcm3	
		A2a	B2a
Min T	17.4	19.3(+1.9)	19.2(+1.8)
Max T	30.5	30.9(+0.4)	31.4(+0.9)
Average	24.0	25.1(+1.1)	25.3(+1.3)

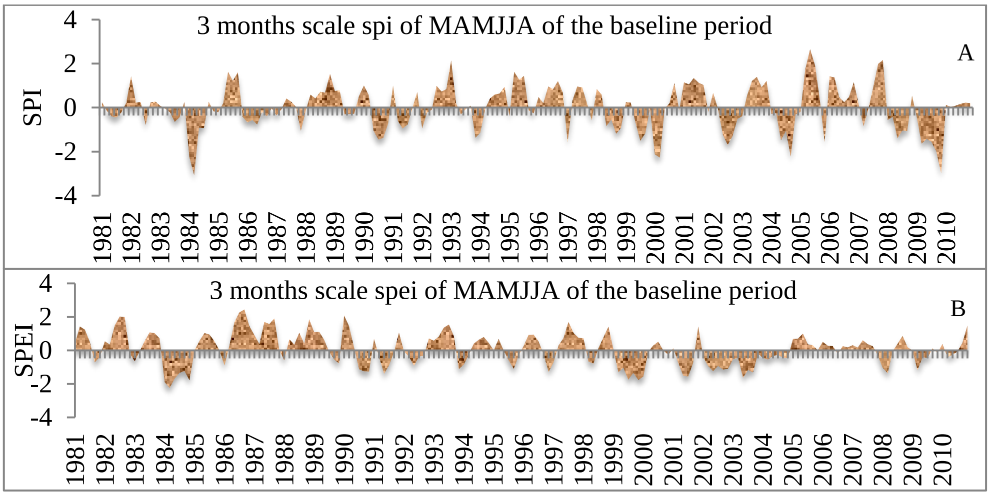


Figure 4) 3 months scale A) SPI, B) SPEI of MAMJJA for baseline period

The drought years of the future climate scenario were identified based on the SPI value of the major crop growing season (MAMJJA). Figure 5) A and B show the time series of the 3 month scale of SPI values of the A2a and B2a scenarios respectively. The drought intensity is defined for values of the SPI according to Mckee et al. (1993) and presented in Table 6. The results indicate that between 2026 and 2055 the study area will experience more severe and frequent droughts for HadCM3A2a scenario than for HadCM3B2a scenario.

Table 5) Historical drought years identified by SPI, SPEI and by both indices

SPI		SPEI		SPI and SPEI	
1984	2000	1984	2002	1984	2008
1986	2002	1989	2003	1989	2009
1987	2004	1990	2004	1991	
1989	2007	1991	2008	1992	
1991	2008	1992	2009	1995	
1992	2009	1995	2010	1999	
1994		1999		2000	
1995		2000		2002	
1999		2001		2004	

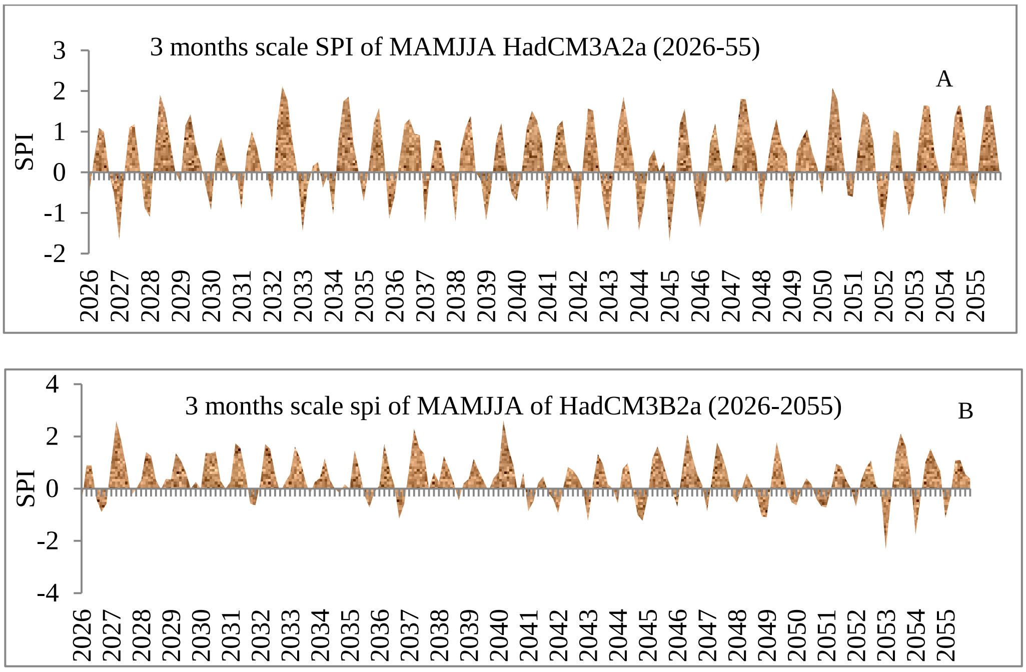


Figure 5) 3 month scale SPI of A) HadCM3A2a B) HadCM3B2a of MAMJJA

Table 6) Drought periods and classification of future climate scenarios

HadCM3A2a	**Drought class**	**year**	**Drought class**
2027	Severe	2042	Severe
2028	Moderate	2043	Severe
2033	Severe	2044	Severe
2034	Moderate	2045	Extreme
2035	Moderate	2046	Severe
2037	Moderate	2048	Mild
2038	Moderate	2052	Severe
2039	Moderate	2054	Moderate
HadCM3B2a	**Drought class**	**year**	**Drought class**
2026	Moderate	2047	Mild
2036	Moderate	2048	Mild
2041	Mild	2049	Moderate
2042	Mild	2053	Extreme
2043	Moderate	2054	Severe
2044	Moderate	2055	Moderate

4.4. Biomass Yield loss of Maize and Cotton

The calibration and validation process of Aquacrop model version 3.1 was conducted for the selected crops as to [13]. The coefficient of determination (r^2) between the simulated and observed values is 0.92 and 0.95 for 95% confidence level for Maize and Cotton respectively.

For each drought years percentage biomass yield losses of Maize and Cotton were simulated for the study area. The output of Aquacrop model simulation is the total biomass production (ton/ha) and its percentage relative to the potential yield. The percentage biomass yield losses were obtained by subtracting the simulated percentage from 100. Table 7 shows the percentage yield loss of the historical drought periods while Table 8 shows the yield loss of the future scenario periods of the two selected crops. The results indicate that the lower limits of yield losses for maize are 9, 21 and 26 percents for baseline, B2a and A2a scenarios; for cotton 16, 28 and 41 percents for the baseline, B2a and A2a scenarios respectively. The Upper limits of yield losses for maize is 100 percent for all scenarios while for cotton 100, 83 and 89 percent for baseline, B2a and A2a scenarios respectively. Based on the absolute range of the percentage yield losses A2a scenario is expected to be the worst scenario but distribution of yield losses within the ranges should be considered to reach at rational conclusion.

Table 7) Historical Biomass % yield loss as simulated by Aqua crop 3.1

Year	Maize	Cotton	Year	Maize	Cotton
1984	27	100	2000	9	43
1989	100	27	2002	58	80
1991	31	48	2004	39	55
1992	10	19	2008	40	64
1995	80	16	2009	100	79
1999	37	60			

Table 8) Future Biomass % yield loss as simulated by Aqua crop 3.1

HadCM3A2			HadCM3B2a		
year	Maize	Cotton	Year	Maize	Cotton
2027	32	57	2026	38	74
2028	69	87	2036	21	35
2033	63	77	2041	21	30
2034	34	85	2042	22	33
2035	64	85	2043	35	63
2037	69	85	2044	50	83
2038	71	85	2047	22	28
2039	33	56	2048	29	42
2042	68	86	2049	31	54
2043	59	80	2053	23	28
2044	100	79	2054	100	28
2045	73	86	2055	21	32
2046	32	46			
2048	26	41			
2052	31	69			
2054	100	89			

4.5. Return Periods and probabilities of yield losses due to Droughts

As droughts are random events, their occurrences and impacts on physical environment like agriculture yield loss can be characterized by the chance of occurrences. In the present study the return periods or probability of occurrence of biomass yield loss of Maize and Cotton due to occurrences of droughts were calculated using CumFreq program. The results of return period analysis are discussed using 3 and 5 years return periods for the two crops of all the scenarios. For 3 years return period, Maize yield losses are between 40 and 58, 69 and 71, 29 and 31 percents while Cotton yield losses are 64, between 80 and 85, 31 and 35 percents for the baseline, A2a and B2a scenarios respectively. For 5 years return period, Maize yield losses are between 58 and 80, 73 and 100, 38 and 50 percents while Cotton yield losses between 79 and 80, 87 and 89, 54 and 63 percents for

the baseline, A2a and B2a scenarios respectively. Therefore, it is concluded that for a given return period yield losses will be higher for A2a scenario

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than B2a compared with the baseline period for both crops.

The probabilities of percentage yield losses due to occurrences of droughts were calculated for the two crops of the baseline and future scenarios. It was calculated as hundred times the reciprocals of the return periods. The results for Maize were presented in Table 9 for both crops in Figure 6 A and B. The results of occurrence probability analysis were discussed using 40 and 70 percent probabilities based on Figure 6 A and B and Table 9. For 40 percent occurrence probability, Maize yield losses are 40, between 64 and 68, between 23 and 29 percents and Cotton yield losses of 64, between 80 and 85, between 35 and 42 percents for baseline, A2a and B2a respectively. For 70 percent probability, Maize yield losses are 27, between 21 and 22, between 34 and 59 percents and Cotton yield losses of between 48 and 54, between 69 and 77, between 30 and 32 percents for baseline, A2a and B2a scenarios respectively. Generally it is concluded that for a given yield loss the probability of occurrence is high for A2a and lower for B2a scenarios than the baseline for both crops.

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Table 9) Maize yield loss and probability of occurrence

HadCM3A2a		**HadCM3B2a**		**Base-period**	
Y/loss(%)	Prob. (%)	Y/loss (%)	Prob. (%)	Y/loss(%)	Prob. (%)
26	86	21	86	10	90
31	85	21	86	12	88
32	85	21	86	26	72
32	85	22	69	27	70
33	84	22	69	29	66
34	84	23	58	31	62
59	60	29	34	37	48
63	50	31	31	39	43
64	48	35	26	40	40
68	37	38	24	58	20
69	34	50	18	100	10
69	34	100	10	100	10
71	29				
73	26				
100	9				
100	7				

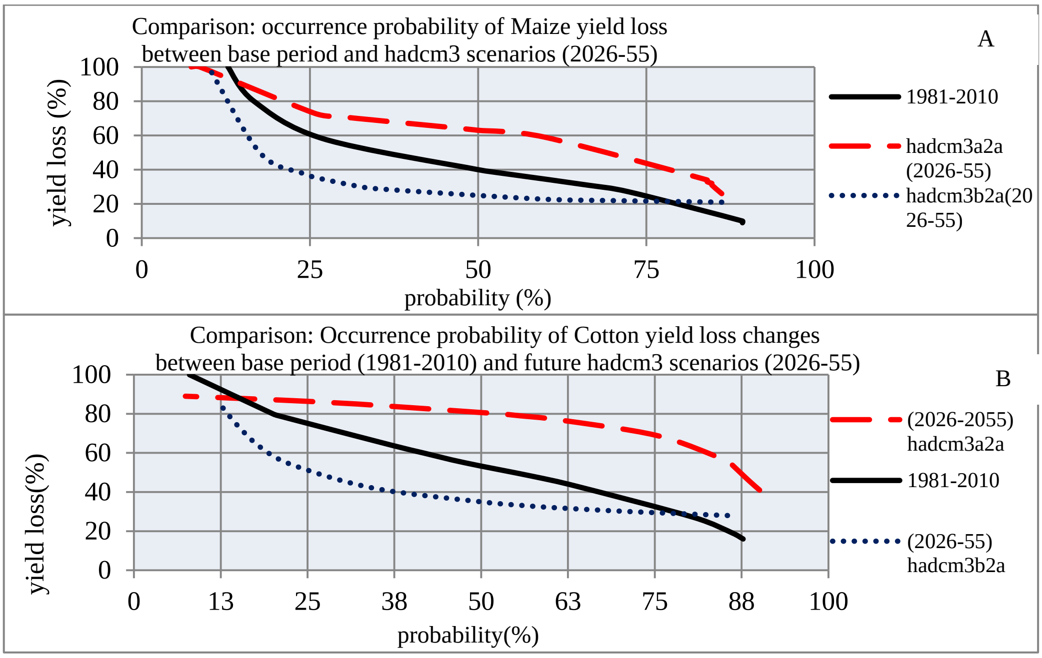

Figure 6) Comparison of probability of percentage yield loss A) Maize, B) Cotton

5. conclusions

- The study pointed out that the increase in GHGs in the atmosphere due to human activities over the globe will change the climate of the study area between 1981-2010 and 2026-2055.
- The study also revealed that average annual rainfall is going to increase by 1.6% and 2.6% for HadCM3 B2a and A2a; the maximum temperature will increase between 0.4^0c and 0.9^0c for A2a and B2a and the minimum temperature will increase by 1.9 ^{0}c and 1.8^0c for A2a and B2a scenarios respectively.
- The study indicated for baseline between 1981 and 2010 the study area experienced two severe droughts in 1999 and 2002, four extreme droughts in 1984, 2000, 2004 and 2009 and two moderate droughts in 1995 and 2008.
- In the future more severe and more frequent droughts are expected to occur for HadCM3A2a than for B2a scenario in (2026-2055) compared to the baseline (1981-2010).
- The lower limits of yield losses due to droughts for Maize are 9, 21 and 26 percents for baseline, B2a and A2a scenarios; for Cotton 16, 28 and 41 percents for the baseline, B2a and A2a scenarios respectively.
- The Upper limits of yield losses for Maize is 100 percent for all scenarios while for cotton 100, 83 and 89 percent for baseline, B2a and A2a scenarios respectively.
- Hence climate change has potential adverse effect on the severity and frequency of droughts and on the production of agricultural crops in the study area.

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