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Downscaling Climate Change Scenarios for Miesso Meteorological Station, Eastern Ethiopia

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Abstract

The knowledge of future climate information at local level has enormous advantage in Ethiopia, where the driver of the economy is agriculture. This study was conducted to downscale the climate change scenarios for Miesso station for the year 2011-2099. Daily climate data and normalized large scale Hadley Centre coupled Model version 3 (HadCM3) model predictors were used for downscaling climate change scenarios. The change for rainfall, minimum and maximum temperatures were developed using the HadCM3 A2a and B2a Emission Scenarios by Statistical Downscaling Model (SDSM) version 4.1software. The SDSM analysis showed an increasing trend for both annual precipitation and temperatures. Accordingly, the average monthly and annual minimum and maximum temperatures were found to rise in 2020, 2050 and 2080s for A2a and B2a emission scenarios. Nevertheless in 2080s, the average annual maximum temperature increment would be high for both A2a and B2a scenarios. Therefore the use of seasonal climate outlook information and introduction of new crops, varieties and management practices that goes in line with the changing climate patterns is suggested for the study area.

Keywords: Climate change, Downscaling, Miesso

Introduction

The issue of climate variability and climate change has become more threatening not only to food security and sustainable development of any nation, but also to the totality of human existence. Overall, human induced change in climate pattern is believed to pose the most damaging impacts on food security and sustainable growth of most developing nations. Accordingly, the projected higher temperature and variable precipitation levels will unequivocally depress crop yields through direct effects as well as indirect impact by triggering insect pests, diseases and weeds (Gadgil *et al*., 1998).

About 66% of the total areas of Ethiopia fall within the arid and semi arid climatic zone (MoA, 1998). Nevertheless, agriculture, which is highly sensitive to climate change, is the driver of the country's economy as it accounts for half of GDP and 80% of employment (MoARD, 2007). Thus, the dependence of Ethiopia on agriculture makes its economy extremely vulnerable to the risks associated with climate change. No doubt climate change is and will form a serious concern for both researchers and development planners in Ethiopia.

Apart from the detailed analyses and quantification of past observational climate data, downscaled climate information from General Circulation Model (GCM) predictors is essential for ex-ante vulnerability assessment and impact mapping against agricultural systems while enhancing the potential to adapt to the changes (CIES, 1997; Wilby *et al*., 2004). Knowledge and management of the future state of climate are critical issues in order to reduce the negative impacts of climate change on agriculture. General Circulation Model outputs could provide computationally inexpensive and site specific future climate information that can reveal future trend and variability over a given region. Augmentation of future climate data from GCM outputs is built based on various assumptions of greenhouse gas concentrations including doubling of carbon dioxide concentration.

The Miesso area, which is located in the eastern escarpment of the Central Rift Valley of Ethiopia, is one of the areas hit by climate change impacts. There is a considerable uncertainty about the potential impacts of climate change on crop production and productivity in this area. The knowledge of predicted meteorological change on crop production and productivity is important so as to develop viable climate change adaptation options in a given area. The main objective of this study was therefore to predict change in rainfall, minimum and maximum temperatures for the year 2011-2099 for Miesso station.

Materials and Methods

Description of the Study Area

Miesso is located in the Eastern escarpment of the Central Rift Valley of Ethiopia that forms the heart and corridor of the Ethiopian Rift Valley. The geographical location of Miesso district is 9° 23′ N latitude and 40° 75′ E longitudes and found at an altitude 1400 meter above sea level (Mamo, 2005). The soil type of the study area is has developed almost entirely from volcanic material and includes both alkaline (basalts) and acidic (rhyolites, ignimbrites, pumices and ash) rock types (Smith, 1982). According to Kidane *et al.* (2006), Miesso has four types of soil: regosols, lithosols, luvisols and cambisols where the dominant type is eutric regosols (eRG). The soil texture is mainly Silty Clay loam with slightly alkaline pH ranging from 7.8 to 8.3 (Worku, 2006; Lemma, 2008).

Climate Parameters and Database Used for the Study

Daily rainfall data, maximum and minimum (1973-2009) temperatures were obtained from the National Meteorological Agency of Ethiopia archives (NMA). Normalized large scale HadCM3 model predictors were obtained from website of the National Center for Environmental Prediction (NCEP) reanalysis data set gridded at 2.5° latitude x 3.75° longitudes (www.cics.uvic.ca/scenarios/index.cgi?scenarios). Before analysis, missing values were patched using Markov chain simulation model of INSTAT v.3.36 (Stern *et al.*, 2006). Quality control check was also done for maximum and minimum daily temperature values by running a macro which undertakes automatic checking (minimum temperature greater than maximum temperature) and graph the data for any of the years that fail the check (Stern *et al.*, 2006).

Developing Climate Change Scenarios

Statistical Downscaling Model (SDSM Version 4.1) was adopted for spatial downscaling of daily rainfall, minimum and maximum temperature from global GCM predictors to the scale of the study area (Wilby and Dawson, 2007). For the purpose of the analysis, data were downloaded from HadCM3 (UK Hadley Centre for Climate Prediction and Research) global model grid box between 10° N and 41.25° E (Figure 1).

In order to identify large scale downscaling predictor variable(s) showing significant correlation at 5% significant level, screening of potential downscaling predictor variables were done for observed Miesso station time series (1973-2000) of rainfall and minimum and maximum temperatures. To develop multiple a linear regression relationship between the predictor variables selected and the local station data, the SDSM was calibrated using twenty years (1973-1992) observed station climate data and daily observed (standardized) gridded data (1961-2000). The model was validated using the remaining station data from 1993 to 2000 in order to make series of amendments before further analysis was carried out on the data.

The Hadley Centre Coupled Model version 3 (HadCM3) A2a and B2a were the two daily GCM-derived predictor variables used for scenario generation. The A2a and B2a are story-line scenarios developed by IPCC Special Report on Emission Scenarios (SRES). The A2a scenario describes a highly heterogeneous future world with regionally oriented economies (high rate of population growth, increased energy use, land-use changes and slow technological change). Likewise, B2a is regionally oriented but with a general evolution towards environmental protection and social equity (lower rate of population growth, a smaller increase in GDP but more diverse technological changes and slower land-use changes).

The Hadley Centre Coupled Model (HadCM3) scenario generation operation produces ensembles of daily weather series under future forcing (H3A2a 1961-2099 and H3B2a 1961-2099) with two (A2 and B2) emission scenarios relative to the 1961-1990 normal (base period). As a final product of downscaling twenty ensembles of daily climate data was generated for this study. The downscaled future daily ensembles of climate data were then used to examine monthly patterns and general trend of annual rainfall, average annual minimum and maximum temperatures of the study area for current (base period) and future (2011-2099) periods by averaging the twenty independent ensemble data. Moreover, climate change scenarios were projected for the periods 2020(2011-2040), 2050(2041-2070) and 2080 (2071-2099).

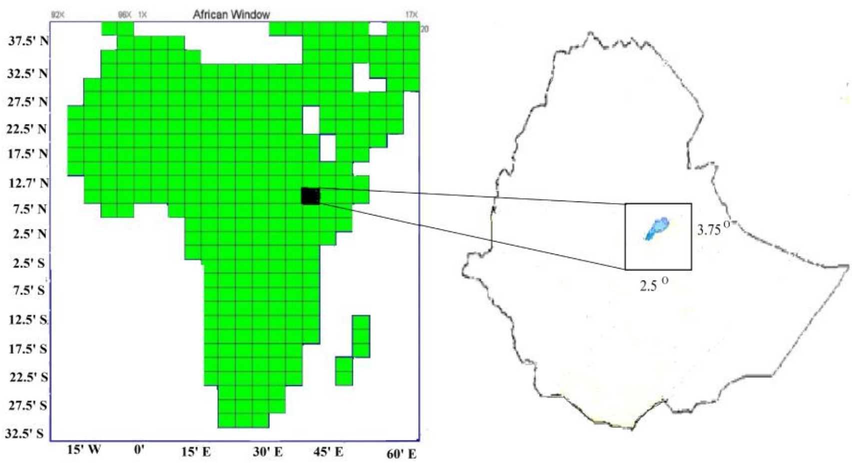


Figure 1. The African Window with 2.5° latitude x 3.75° longitude grid size from which grid box for the study area is selected.

Result and Discussion

Screening predictor variables

The type and notations of large scale Global Circulation Models (GCM) predictor variables which gave better correlation with Miesso station measured daily precipitation, daily minimum and maximum temperature at 5% significant level are shown in Table 1.

Table 1. List of large scale predictors that showed better correlation results at P<0.05

Predictand	Predictor	Notation	Partial r*
Rainfall	Mean sea level pressure	mslpaf	0.093
	Relative humidity at 500 hPa	r500af	0.063
Maximum temperature	Mean sea level pressure	mslpaf	-0.393
	500 hPa geopotential height	p500af	0.189
	Relative humidity at 850 hPa	r850af	-0.106
Minimum temperature	Mean sea level pressure	mslpaf	-0.300
	Surface airflow strength	p_faf	0.158
	850 hPa geopotential height	p850af	0.237
	Near surface relative humidity	rhumaf	0.149

*The partial correlation coefficient (r) shows the explanatory power that is specific to each predictor significant at 5% significant level.

The partial correlation coefficients indicated that on average mean sea level pressure has strong correlation with local precipitation and strongest correlation with maximum temperature. On the other hand, mean sea level pressure followed by geopotential height at 850 hPa is strongly correlated with minimum temperature (Table 1).

Calibration and validation of the SD model

The partial correlation coefficient obtained during calibration and validation of the Statistical downscaling (SD) with daily rainfall data showed poor agreement between predictors and observed rainfall (Table 2). However, this results collaborates the findings of Wilby and Dawson (2007) who had reported that rainfall is a conditional process as it is dependent on an intermediate process between regional forcing and local weather (e.g., on wet or/and dry day occurrence, humidity, cloud cover and atmospheric pressure). Therefore, the statistics obtained during calibration and validation of SD model using conditional process like rainfall may not show significant correlation with its corresponding predictor variables (Wilby and Dawson, 2007).

Table 2. Calibration and validation statistics of monthly precipitation at Miesso

Model statistics	R^2		Standard error	
	Unconditional	Conditional	Unconditional	Conditional
Calibration	0.011	0.121	0.231	11.73
Validation	0.054	0.170	0.386	9.638

Likewise, calibration of daily minimum and maximum temperatures was carried out on annual model basis. The minimum and maximum temperature simulations showed better agreement with large scale General Circulation Model (GCM) predictor variables with partial r values of 0.433 and 0.687, respectively (Table 3). Moreover, the correlation statistics obtained during calibration steps were fully maintained during the validation period (Table 3).

Table 3. Calibration and validation statistics of annual maximum and minimum temperature

Predictand	Calibration		Validation	
	R^2	Standard error	R^2	Standard error
Maximum temperature*	0.433	2.585	0.658	1.588
Minimum temperature *	0.685	2.313	0.791	1.663

* = Unconditional.

Given better multiple regression relationship between observed Miesso daily climate data and large scale predictor variables, the Statistical downscaling model (SDSM) has been used for generating Miesso station climate scenario for the period from 2011-2099.

Base line scenarios

Precipitation

The SDSM is able to simulate the rainfall except the extreme events (Figure 2), since the model overestimates the extreme values and keeps more or less the average values of rainfall. The lack of replicating the extreme values was also observed by Wilby *et al*. (2005) and he described it as "the model is less skilful at replicating the frequency of events". The total precipitation values are found to be overestimated both seasonally and annually (Figure 3). The model was able to simulate only *bega* (October-November-December-January-February) and *belg* (March-April-May) season rainfall with slight accuracy. Therefore, the GCM outputs did not show good agreement with the observed rainfall data of Miesso.

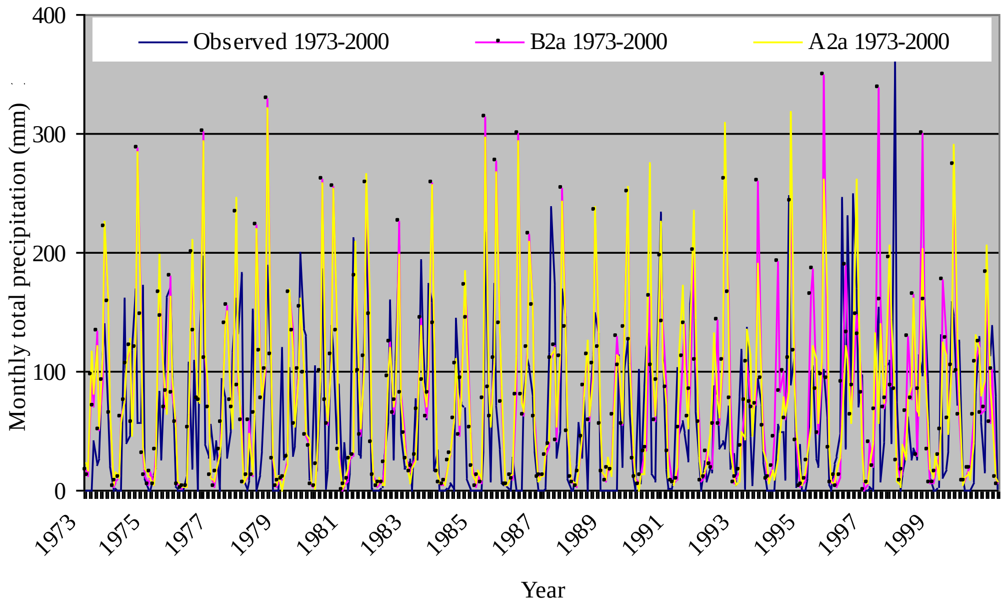
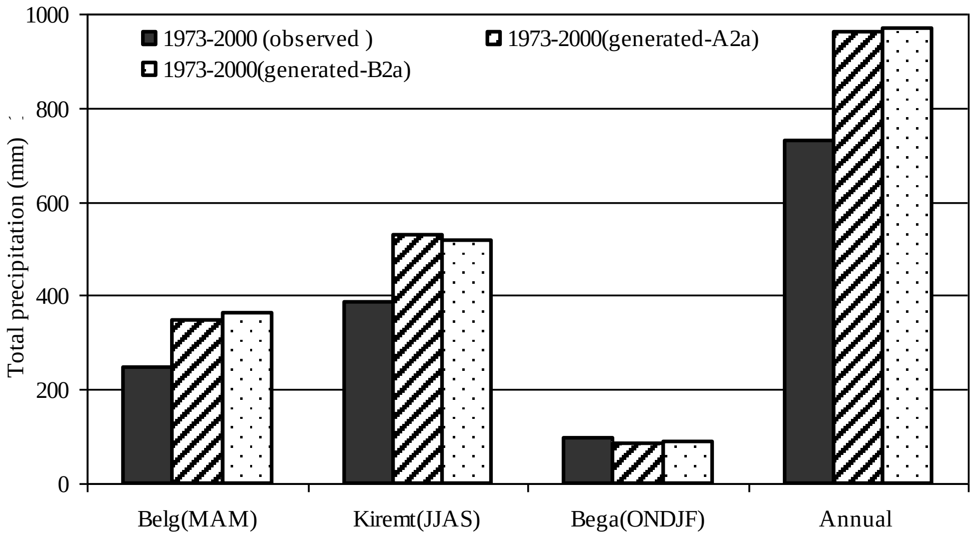


Figure 2. Observed and simulated pattern of monthly rainfall at Miesso for the base period (1973-2000).



MAM=March-April-May; JJAS=June-July-August-September; ONDJF=October-November-December-January-Febrauary.
Figure 3. Observed and simulated average seasonal precipitation of Miesso for the base period (1973-2000).

Minimum and maximum temperature

The downscaled temperature values were averaged to monthly time steps in order to compare with the observed values. The SDSM was able to simulate minimum temperature reasonably well except its poor performance in estimating the extreme high (April, May and June) and low (December) temperature events (Figure 4). Except for months of April, May and June in which values were underestimated, the model showed good agreement with observed minimum temperature data. The SDSM performs reasonably well in estimating mean daily maximum temperature in all months except May and June, in which the model showed slight underestimation (Figure 5). In general, the mean daily temperature patterns showed the same trend as observed data indicating that the Statistical Downscaling Model (SDSM) could provide more skillful prediction of maximum temperature. As all the simulated results indicate that the SDSM could simulate potentially all the patterns of predictands (rainfall, minimum and maximum temperature) except the extreme rainfall events, the SDSM could be used as a tool to predict future climate of the study area.

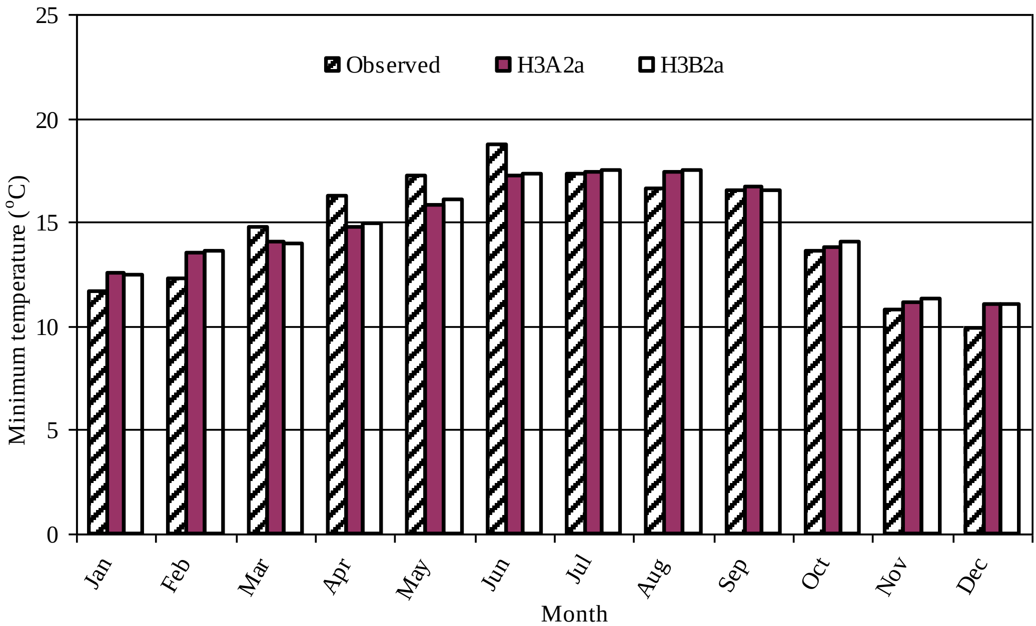


Figure 4. Pattern of observed and simulated mean daily minimum temperature for the base period (1973-2000).

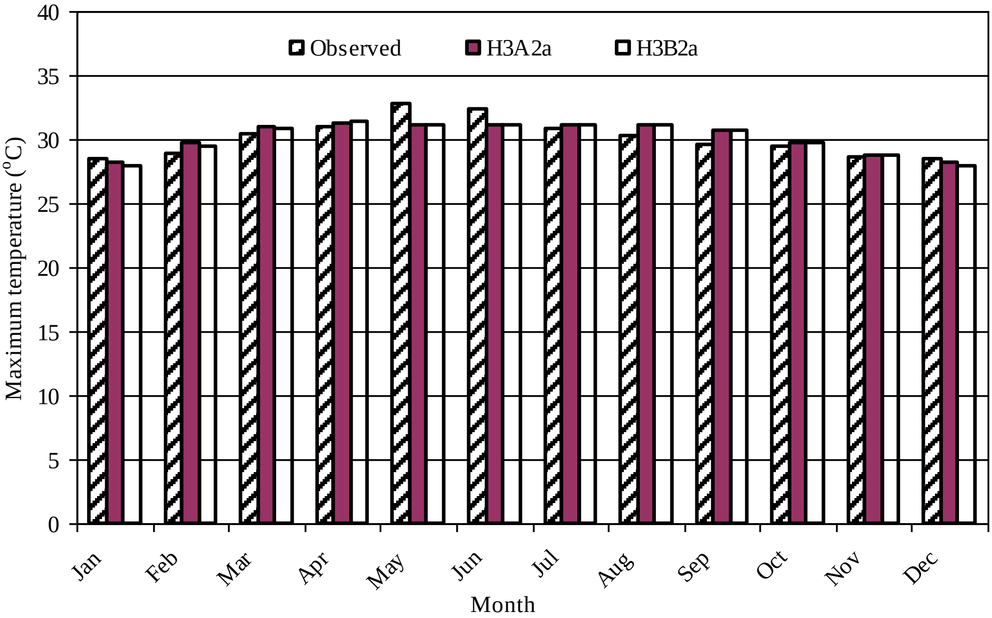


Figure 5. Pattern of observed and simulated mean daily maximum temperature for the base period (1973-2000).

Climate change scenarios projected for the period 2011-2099

Precipitation was projected under two Global model emission scenarios (H3A2a and H3B2a) and trends of future annual total rainfall were done (Figure 6). The Figure showed that annual total precipitation will increase slightly at Miesso under both emission scenarios. In addition, Figure 22 showed future patterns of minimum and maximum temperature at Miesso relative to the base period for A2a and B2a emission scenario. The projected mean annual minimum and maximum temperatures showed a consistent increasing trend from the base period values under both emission scenarios. The projected mean monthly rainfall total at Miesso under A2a and B2a scenarios (Figure 8 a & b), when compared to the base period showed an increasing trend in total rainfall during the months of February and March, while in May the rainfall total indicated a decreasing trend by the 2020s, 2050s and 2080s. In April the rainfall showed a decrease in total amount from the base period but, the amount will experience an increase total amount from 2020s through to 2080s under A2a scenario. In the main rainy (JJAS) season, the rainfall amount will experience a consistent decrease in total amount in June and July. In August and September, the rainfall will increase in total amount by the 2020s, 2050s and 2080s. In the drier months, rainfall amount will increase slightly when compared to the base period in A2a scenario (Figure 8 a).

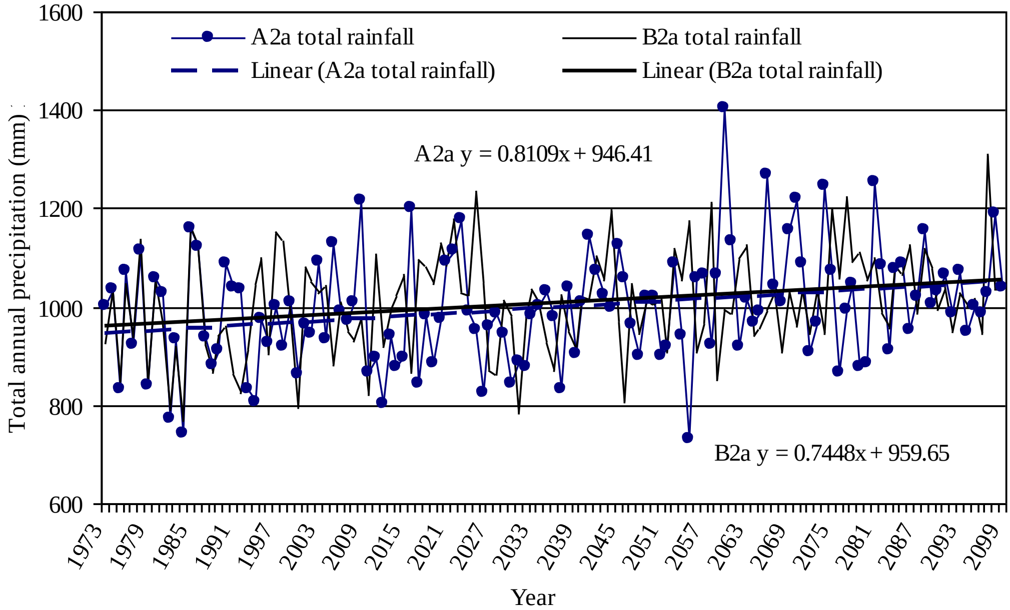


Figure 6. Future pattern of annual precipitation at Miesso station for the past (1973-2010) and future (2011-2099) periods.

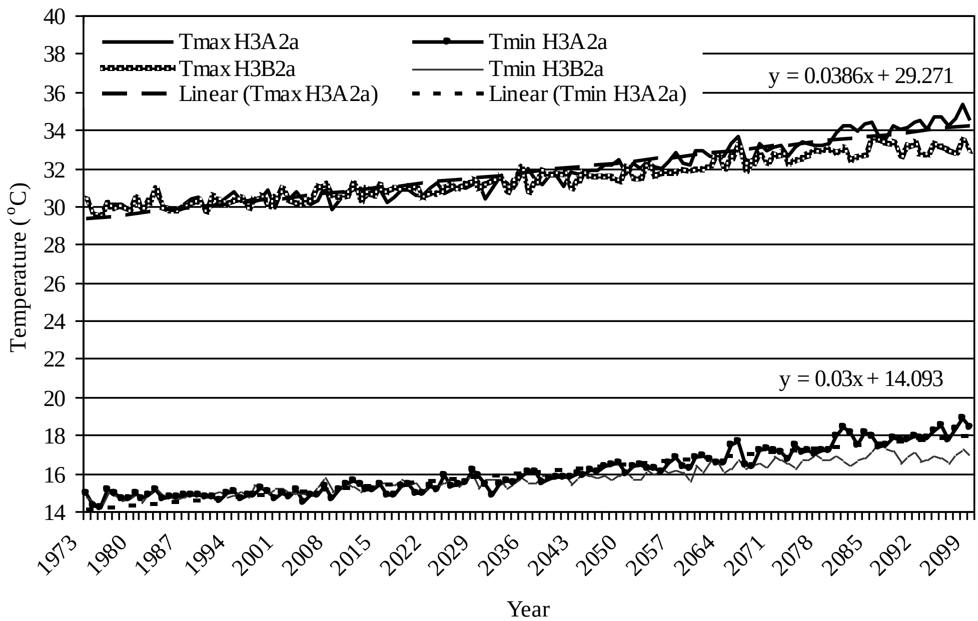


Figure 7. Simulated future pattern of average annual minimum and maximum temperatures at Miesso for the past (1973-2010) and future (2011-2099) periods.

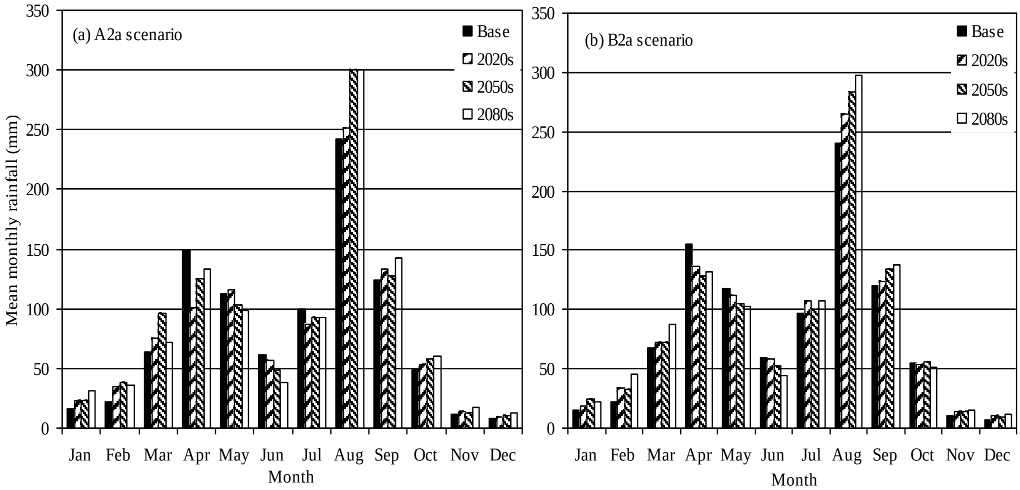


Figure 8. Projected mean monthly precipitation pattern at Miesso compared to the base period under A2a (a) and B2a (b) scenarios.

However, under B2a scenario, for months of February, March, August and September, the rainfall amount will experience an increasing trend whereas, in April, May and June the rainfall amount will experience a decreasing trend in the future (Figure 8b). Similarly, the projected rainfall amount will show decreasing trend in October, and probably a slight increase in amount in the dry months (November-January).

Minimum and maximum temperature

Figure 9 (a & b) shows monthly future changes (absolute values in °C) in minimum temperature from base period values. Though the change in minimum temperature for future periods will vary from month to month, the highest increase in minimum temperature (0.9 ^{o}C in 2020s to 3.3 ^{o}C in 2080s) will occur for months of May, June, September, October and November for the A2a scenario; and an increase of 0.9 ^{o}C in 2020s to 2.5 ^{o}C in 2080s in the months of May, June, July and September for the B2a scenario. The projected mean annual minimum temperature in 2020s will rise up to 0.7 ^{o}C in both emission scenarios. In 2050s, the minimum temperature will increase by 1.6 and 1.3 ^{o}C under A2a and B2a emission scenarios, respectively. In 2080s, minimum temperature will increase by 2.9 ^{o}C and 3.2 ^{o}C for A2a and B2a scenario, respectively.

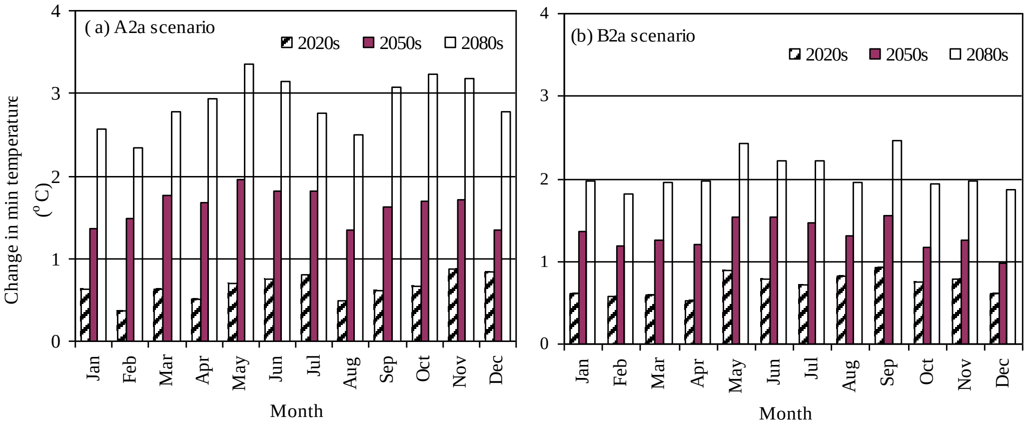


Figure 9. Change in average monthly minimum temperature in the future (2011-2099) from the base (1973- 2000) period under A2a (a) and B2a (b) scenarios.

Regarding maximum temperature, highest monthly temperature increase during the 2020s, 2050s and 2080s will occur during January, May, June, July and September under A2a scenario (Figure 10 a & b). Under B2a scenario, the monthly future change in maximum temperature follows the same increasing trend as of A2a scenario except the lower increasing temperature values. On the other hand, the downscaled maximum temperature in 2020s showed an increase in maximum temperature by 1.1 °C and 1.2 °C for A2a and B2a emission scenarios, respectively. For 2050s the increase will be 3 °C for A2a and 2.4 °C for B2a scenarios, respectively.

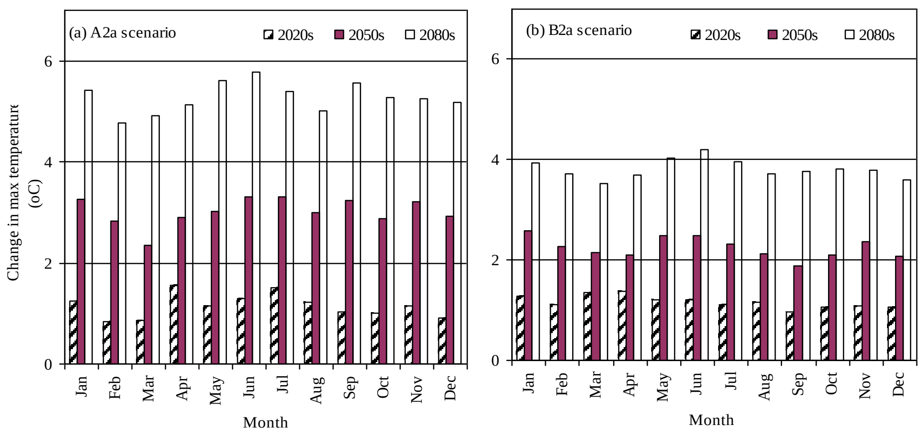


Figure 10. Change in average monthly maximum temperature in the future (2011-2099) from the base (1973-2000) period under A2a (a) and B2a (b) scenarios.

The annual average increment will be high in 2080s, which is 5.3 ^{o}C for A2a and 3.8 ^{o}C for B2a scenarios. In general, the future will experience an increasing trend of maximum temperature at the study area under both A2a and B2a scenarios.

Conclusion and Recommendation

The SDSM projected climate scenarios results showed slightly an increasing trend of annual average rainfall and consistent increasing trend of minimum and maximum temperature. Therefore, crop producers should use seasonal climate outlook information in order to adjust their farming systems. Introduction of new crops, varieties (drought or heat tolerant) with optimum maturity period and crop management practices that go in line with the changing climate patterns should be the priority for research and development planners in order to arrest the impact of future climate change at the study area.

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