ABHINAV
NATIONAL MONTHLY REFEREED JOURNAL OF RESEARCH IN SCIENCE & TECHNOLOGY
www.abhinavjournal.com

STATISTICAL DOWNSCALING OF DAILY TEMPERATURE AND RAINFALL DATA FROM GLOBAL CIRCULATION MODELS: IN SOUTH WOLLO ZONE, NORTH CENTRAL ETHIOPIA

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ABSTRACT

Statistical downscaling models for temperature and precipitation in South Wollo Zone, which is located between 10° 05'N, and 14°05'N latitude and 38°00' and 40°25'E longitude, Ethiopia, have been developed and applied to calculate the changes in historic, current and the future climate changes. Projected changes in precipitation and temperature were analyzed using outputs from GCMs and daily station data (1980-2012) which were collected from 6 observed meteorological stations (predictand) using SDSM version 4.2.9. A historical-modification procedure was used to downscale large scale outputs from GCM models to station climate data. The study then investigated how these changes in temperature and precipitation might translate into changes in livelihoods of people and other biophysical components using impact assessment. The objective of this paper was to see the effect of grid size on model accuracy, to evaluate the statistical downscaling methods in estimating monthly average rainfall and temperature, and to project the future climate situation. Accordingly, the results revealed that both temperatures showed an increasing trend; the increase in mean maximum temperature and mean minimum temperature change were 6.17˚C and 5.65˚C respectively by 2080s from the base period 1980-2012. While, a decreased in percentage change of about 14.2 to 43.3% from the mean annual precipitation was recorded by the year 2080s. Therefore, it can facilitate the decision makers to incorporate climate change scenarios for devising sustainable strategies, including: Water harvesting technologies, supplementary irrigation, using improved seeds, which can tolerate moisture stresses, aforestations and reforestation programs, and soil and water conservation techniques. Moreover, crop diversifications, agricultural extension services access, related strategies, and measures are highly recommended for climate change resiliencies strategies.

Keyword: Climate change, GCMs, Statistical Downscaling, Climate rejections

INTRODUCTION

The need for climate change information at the regional to local scale is one of the central issues within the global change debate. Such information is necessary in order to assess the impacts of climate change on human and natural systems and to develop suitable adaptation and mitigation strategies at the national level. The end user and policymaking communities have long sought reliable regional and local scale projections to provide a solid basis for guiding response options (Filippo,2009). To data, most regional climate change information has been based on the use of Coupled Atmosphere Ocean General Circulation models (AOGCMs) enabled by the World Climate Research Program (WCRP) during the past 30 years. AOGCMs have proved to be the most valuable tools in understanding the processes that determine the response of the climate system to anthropogenic forcings, such as increases in greenhouse gas (GHG) concentrations and changes in land use and atmospheric aerosol loadings. They have also provided valuable information on climate change at the global to sub-continental scale (IPCC, 2007). Although we have seen significant improvements in these models, especially in the past decade, due to better representation of atmospheric and Earth surface processes and enhanced computational capabilities, the horizontal resolution of most present day AOGCMs is still of the order of a few hundred kilometers (*Meehl et al*., 2007). This prevents them from capturing the effects of local forcings (e.g. complex topography and land-surface characteristics) which modulate the climate signal at fine scales.

Coarse resolution also precludes global models from providing an accurate description of extreme events, which are of fundamental importance to users of climate information with respect to the regional and local impacts of climate variability and change. In other words, a fundamental spatial scale gap still exists between the climate information provided by AOGCMs and the input needed for impact assessment work. In order to circumvent this problem, various “regionalization” or “downscaling” techniques have been developed to spatially refine the AOGCM climate information and bridge this spatial scale gap (Giorgi *et al*., 2001). Dynamical downscaling (DD) makes use of physically based models, such as high-resolution and variable-resolution global atmospheric models (AGCMs and VARGCMs, respectively) run in “time-slice” mode (e.g. Cubasch et al., 1995; Deque and Piedelievre, 1995) and limited-area “regional climate models” or RCMs (Giorgi and Mearns, 1999).

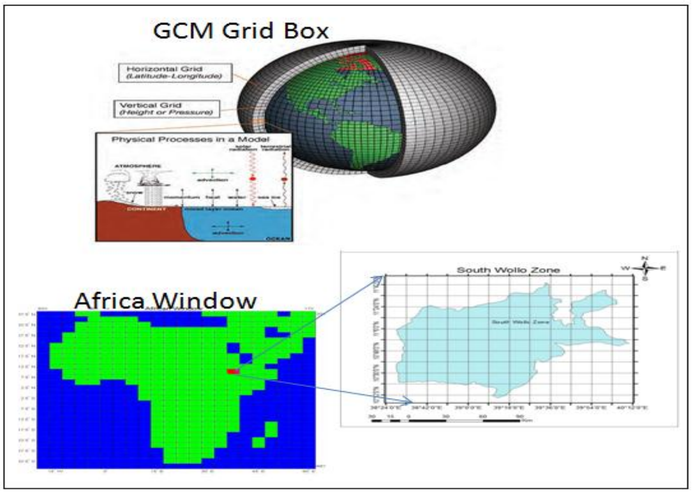
While climate change is already manifesting in Ethiopia through changes in temperature and precipitation, its magnitude is poorly studied at regional levels. Statistical downscaling models for temperature and precipitation in South Wollo Zone, Ethiopia, have been developed and applied to calculate the changes in the future climate changes due to projected changes in the atmospheric composition. The models are based on multiple linear regressions, linking large-scale predictors at monthly time resolution to regional statistics of daily precipitation on a monthly basis. The following objectives have been set for our study. First, to see the effect of grid size on model accuracy, secondly to evaluate the statistical downscaling methods in estimating monthly average rainfall and temperature at weather stations in South Wollo Zone and third,to project the future climate situation of South Wollo Zone for measures to be taken for the concerned bodies.

MATERIALS AND METHODS

South Wollo is one of the ten Zones in the Amhara Regional States of Ethiopia. It acquired its name from the former province of Wollo. The zone covers the three main agro-ecological areas, namely: *dega*, above 2,500m; *weyna dega* between 1,600m and 2,500 m a.s.l ; *kolla*, from 1,300-1,600m within 17 rural districts and two urban districts. Its highest point is Mount Amba Ferit. In most of the areas, rainfall is bimodal, with short *belg* rains from March to April and longer *keremt* rains from July to September. Most of the study area came under *belg*-dependent production. The monthly average maximum temperature is 26.4 ^{0}C whereas the minimum is 12.6 ^{0}C. and the annual rainfall is found to be 1185.1mm. Rainfall is common mainly during summer time, but there is also during spring and autumn seasons.

METHODS

Thirty two years observed rainfall data (1980-2012) was collected from National Meteorological Agency (NMA) of Ethiopia from 6 meteorological stations in South Wollo Zone. Most stations do not have data older than 15 years since established recently. 6 stations were selected based on the availability of historical weather data more than 30 years old . According to the availability of the data, the average representative of the data was calculated as of their establishment data and taken as representative of the region. The GCM data were collected from the IPCC Data Distribution Center (DDC) which however, because the daily fields are only available directly from the respective modeling centers, the climatic data used for SDSM were collected from the Canadian Institute for climate studies website for model output of HadCM3. The predictor variables were supplied on a grid basis of size 2.5° latitude by 3.75° longitude so that the data were downloaded from the nearest grid box to the study area. The nearest grid box for the HadCM3 model is 10°05′N and 14°05′N latitude and 38°00′ and 40°25′E longitude. (Y = 30 Latitude 10°N and X = 10) (Figure 2).



Source: [http://www.cics.uvic.ca/scenarios/sdsm/select.cgi]

Figure 1. GCM Grid box of the study area

DATA ANALYSIS

SDSM provides means of interrogating both downscaled scenarios and observed climate data with the Summary Statistics and Frequency Analysis. In return, SDSM displays a suite of diagnostics including monthly/ seasonal/ annual means, measures of dispersion, serial correlation, and extremes. Graphical analysis was provided by SDSM 4.2.9 through the Frequency Analysis, Compare Results, and the Time Series Analysis. Analyses include Empirical, Gumbel, Stretched Exponential and Generalised Extreme Value distributions were applied. Delta Statistics of the historic and projected climate statistics were calculated as follows for absolute calculations (Temperature calculations),

$$\Delta 2020s = \frac{(V2020s - \text{Vbase}) * 100}{\text{Vbase}}$$

$$\Delta 2050s = \frac{(V2050s - \text{Vbase}) * 100}{\text{Vbase}}$$

$$\Delta 2080s = \frac{(V2080s - \text{Vbase}) * 100}{\text{Vbase}}$$

Whereas for percentage calculations (case of rainfall) :-

$$\Delta 2020s = 2020s - Vbase$$

$$\Delta 2050s = 2050s - Vbase$$

$$\Delta 2080s = 2080s - Vbase$$

*V*base is the mean of all ensembles (or a specific ensemble if selected) for each statistic for the base period. Likewise, V2020s is the mean of all ensembles (or a specific ensemble) for each statistic for period A, and so on for *V*2050s and *V*2080s. Generalized extream weather values were shown by graphics as the three-parameter (ξ, β, k) Generalised Extreme Value (GEV) distribution to the data of the form:

$$F(X) = \exp\left(\left(1 - \mathrm{K}\left(\frac{x-\xi}{\text{Vbase}}\right)^{1/k}\right)\right)$$

The parameters (ξ, β, k) are estimated using the method of l moments in which the first three l moments (l 1, l 2, l 3) are estimated from the data (Kysely, 2002). The parameters are then calculated according to:

$$K = 7.8590z + 2.955z^2$$

$$\beta = \frac{l2K}{(1 - 2^{-k})\Gamma(1 + K)}$$

$$\xi = l1 + \beta\,\frac{\Gamma(1 + K) - 1}{K)}$$

In which

$$\mathrm{Z} = \left[\frac{2}{3 + \frac{l3}{l2}} - \frac{in2}{in3}\right]$$

The results are plotted up to a return period of 100 years Plotted GEV using the data. For values of *k* approaching zero (-0.005<*k*<0.005 in SDSM) the two-parameter Gumbel distribution is applied using the following equations (Kysely, 2002):

$$F(X) = \exp\left(-\exp\left(-\frac{x - \xi}{\beta}\right)\right)$$

Where, $$\beta = \frac{l2}{in2}$$

$$\xi = l1 - \gamma \frac{l2}{in2}$$

Where: γ is the Euler constant (0.577215655)

Gumbel

Fits a Gumbel Type 1 distribution to the data using the annual maximum series after the method of Shaw (1994):

$$F(X) = 1 - e^{-e^{-\frac{(x-\mu)}{\sigma}}}$$

Thus, the annual maximum for a return period of T-years can be calculated from:

$$QT = Q * + K(T) S\sigma$$

$$(K\,T) = -\frac{\sqrt{6}}{\pi}\left(\gamma + \text{in in}\left[\frac{T(X)}{T(X) - 1}\right]\right)$$

In which Q is the mean of the annual maximums, SQ is the standard deviation of these maximums, K(T) is a frequency factor, T(X) is the return period in years, and γ is the Euler constant (0.577215655).

Stretched Exponential

Fits the data to a Stretched Exponential distribution of the form:

$$P(R > \gamma) = \exp\left(1\left(\frac{\gamma}{R0}\right)c\right)$$

It is used to calculate the probability that an event is greater than a threshold, r. R0 is the mean of all events, and c is determined from the data fitting. The data are truncated according to the specified threshold value.

RESULTS AND DISCUSSIONS

Selection of Potential Predictor Variable

The first step in the downscaling procedure using SDSM was to establish the empirical relationships between the predictand variables (minimum temperature, maximum temperature, and precipitation) collected from stations and the predictor variables obtained from the NCEP re-analysis data for the current climate. This was involved in the identification of appropriate predictor variables that have strong correlation with the predictand variable. The next step was the application of these empirical predictor-predictand relationships of the observed climate to downscale ensembles of the same local variables for the future climate. Data supplied by the HadCM3 for the A2 and B2 emission scenarios for the period of 1961–2099 for South Wollo meteorological stations. This is based on the assumption that the predictor-predictand relationships under the current condition remain valid under future climate conditions too. Therefore, according to the above procedure the potential predictors selected for maximum temperature, minimum temperature, and precipitation for the study area were listed in (Table 1).

Table 1. List of selected predictor variables that gave better correlation results at $p < 0.05$

Predictand	Predictorors (NCEP Reanalysis)	Symbol	Parti.cor.
Maximum Temperature	Surface zonal velocity	ncepp_uaf.dat	0.115
	500 hPa airflow strength	ncepp_zaf.dat	0.182
	500 hPa zonal velocity	Ncepp5_uaf.dat	-0.217
	850 hPa zonal velocity	Ncepp8_uaf.dat	0.200
	850 hPa geopotential height	Ncepp850af.dat	0.124
	850 hPa divergence	Ncepp8zhaf.dat	0.115
Minimum Temperature	850 hPa zonal velocity	Ncepp8_uaf.dat	–0.15
	Surface specific humidity	Ncepshumaf.dat	0.31
	Mean temperature at 2 m	Nceptempaf.dat	0.47
	Mean sea level pressure	Ncepmslpaf.dat	0.38
Precipitation	Mean temperature at 2 m	Nceptempaf.dat	0.47
	Mean sea level pressure	Ncepmslpaf.dat	0.38
	Surface specific humidity	Ncepshumaf.dat	0.31
	850 hPa zonal velocity	Ncepp8_uaf.da	0.16

The partial correlation coefficient (r) shows the explanatory power that is specific to each predictor. All are significant at $p \leq 0.05$. 2hpa: is a unit of pressure, 1 hPa = 1 mbar = 100 Pa = 0.1 kPa. Correlation matrix was used to investigate intervariable correlations for specified sub–periods (annual, seasonal or monthly). SDSM also reports partial correlations between the selected predictors and predictand. These statistics help to identify the amount of explanatory power that is unique to each predictor.

Temporal variations in predictor strength

The **Analyses** button in the SDSM interface is used to investigate the percentage of variance explained by specific predictand–predictor pairs. The strength of individual predictors often varies markedly on a month by month basis (Figure 5.2). The most appropriate combination of predictor for a given season and predictand. As stated above, the local knowledge base is also invaluable when determining sensible combinations of predictors.

Table 2 variance explained by specific predictand–predictor pairs

Predictors	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec.
ncepp_uaf.dat	**0.347**	**0.048**	**0.252**	0.066	0.034		0.004	0.021	0.023	0.023	**0.348**	**0.324**
ncepp_zaf.dat	0.310	0.022	0.234	0.187		0.214	0.312	0.016		0.184	0.152	0.006
Ncepp8_uaf.dat	0.030	0.027	0.043	0.302	0.163	0.113	0.221	0.067	0.273	**0.238**	0.023	0.101
Ncepp5_uaf.dat	0.088	0.105	0.233	**0.386**	**0.313**	**0.499**	**0.488**	**0.485**	**0.467**		0.345	0.111
Ncepp850af.dat	0.274	0.108	0.206	0.037		0.345	0.022	0.012	0.085	0.212	0.122	0.212
Ncepp8zhaf.dat	0.030	0.317	0.023		0.234		0.156	0.145		0.123		0.231

The strongest correlation in each month is shown in bold, (Table2) indicating that the relationship between maximum temperature and *p500* and *p__u* are most important. Blanks represent insignificant relationships at the chosen significant level 0.05.

Model Calibration

The Calibrate Model process constructs downscaling models based on multiple regression equations, given daily temperature data of the study area (the predictand) and regional–scale, atmospheric (predictor) variables. SDSM optimizes the model using either dual simplex or ordinary least squares optimization in the advanced settings of SDSM 4.2. The model structure were arranged by monthly, seasonal and annual at different times as sub–models required by unconditional and conditional settings for rainfall and temperature respectively (Table 3).

Table 3. Calibration statistics of daily maximum temperatures

Predictor variable		R square value												
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec.	Mean
ncepp_uaf.dat ncepp_zaf.dat Ncepp8_uaf.dat Ncepp5_uaf.dat Ncepp850af.dat Ncepp8zhaf.dat	R^2	0.85	0.81	0.72	0.64	0.71	0.83	0.83	0.75	0.71	0.58	0.78	0.85	0.76
	SE	2.40	2.33	2.20	2.33	2.42	2.34	2.20	2.43	2.40	2.30	2.23	2.32	2.32
	DW	2.283	2.21	2.05	2.00	2.19	2.12	2.19	2.05	2.04	2.10	2.08	2.12	2.12

Weather Generator

Ensembles of synthetic daily weather series were generated and given observed (or NCEP re–analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series for present climate conditions of the study area (10957 days) (Table 4).

Table 4. SIM file produced by the Weather Generator operation

Predictors variable	Line order and representations	
TMAX.DAT ncepp__uaf.dat ncepp__zaf.dat ncepp5_uaf.dat ncepp8_uaf.dat ncepp850af.dat ncepp8zhaf.dat	Order	Representations
	[1]	the number of predictor variables
	[2]	the number of regression models used (1=annual, 4=seasonal, 12=monthly);
	[3]	the maximum number of days in a year (here a calendar year is used, so there are up to 366 days in leap years);
	[4]	the start date of the data used for model calibration
	[5]	] the number of days simulated
	[6]	whether or not the predictand is a conditional (#TRUE#) or unconditional (#FALSE#) variable
	[7]	the number of ensemble members
	[8]	the variance inflation parameter in advanced setting
	[9]	the transformation code for conditional variables (1=none, 2=fourth root, 3=natural log, 4=inverse normal)

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Table 4. SIM file produced by the Weather Generator operation (Contd….)

Predictors variable	Line order and representations	
	[10]	the bias correction parameter in advanced setting
	[11]	the predictand file name (Tmax)
	[12]	The predictor file (onward the predictor file)

ANALYSIS OF OBSERVED AND DOWNSCALED DATA

Statistical analyses of observed and downscaled weather data were handled in slightly different ways by SDSM but both were performed in the Summary Statistics screen. Common diagnostic tests are available for both observed and synthetic data. These statistics include the variable mean, maximum, minimum, variance, peaks above/below thresholds, percentiles, percent wet–days, and wet–/dry–day spell– lengths, computed on a calendar annual basis. The Frequency Analysis allows to plot various distribution diagnostics for both modeled (ensemble members) and observed data. The frequency analysis at 95% level of confidence, Empirical, Generalized Extreme value (GEV), Gumbel and strtched exponential statistics with the threshold value of 10 were calculated and summarized in the following.

A Quantile-Quantile (Q – Q) plot is used to compare a modelled data set with an observed data file. The procedure worked by sorting each of the data files into order and calculating the percentiles (1 to 99). These are then plotted against one another on a scatter chart with observed data on the y-axis and modeled data on the x-axis with empirical frequency analysis (Figure 8). Accordingly, it shows that there is a strong relationship between the global predictor and local predictands of the study area.

The PDF plot also shows Probability Density Function of the selected data files. The datas are first sorted into order, then into categories. A count is made of the number of data points in each category. The resultant density is plotted on a line chart (Figure 2).

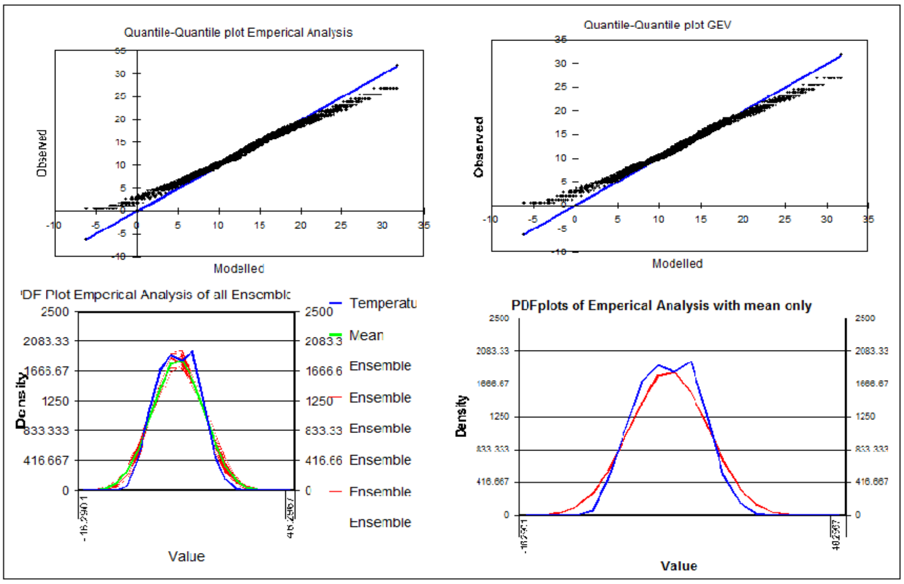

Figure 2. Q-Q and PDF plot of observed and modeled

Line Plot (figure 3) produced is a simple time-series chart of only a maximum ten years of data. In this case, the ensemble mean of the maximum temperature and precipitation downscaled from NCEP re analysis data plotted against the observed temperature and precipitation separately for south wollo for the period 1980-1990.

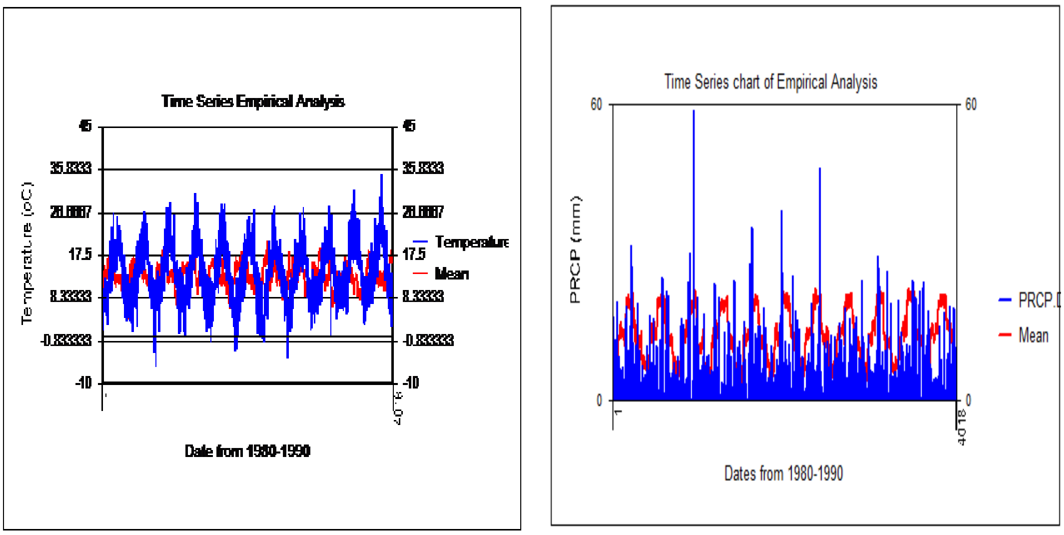

Figure: 3 Time series plots daily Precipitation and Temperature observed data (blue line) and ensemble mean downscaled from NCEP (red line)

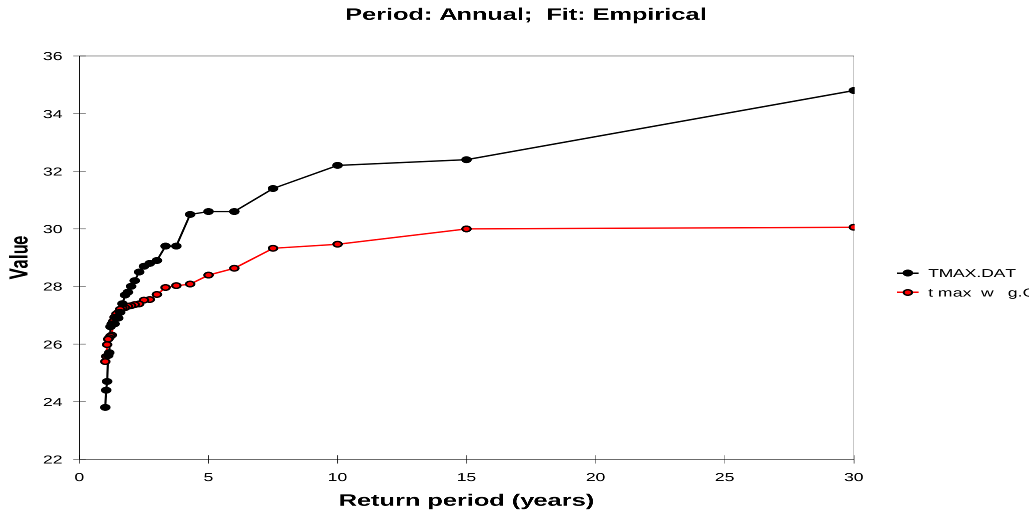

Figure 4. Empirical fit to observed and downscaled maximum daily temperature Projected Climate Changes

Future Climate Projections

To estimate the level of climate change over South Wollo Zone, climate change scenarios were developed using the outputs of HadCM3 coupled atmosphere ocean GCM model; A2 and B2 SRES emission scenarios (Predictors). According to Francis and Hengeveld, (1998) extensive area specific research conducted in various parts of the world, had concluded that, even a slight warming in average surface temperatures increased the likelihood of extreme weather (hail, lightning, tornadoes, heat waves and/or damaging winds). The findings in this paper also showed similar conditions. Both temperatures showed an increasing trend; the increase in mean maximum temperature and mean minimum temperature change were 6.17˚C and 5.65˚C respectively by 2080s from the base period 1980-2012. While, a decreased in percentage change of about 12.2 to 42.3% from the mean annual precipitation was recorded by the year 2080s (Table 5&6). A similar study was done by, Dereje *et al.*, (2012), in their title 'Outlook of future climate in northwestern Ethiopia', in ANRS and confirmed almost a similar results.

Table 5. Summery statistics mean of maximum temperature in south wollo zone

	Statistics			
year	**Mean**	**Std**	**Maximum**	**Minimum**
1980-2012 (Base)	22.46	2.13	30.2	14.72
2020s	24.47	2.58	32.54	16.4
2050s	26.625	2.75	34.67	18.58
2080s	28.63	2.95	36.83	20.43
Change (base to 2080)	6.17		6.63	5.71

Table 6. Summered statistics mean of minimum temperature in south wollo Zone

	Statistics			
year	**Mean**	**Std**	**Maximum**	**Minimum**
1980-2012	9.91	2.14	14.71	5.11
2020s	11.88	2.28	16.39	7.37
2050s	14.02	2.78	18.57	9.47
2080s	15.56	2.96	20.42	10.70
Change (base to 2080)	5.65		5.71	5.6

CONCLUSION AND RECOMMENDATION

Ethiopia is known to be one of the countries most affected by drought. Given a large part of the country is arid or semi-arid and highly prone to drought and desertification, a further increase in temperature and decrease in precipitation could increase the frequency and intensity of droughts in the country. Also, Ethiopia has a fragile highland ecosystem that is currently under stress due to increasing population pressure. Our analysis suggests that the South Wollo Zone, northern highlands of the country could experience increased temperature and reduced rainfalls, and hence become susceptible to more severe drought conditions. Downscaling of temperature and precipitation using SDSM and HadCM3 coupled atmosphere-ocean GCM model (A2 and B2 SRES emission scenarios) the following conclusions

An increase in projected temperatures and a decrease in precipitation resulted in increased number of more projected hot days, fewer number of projected cold days and decreased number of projected days with precipitation; these events may lead to increase occurrences of drought in South Wollo Zone. Therefore, it can facilitate the decision makers to incorporate climate change scenarios for devising sustainable strategies, including: Water harvesting technologies, supplementary irrigation, using improved seeds which can tolerate moisture and temperature stresses, aforestations and reforestation programs and soil and water conservation techniques. Moreover, crop diversifications and agricultural extension services access and related strategies and measures are mandatory. The result of any model depends on the quality of the input data; therefore, to make the evaluation of climate change impact more complete, it is appreciable to use other physically based regional downscaling methods with increased number of meteorological observed stations having reliable historical data and investigation of different adaptation options for the impact of future climate scenarios should be done.

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