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Building Climate Change Scenarios of Temperature and Precipitation at Mount Makulu Using the Statistical Downscaling Model

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***Abstract*— Global Climate Models (GCMs) are tools used for representing future climate conditions, but their coarse spatial resolution cannot be used at local-scale in impact studies. Downscaling techniques are used to adapt the coarse GCM output to the local features of a given region. Therefore, the study objective was to evaluate the adaptability of the Statistical DownScaling Model (SDSM) in downscaling temperature and precipitation using HadCM3 GCM for A2 and B2 SRES scenarios at Mount Makulu (latitude: 15.550^o S, longitude: 28.250^o E, Altitude: 1200 m above sea level). Result showed that SDSM simulated minimum (Tmin) and maximum (Tmax) temperature with reasonable accuracy. However, the results showed that SDSM was not very robust in simulating precipitation. Projected annual Tmin and Tmax change for Mount Makulu would be 0.203^{o}C, 0.563^{o}C, and 1.032^{o}C and 0.177^{o}C, 0.462^{o}C, and 0.910^{o}C in 2020, 2050 and 2080 under A2 SRES scenario, respectively. Under B2 scenario, Tmin and Tmax would increase by 0.192^{o}C, 0.409^{o}C, and 0.708^{o}C and 0.132^{o}C, 0.389^{o}C, and 0.910^{o}C in 2020, 2050 and 2080, respectively. Precipitation would increase under A2 and B2 scenarios by 3.741% (2020s), 15.604% (2050s), and 28.257% (2080s) and 5.837% (2020s), 10.205% (2050s) and 19.312% (2080s), respectively. Furthermore, the number of days with precipitation and the amounts (mm/year) would increase during 2020s, 2050s and 2080s. A2 scenario predicted the greatest changes in Tmax, Tmin and precipitation by the end of the century. Changes in Tmax, and Tmin and precipitation would affect crop growth rates, photosynthesis, evapotranspiration, as well as soil water and nutrient availability.*

***Keywords*— climate scenarios, GCM, HadCM3, SDSM, Statistical downscaling*

INTRODUCTION

Global climate models (GCMs) provide information at a coarse resolution and cannot be used directly in modeling impact studies [1]. Downscaling techniques are therefore; used to obtain high-resolution climate or climate change information from relatively coarse-resolution GCMs. GCMs indicate that rising concentrations of greenhouse gases (GHGs) will have significant implications for climate at global, regional and local scales. Less certain is the extent to which meteorological processes at individual sites will be affected, yet these potential changes at smaller scales are exactly what engineers, researcher, modelers, consultants and land managers are most concerned about [2]. There are two broad approaches to downscaling available: dynamical and statistical [3], [4]. Dynamical downscaling technique uses high-resolution model called regional climate models (RCMs) driven by boundary conditions from a GCM and are far more computationally demanding [2], [5] than statistical downscaling. Statistical downscaling (SD) also called empirical downscaling (ED) methods are much more popular than dynamical downscaling techniques for deriving future climate scenarios [5].

Statistical downscaling (Transfer functions/Regression based approaches; Synoptic weather typing/Weather classification; and Stochastic weather generators) involves the establishment of empirical relationships between historical and/or current large-scale (predictors) atmospheric and local (predictands) climate variables [6]–[9].The assumption is that the relationships developed under the present climate conditions are also valid for future climate conditions [10]. Once a relationship has been determined and validated, future atmospheric variables that GCMs project are used to predict future local climate variables [5], [11], [12]. Statistical downscaling models are used to downscale monthly to seasonal climate forecasts, from numerical climate models to time series datasets for use as inputs in crop simulation or impact models.

One explanation for limited penetration in adaptation planning is that many downscaling models are restricted in their use to specialists and/or research institutions [2] and development of adaptation measures relies on data from climate impact models [13]. Researchers such as [14] and [2]reported that the Statistical DownScaling Model (SDSM) has been applied in different countries in independent assessments to test its capabilities. Extensive research in the field of climate change at the global scale has used the SDSM model for downscaling process. Additionally, at regional scale studies focusing on the effects of climate change on climatic variables and temperature extreme have been conducted in East and South-East Asia [15]. These studies have shown that SDSM yields reliable estimates of extreme temperatures, seasonal precipitation totals, areal and inter-site precipitation behaviour. Frequency estimation of extreme precipitation amounts in dry seasons is less reliable. A meta-analysis of SDSM outputs shows a preponderance of research in Canada, China and the UK, whereas the United States and Australasia including Zambia are under-represented. The SDSM is a freely available downscaling tool that produces high resolution climate change scenarios at sites for which there are sufficient daily data for model calibration and GCM output to generate scenarios of the 21st century. Reliable prediction of climate change and its effect are importance for identifying appropriate mitigation and adaptation strategies [16]. Therefore, the objective of this study was to evaluate the adaptability of SDSM weather generator in downscaling temperature and precipitation using NCEP-re-analysis and HadCM3.

2 Materials and Methods

2.1 Weather data

The weather data (1981-2010) for Mount Makulu in Zambia (latitude: 15.550^{o} S, longitude: 28.250^{o}Altitude: 1200 m above sea level) used in this study was obtained from the Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) Climate Forcing Dataset for Agricultural Modeling. The AgMERRA climate forcing datasets were created as an element of the Agricultural Model Intercomparison and Improvement Project (AgMIP) to provide consistent, daily time series over the 1980-2010 period with global coverage of climate variables required for agricultural models [17]. The AgMERRA datasets are stored at 0.25°×0.25° horizontal resolution (~25km). Using a 30-year period to define climatology is a common practice and this period has become a key to perform model calibration, and evaluations, climate sensitivity studies and climate analysis. The World Meteorological Organization (WMO) adopted the 30-year for defining normals. Monthly climatology values for the Mount Makulu are presented in **Error! Reference source not found.**.

2.2 Description of Statistical DownScaling Model (SDSM)

The Statistical DownScaling Model (SDSM) coded in Visual Basic 6.0 is best described as a hybrid of the stochastic weather generator and transfer function methods [10]. The SDSM was developed as a regional climate change scenario generator to support climate risk assessment and adaptation planning [2], [14], [18]. It is a robust statistical downscaling technique that facilitates the rapid development of multiple, low-cost, single-site ensemble scenarios of daily weather variables under present and future regional climate forcing [12], [18]. Furthermore, it is built on the premise that downscaled scenarios should be informed by climate models [14]. Additionally, the SDSM model also performs ancillary tasks of data quality control and transformation, predictor variable pre-screening, model calibration, weather generation, statistical analyses, graphing of climate model output and scenario generation [18]. The SDSM uses multiple empirical regression equations between large-scale (predictor) atmospheric conditions and the site observed daily local scale (predictand) weather conditions, combined with a stochastic element to improve the reproduction of daily variability not suitably captured by the large-scale variables [10], [19], [20].

There are two kinds of sub-models in SDSM, unconditional and conditional used according to the requirement of the predictands. The unconditional sub-model is used for an independent variable such as temperature and the conditional is used for a conditional (dependent) variable like precipitation [10]. In conditional models, there is an intermediate process between large scale variable and local scale weather e.g., local rainfall amounts depend on the occurrence of wet-days, which in turn depend on large scale predictors such as humidity and atmospheric pressure [21].

2.3 Model Inputs

Quality observed daily data are required for both local-scale (predictand) and large-scale (predictor) climate variables to calibrate the SDSM. In SDSM version 4.2.9 daily National Center for Environmental Prediction (NCEP) predictor variables are available from the SDSM portal (http://copublic.lboro.ac.uk/cocwd/SDSM/data.html) using the site latitude and longitude for the period 1948-2015 whose grid cell sizes are: 2.5^{o} latitude x 2.5^{o} longitude coordinates at the center of the cell [14], [22], [23]. This new data portal was incorporated within the SDSM web-site to facilitate convenient global usage of SDSM model. The user can supply daily meteorological data (1948-2015) for the study site in question. There are 28 predictor variables which originate from the NCEP re-analysis. These raw and derived variables describe atmospheric circulation, thickness, stability and moisture content at various levels (near surface, 850 hPa and 500 hPa) using observations assimilated from stations, upper air and satellite measurements between 1948 and 2015. Precipitation values less than 0.01 mm/day are set to zero. All daily predictor variables are delivered as individual, single column ASCII files, bundled by 2.5° x 2.5° grid-box and zipped. Predictor variables are available globally except for the poles.

The Canadian Climate and Data Scenarios (CCDS) website (http://ccds-dscc.ec.gc.ca/) provides predictors for NCEP, Hadley Centre Couple Model version 3.0 (HadCM3; http://ccds-dscc.ec.gc.ca/?page=pred-hadcm3) and Canadian Centre for Climate Modeling and Analysis, 2nd version of the coupled Canadian Global Climate Model (CGCM2) [24], respectively. The Hadley Centre Couple Model version 3.0 (HadCM3; http://ccds-dscc.ec.gc.ca/?page=pred-hadcm3) was developed and is supported by the Hadley Centre for Climate Prediction and Research, United Kingdom. The atmospheric component of the HadCM3 model has a horizontal resolution at 45^{o} latitude of 2.5^{o} x 3.75^{o} (approx. 295 km x 278 km) and is comprised of 19 atmospheric levels and four soil layers [25]. The oceanic component of HadCM3 has a horizontal resolution of 1.25^{o} x 1.25^{o} and comprises 20 levels. The HadCM3 GCM is ranked highly (fourth out of 22 CMIP3 models) when compared with other GCMs. The simulation of HadCM3 assumes the year length in 360 day calendar with 30 days per month [26], [27]. The model was developed in 1999 and was the first coupled atmosphere-ocean which did not require flux adjustments [28]. The HadCM3 model was used in the IPCC Third and Fourth Assessments and also contributed to the Fifth Assessment Reports [29]. It also has the capability to capture the time-dependent fingerprint of historical climate change in response to natural and anthropogenic forcings and this has made it an important tool in studies concerning the detection and attribution of past climate changes [29].

2.4 Special Report on Emissions Scenarios (SRES)

In 2000, the IPCC published a set of emissions scenarios for use in climate change studies (Special Report on Emissions Scenarios, SRES). The SRES scenarios were constructed to explore future developments in the global environment with special reference to the production of greenhouse gases (GHGs) and aerosol precursor emissions [30]. The Fourth Assessment Reports of the Intergovernmental Panel on Climate Change suggest that due to the increase in GHG emissions over the last century, average global temperature has increased about 0.4 to 0.8^{o}C [15], [31]. The SRES defined four narrative storylines (A1, A2, B1 and B2) and these explore alternative development pathways, covering a wide range of demographic, economic and technological driving forces and resulting GHG emissions. There are approximately 40 different SRES scenarios that are organized into families based on population and economic growth, which house scenarios that are most similar to each other in terms of the assumptions about their driving forces during the 21st century for large world regions and globally.[32], [33] (**Error! Reference source not found.**). In this study, A2 and B2 scenarios were selected for climate change assessment at Mt Makulu.

2.5 Selection of predictors

The selection of predictors in SDSM is an iterative process, partly based on the user's subjective judgment [10] while developing predictand-predictor relationship. As a consequence, the predictors should be selected based on both their relevance to the downscaled predictand and their accurate representation by the climate model [11], [12]. Predictors were selected based on a combination of the correlation matrix, partial correlation and p-value. More details on selection of predictor are presented by [34] and [18]. All input and output files in SDSM model are in text format only and individual predictor and predictand files are one variable to each file. Different studies have shown that 1-3 large scale variables are enough to capture the variation of a predictand during calibration [10], [34]. The most commonly used predictors for downscaling minimum and maximum temperature are the mean sea level pressure, the vorticity at the surface, 850 and 500 hPa, and the 850 hPa geopotential height whilst surface zonal velocity, meridional velocity at 850 hPa, surface vorticity, geopotential height and specific humidity at 500 hPa are used to downscale precipitation [35]. As the number of predictors increases in the regression equation, the chances of multiple co-linearity also increase [34].

2.5 Calibration, validation and performance of the SDSM model

Two series of predictor datasets were used to calibrate and generate future climate scenarios: NCEP re-analysis data from SDSM portal, and NCEP and HadCM3 from CCDS. Re-analysis and observed time series datasets are required to define and calibrate the SDSM model [36]. The scenario results were analyzed to evaluate the effect of the interpolation procedure and to see if the results of the two datasets (NCEP re-analysis and HadCM3) outputs are consistent with the NCEP re-analysis as a reference from SDSM portal. Three measures of calibration fit provided by SDSM can be used: the fraction of explained variance (Pearson RSquared); the standard error of the estimate (SE); and the Durbin-Watson (to detect presence of autocorrelation in model residuals, where a value near 2 indicates no autocorrelation, 0 and 4 are positive and negative autocorrelation, respectively). In this study only the fraction of explained variance and the standard error of the estimate are presented.

The calibration results in SDSM are exhibited with percentages of explained variance computed with the equation provided by [37] [Equation 1] where S_i is the simulated value for day *i*, O_i is the observed value at day *i*, Õ is the mean of the observation S for the period and *n* is the number of days of the period of SDSM run and observed data.

$$\%ev = \frac{\sum_{i=1}^{n}(S_i - \tilde{O}_i)}{\sum_{i=1}^{n}(O_i - \tilde{O}_i)} x100 \qquad \text{[Eq. 2]}$$

In the SDSM model, a recursive algorithm is implemented to compute partial correlation using [Equation 3]. This recursive algorithm has a limitation, i.e. when the partial correlation between two variables is computed; the number of variables that can be used is limited to 12. However, the number of NCEP predictors used for partial correlation analysis is usually about 26. Summary statistics and frequency analysis are the means provided by SDSM for interrogating both downscaled scenarios and observed climate data.

$$t = \frac{R}{\sqrt{\frac{1-R^2}{n-2}}} \qquad \text{[Eq. 4]}$$

The other statistical indices used to evaluate the performance of the SDSM model were correlation (r), coefficient of determination (R^2), Root Mean Square Error (RMSE) and mean absolute error (MAE). According to [38], the d-stat of a "good" model should approach unity and the RMSE approach zero. The MAE and RMSE are among the best overall measures of model performance, as they summarize the mean difference in the units of observed and predicted [38] as presented in the equations below ([Equation 5] and [Equation 6]). Statistics defined by [38] should be used as an agreement index instead of correlation coefficients which has limitations.

$$MAE = N^{-1} \sum_{i=1}^{n} |P_i - O_i| \qquad \text{[Eq. 7]}$$

$$RMSE = [N^{-1} \sum_{i=1}^{n} (P_i - O_i)^2]^{0.5} \qquad \text{[Eq. 8]}$$

2.6 Baseline and future climate scenarios downscaling

The HadCM3 has two scenarios A2 and B2. For each scenario, twenty ensembles of synthetic daily time series data were generated for 139 years (1961-2099). The SDSM supports A2 and B2 scenarios for the HadCM3 GCM. Climate scenarios were generated for the current and future scenarios using SDSM v4.2.9. The NCEP-reanalysis and HadCM3 GCM were used to calibrate and generate transient weather data for 2020s (20011-2040), 2050s (2041-2070), and 2080s (2071-2099), respectively. The calibration results are used based on the assumption that predictor-predictand relationship under the current condition remains valid for future climate change conditions [39]–[41].

3 Results and Discussion

3.1 Screening of predictors

The NCEP re-analysis predictors from SDSM Portal and CCDS were used to calibrate the SDSM model as presented in **Error! Reference source not**

found.. These are selected through screening using statistical downscaling model. The future projections discussed here are based upon the A2 and B2 SRES scenarios. The multi-model total precip, mean tmin, and tmax are associated with uncertainty for 2020s, 2050s and 2080s relative to 1981-2010 under A2 and B2 SRES scenarios.

3.2 Calibration tests

The calibration of the SDSM involved the establishment of statistical relationships between the selected predictors and predictands. In this study the selected predictors are presented in **Error! Reference source not found.**. To build confidence in the performance of SDSM, precipitation (precip) monthly totals and mean minimum (tmin) and maximum (tmax) temperature are compared graphically with the observed data. The graphical comparisons below are able to identify pattern and variations captured by the model [42]. The precip, Tmax and Tmin between the observed and generated data during the calibration are illustrated in **Error! Reference source not found.** and **Error! Reference source not found.** for the study site. For tmax and tmin, the SDSM simulated NCEP (1948-2015) and NCEP (1961-2001) re-analysis predictors well, deducing that future projections would also be well simulated.

The adaptability of SDSM in providing quality downscaled temperature and precipitation time series data relies on model calibration, which is described with percentages of explained variance (**Error! Reference source not found.** and **Error! Reference source not found.**). The percentages of explained variance are higher for tmax and tmin [43], which is more spatially conservative than precipitation as presented in **Error! Reference source not found.** and **Error! Reference source not found.**. The computed values for precip are very low (0.1-73.6%). As a consequence, these results are similar to those of other studies [44]. During the calibration of SDSM using NCEP re-analysis predictors, two indicators: Explained Variance and Standard Error (SE) were used to check the model's performance [34]. The mean explained variances, calculated from NCEP re-analysis 1961-2001 and 1948-2014 ranges between 36.4-66.0% and 46.1-71.8% for Tmax and Tmin, respectively and the mean standard error lies between 0.637-3.199, 0.731-1.285 and 0.119-12.442 for Tmax, Tmin and precip, respectively. According to [43], it is not possible to have acceptable levels of explained variance as SDSM model skills differs for diverse geographical location even for predictors. The computed results are satisfactory and comparable to some previous studies conducted by researchers such as [10] and [45]. A study in Toronto that used SDSM reported mean values of 73% and 72% for maximum and minimum temperatures and 28% for precipitation [10], [44]. The SDSM algorithm were applied in mountainous regions of Japan and obtained seasonal values varying from 70% to 90% for temperature, and from 15% to 45% for precipitation [46], [45]. [47] tested the SDSM model in the Greater Montréal region and obtained values between 71%

and 79% for temperature, and between 6% and 10% for precipitation.

In this study, the calibration of the SDSM using NCEP re-analysis (1948-2014) and NCEP re-analysis (1961-2001) was better although generated precipitation was over-estimated for all the months and this affected all generated scenario for 2020s, 2050s and 2080s. The NCEP re-analysis (1961-2001) and NCEP re-analysis (1948-2014) statistic for the calibration performance are presented in **Error! Reference source not found.** for precip, Tmax and Tmin. During calibration of precip, the generated precip was over-estimated for both NCEP re-analysis data sets. The d-stat, R and R^2 for NCEP re-analysis (1961-2001) and NCEP re-analysis (1948-2014) as presented in **Error! Reference source not found.** are unit. The results indicate that the calibration performance of SDSM model was excellent.

3.3 Future climate scenarios downscaling

In this study, future climate scenarios were generated for precip, Tmax and Tmin at Mt Makulu. In SDSM-based statistical downscaling method, the A2 and B2 emission scenarios from HadCM3 were used. The regression equations established during the calibration process of SDSM were used to build the current (1981-2010) and future climate scenarios for 2020s (2011-2040), 2050s (2041-2070) and 2080s (2071-2099).

3.3.1 Temperature

The future projections discussed here are based upon the HadCM3 A2 and B2 SRES scenarios. The monthly mean Tmin and Tmax under A2 and B2 scenarios are shown in **Error! Reference source not found.** and **Error! Reference source not found.**. Projected annual mean Tmin rise for Mount Makulu would be 0.203^{o}C, 0.563^{o}C and 1.032^{o}C while the tmax would be 0.177^{o}C, 0.462^{o}C and 0.910^{o}C in 2020, 2050 and 2080 under A2 scenario, respectively. The analysis shows that projected mean Tmin and Tmax would increase by 0.192^{o}C, 0.409^{o}C and 0.708^{o}C and 0.132^{o}C, 0.389^{o}C and 0.618^{o}C in 2020, 2050 and 2080 under B2 scenario from the baseline (1981-2010), respectively (**Error! Reference source not found.**). The temperature rise is with reference to the mean of all ensembles of the 1981-2010 normal. It is worth noting that the computed values based on A2 and B2 scenarios shows increasing trends of Tmax and Tmin at each time slice (2011-2040, 2041-2070 and 2071-2099). Both scenarios show different increase in temperature for the future scenarios. Literature revealed indicated that the mean annual temperature in Zambia has increased by 1.3^{o}C since 1960, an average of 0.29^{o}C per decade [48]–[50]. [51] agrees with the finding of this study that projections from GCMs suggest an increase in temperature. Climate change assessments for Zambia also suggest that projected mean temperatures (between 2010 and 2070) are set to increase relative to baseline mean temperatures (1970 - 2000) by approximately 2°C (HadCM3 GCM).

According to IPCC, global temperature change under B2 would be 1.4^{o}C (2050), 2.7^{o}C

(2100) and under A2 it would be 1.4^{o}C (2050), 3.8^{o}C (2100). On the other hand, IPCC observed that, the A2 and B2 scenario have temperature changes in the range of 2.0-5.4^{o}C and 1.4-3.8^{o}C, respectively. The study results indicate that the increases in Tmin and Tmax are below the ranges computed by IPCC under A2 and B2 SRES scenarios (**Error! Reference source not found.**). On a global scale the mean annual surface temperature has increased over the past century by 0.6°C [52]. The generated future climate scenarios are based on a set of key assumptions on international geopolitics, change on economic development and population growth rate and technological changes. These assumptions are dependent on the local dynamics of the system that cannot be accurately described [53]. On the other, the Tmin variance shows a decreasing trend (0.047 [2020s], -0.441 [2050s], -1.164 [2080s]) while, the Tmax variance shows a decreasing (0.065 [baseline], -0.013 [2020s], -0.334 [2050s]) and increasing trend (0.476 [2080s]).

3.3.2 Precipitation

The monthly total and variance of precipitation values were over-estimated (**Error! Reference source not found.**) compared to the observed values. Impacts researchers such as [54] are urged to use caution when using downscaled monthly precipitation values from SDSM or any other regression based downscaling studies. The analysis shows that precipitation amounts would increase under A2 by 3.741% (2020s), 15.604% (2050s) and 28.257% (2080s). On the other hand, precipitation amounts would increase under B2 scenario by 5.837% (2020s), 10.205% (2050s) and 19.312% (2080s) (**Error! Reference source not found.**). Results also indicate that the number of days with precipitation and the amounts (mm/year) would increase as presented in **Error! Reference source not found.**. However, literature reviewed shows that in SDSM daily precipitation amounts at weather stations is the most problematic predictand variable to downscale because amounts at individual sites are relatively poorly resolved by regional-scale predictors and research is on-going to address this limitation [12], [18], [21], [35]. This problem arises due to the generally low predictability of daily precipitation amounts at local scales by regional forcing factors. Other factors leading to complexity of modelling precipitation is related on some characteristics specifically intermittency, rain extremes, high rain rate variability and multiple scaling regimes. The unexplained behaviour is currently modelled stochastically within SDSM by artificially inflating the variance of the downscaled series to accord better with daily observations.

3 CONCLUSION

Climate parameters downscaled were daily Tmin, Tmax and precipitation using the HadCM3 GCM. The calibration results of the SDSM using NCEP re-analysis data for Tmin and Tmax demonstrated that the model could be used in generating synthetic weather data for the current and future climate scenarios. The downscaled scenarios in this study were generated using only one GCM model and A2 and B2 scenarios. The generated future scenarios of Tmax, and Tmin and precip generally showed an increasing trend relative to the baseline period (1981-2010). The GCM under investigation was HadCM3 with A2 and B2 scenarios. In both HadCM3 SRES scenarios, the Tmax, and Tmin and precipitation would increase. In general A2 scenario predicted the greatest changes in Tmax, Tmin and precipitation by the end of the century. The changes in Tmax, and Tmin and precipitation would affect crop growth rates, photosynthesis, evapotranspiration, as well as soil water and nutrient availability. The outputs of downscaled future scenarios for climate change impact assessment are highly dependent on the input data and uncertainty of the models. The generated future climate scenarios are based on a set of key assumptions on international geopolitics, economic structure and population growth rate and technological development. SDSM may be used to generate long time-series of weather data at local-scale suitable for climate risk assessment and adaptation planning.

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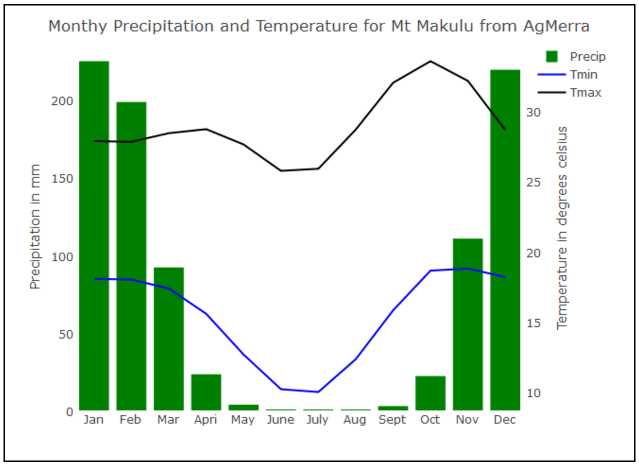

Figure 1: Monthly precipitation and temperature

Table 1: CO_2 concentrations (ppm) for selected climate scenarios specified in the Special Report on Emissions Scenarios (SRES) [55], [56]

Scenario	Key assumption	CO_2 concentration 2011-2030	2046-2065	2081-2100
B1 (“low” GHG emission scenario”)	Population convergence throughout the world, change in economic structure (pollutant reduction and introduction to clean technology resources). Global environmental sustainability 1.1 - 2.9°C	410	492	538
A1B (“medium” GHG emission scenario)	Rapid economic growth, maximum population growth during half century and after that decreasing trend, rapid modern and effective technology growth. Rapid economic growth (groups: A1T; A1B; A1Fl) 1.4 - 6.4°C	418	541	674
A2 (“high” GHG emission scenario)	Rapid world population growth, heterogeneous economics in direction of regional conditions throughout the world. Regionally oriented economic development 2.0 - 5.4°C	414	545	754
B2	B2 describes a world with continuously increasing global population, at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. Local environmental sustainability 1.4 - 3.8°C	367	478	615

Note: CO_2 concentration for the baseline scenario, 1960-1990, is 334 ppm

Table 2: Partial correlation between the predictand and predictor for precipitation and temperature

Predictors	NCEP 1961-2001						NCEP 1948-2015					
	Predictands						Predictands					
	Tmax		Tmin		Precip		Tmax		Tmin		Precip	
	PC	0.05	PC	0.05	PC	0.05	PC	0.05	PC	0.05	PC	0.05
dswr							0.088	0.0000	0.042	0.0000		
Mslp	-0.39	0.0000	-0.334	0.0000			-0.138	0.0000	-0.089	0.0000		
p_u			-0.134	0.0000			-0.048	0.0000				
p_v	-0.167	0.0000	-0.107	0.0000								
p_z	0.184	0.0000	0.196	0.0000					0.044	0.0000		
p5_u									-0.043	0.0000		
p500	-0.114	0.0000	0.22	0.0000			-0.05	0.0000				
p8_v			0.13	0.0000			-0.034	0.0008				
p850	0.316	0.0000	0.103	0.0000			0.105	0.0000	0.042	0.0000		
p500					0.118	0.0000						
p850					-0.151	0.0000						
rhum											-0.091	0.0000
shum											0.121	0.0000

NB: PC = Partial correlation; 0.05 = p-value

Key of predictors:

mslp	mean sea level pressure
p_u	surface zonal velocity
p_v	surface meridional velocity
p_z	surface vorticity
p8_v	meridional velocity
p500	geopotential height at 500 hPa
p850	geopotential height at 850 hPa
pr500	Relative humidity at 500 hPa

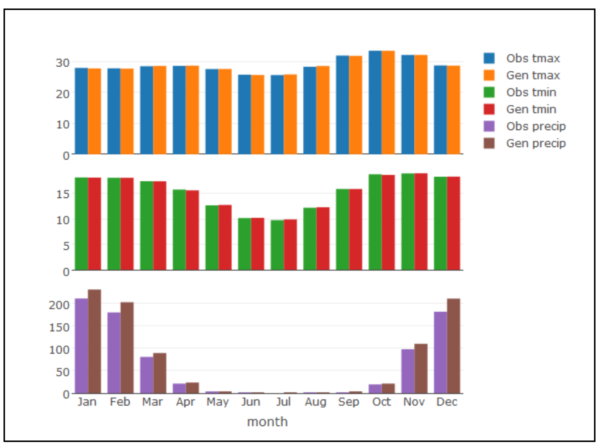

Figure 2: Calibration tests for NCEP re-analysis (1948-2015)

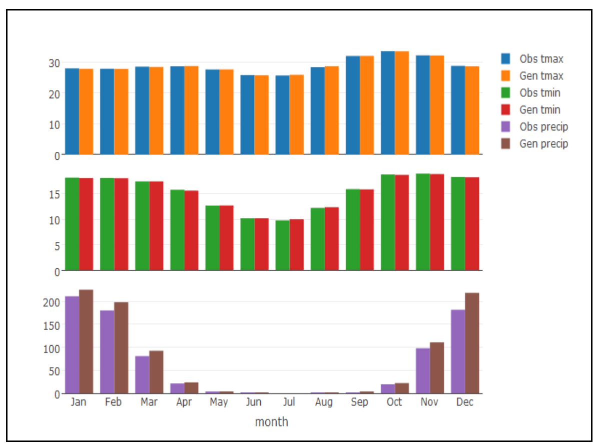

Figure 3: Calibration tests for NCEP re-analysis (1961-2001)

Table 3: Performance of SDSM during the calibration periods (1981-2010)

NCEP 1948-2014						
	Tmax		Tmin		Precip	
Month	Rsquared	Standard Error	Rsquared	Standard Error	Rsquared	Standard Error
Jan	0.364	2.213	0.552	0.731	0.002	10.304
Feb	0.424	1.891	0.461	0.739	0.001	10.534
Mar	0.555	1.737	0.643	0.851	0.015	8.202
Apr	0.635	1.456	0.661	1.019	0.010	7.649
May	0.638	1.442	0.702	1.030	0.084	2.153
Jun	0.610	1.540	0.671	1.114	0.103	0.538
Jul	0.660	1.595	0.654	1.110	0.705	0.516
Aug	0.639	1.748	0.716	1.190	0.736	0.330
Sep	0.528	2.015	0.670	1.285	0.327	3.994
Oct	0.445	2.481	0.585	1.281	0.005	7.511
Nov	0.416	3.199	0.549	1.246	0.001	11.014
Dec	0.437	2.911	0.515	0.907	0.001	12.442
Mean	0.529	2.018	0.615	1.042	0.166	6.266

Table 4: Performance of SDSM during the calibration periods (1981-2010)

NCEP 1961-2001						
	Tmax		Tmin		Precip	
Month	Rsquared	Standard Error	Rsquared	Standard Error	Rsquared	Standard Error
Jan	0.364	2.213	0.552	0.731	0.006	10.286
Feb	0.423	1.893	0.465	0.736	0.005	10.512
Mar	0.556	1.736	0.644	0.850	0.001	8.259
Apr	0.633	1.459	0.664	1.013	0.010	7.647
May	0.637	1.445	0.705	1.030	0.008	2.241
Jun	0.610	1.540	0.671	1.114	0.047	0.555
Jul	0.659	1.598	0.655	1.109	0.984	0.119
Aug	0.635	1.757	0.718	1.187	0.458	0.474
Sep	0.527	2.015	0.674	1.278	0.102	4.613
Oct	0.444	2.484	0.586	1.278	0.005	7.511
Nov	0.417	3.186	0.549	1.246	0.011	10.961
Dec	0.436	2.913	0.516	0.906	0.004	12.423
Mean	0.528	2.020	0.616	1.040	0.137	6.300

Table 5: Performance of SDSM during calibration

Predictands	NCEP re-analysis (1961-2001)					NCEP re-analysis (1948-2014)				
	RMSE	d-stat	r	R^2	MAE	RMSE	d-stat	r	R^2	MAE
Precip	8.34	0.99	1.00	1.00	8.34	12.91	0.99	1.00	1.00	8.24
Tmax	0.13	1.00	1.00	1.00	0.10	0.12	1.00	1.00	1.00	0.10
Tmin	0.10	1.00	1.00	1.00	0.08	0.08	1.00	1.00	1.00	0.06

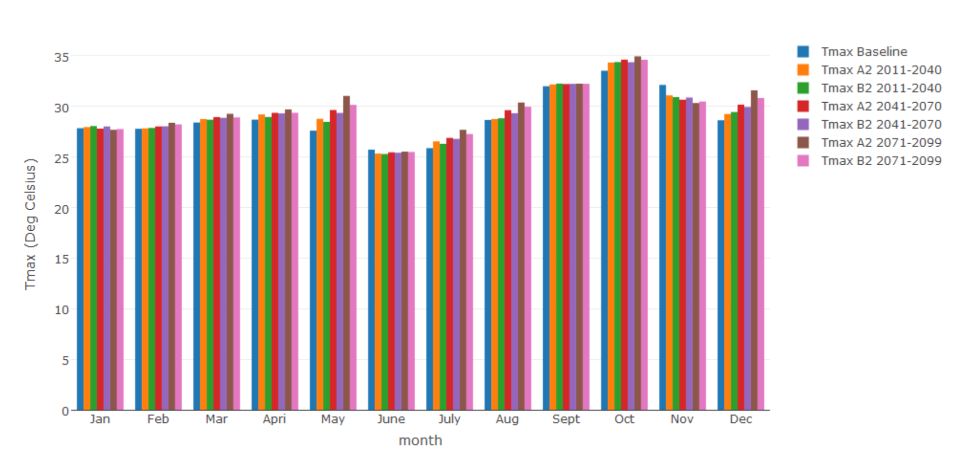

Figure 4: Monthly tmax under A2 and B2 scenarios baseline, for 2020, 2050 and 2080

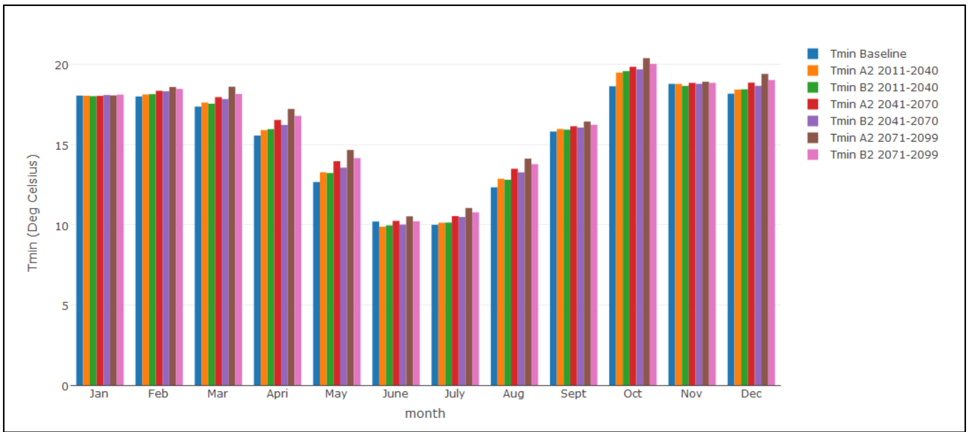

Figure 5: Monthly tmin under A2 and B2 scenarios for baseline, 2020, 2050 and 2080

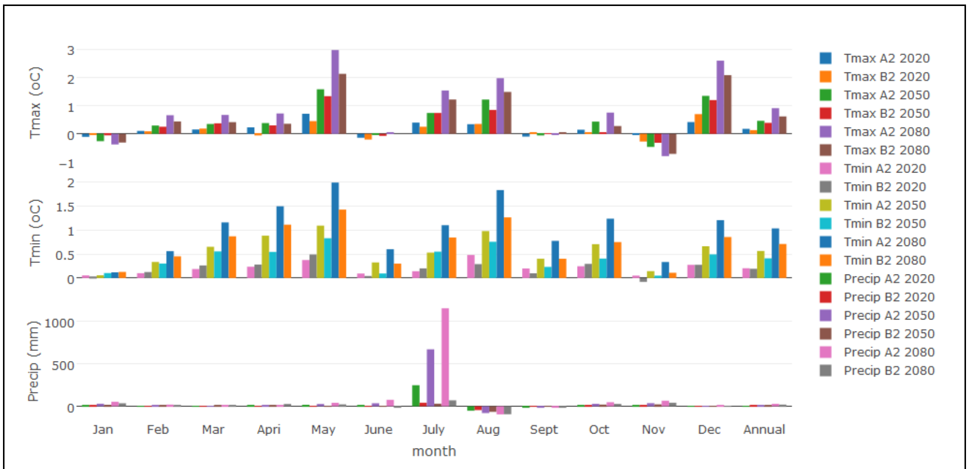

Figure 6: Future monthly Tmax, Tmin and precip change under A2 and B2 scenarios for 2020, 2050 and 2080

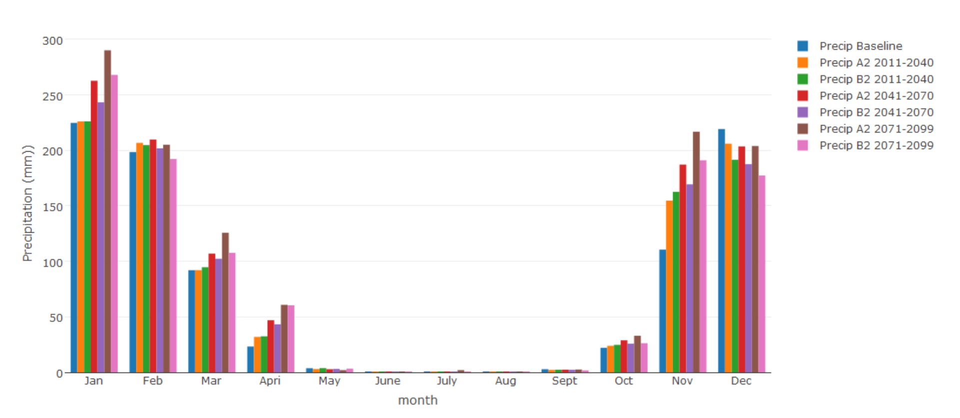

Figure 7: Monthly precipitation under A2 and B2 scenarios for 2020, 2050 and 2080

Table 6: Days with and amount of precipitation

Period	Number of days with precip	Total precip (mm/year)
Baseline	86.0	897.47
A2 2020s	201.5	943.50
A2 2050s	208.0	1050.70
A2 2080s	211.0	1151.60
B2 2020s	203.0	941.20
B2 2050s	205.0	977.10
B2 2080s	207.0	1072.00