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Impact of Climate Change on Precipitation in Zambeze River Basin in Southern Africa

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ABSTRACT

The Intergovernmental Panel on Climate Change (IPCC) concluded that there is a consensus that the increase in atmospheric greenhouse gases will result in climate change, which will cause the sea level to rise, increase frequency of extreme climatic events such as intense storms, heavy rainfall events and droughts. This will increase the frequency of climate-related hazards, causing loss of life, social disruption and economic hardships. There is less consensus on the magnitude of change of climatic variables, nonetheless several studies have shown that climate change will have an impact on the availability and demand for water resources. Southern Africa lies in one of the regions of the world that is most susceptible to climate variability and change. In southern Africa, climate change is likely to affect nearly every aspect of human well-being, from agricultural productivity and energy use to flood control, municipal and industrial water supply as well as wildlife management, since the region is characterized by highly spatial and temporally variable rainfall, and in some cases, scarce water resources. This study presents the future change projection in precipitation under RCP2.6, RCP4.5 and RCP8.5 scenarios of the CanESM2 outputs using the Statistical Downscaling Model (SDSM) for 50 stations in Zambeze River basin during the two future periods: near future (2031-2060) and far future (2071-2100). For assessment of climate change, the baseline period (1979-2013) was partitioned into two periods for SDSM calibration (1979-1996) and validation (1997-2013). The results show that SDSM was not a very robust method for the simulation of precipitation for this study area, the model could not replicate observed precipitation very well. This is due to its conditional nature and high variability in space. The results also showed that there is a decrease in monthly precipitation during wet period (October-March) and an increase during the dry period (April-September). The upward monthly increase in projected precipitation expected is in August (300%, 325%) with RCP4.5 and maximum decrease in March (38%) with RCP4.5 for all scenarios for NF and FF respectively, and the projected annual precipitation is expected to decrease with time for all scenarios. It was observed that the maximum decrease will range from 7-21.8% for near future (NF) and 2-21% for far future (FF).

INTRODUCTION

Anthropogenic greenhouse gas emissions have increased since the pre-industrial era, driven largely by economic and population growth, and are now at record higher than ever. Their effects, together with those of other anthropogenic drivers, have been detected throughout the climatic system and are extremely likely to have been the dominant cause of the observed warming since the mid-20th century (IPCC 2014a). There is a direct correlation between global warming and precipitation (Res & Trenberth 2011). Increased heating leads to greater evaporation, and thus surface drying, thereby increasing the intensity and duration of droughts. With medium confidence, the study conducted by IPCC (2014b) indicated that changes in rainfall patterns or melting snow and ice have changed hydrological systems in many regions including Africa. This has affected water resources in terms of quality and quantity (Solomon et al. 2007). Africa is highly vulnerable to the impacts of climate change and numerous climate change models predict that the continent's weather patterns will become more variable, and extreme weather events are expected to be more frequent and severe, with increasing risk to health and life (IPCC 2014 and Solomon et al. 2007). By 2050, across Zambeze River Basin there is an expected 10-25% increase in evaporation and 10-15% reduction in rainfall, relative to the baseline (1961-1990). Overall, the Zambeze will be both drier and more variable, experiencing more prolonged drought periods and more extreme floods (Beilfuss 2012). The Zambeze Basin is already experiencing drastic changes to its climate. In recent years the annual rainfall in the region decreased considerably, which in turn affected the annual flow levels of the Zambeze. Over 128 million inhabitants that are part of the Zambeze River Basin are dependent on this "Great River" directly or indirectly as a source of food and water. In total, the countries which constitutes the Zambeze Basin (excluding Tanzania) have 2.17 million km^2 of agricultural land, of which just 2,02,900 is arable. Mozambique holds the largest amount of agricultural land in relation to total land area. Nevertheless, because of increased agricultural land, there is also an increased need for irrigation to sustain agricultural production and mitigate the variability of rainfall. In the entire basin, agriculture is the dominating consumer of water. According to the Food and Agriculture Organization, Botswana uses just 41 per cent of its water resources for agriculture, while 18 per cent go into mining and energy production. In comparison, Mozambique, Namibia, Zambia and Zimbabwe use over 70 per cent of their freshwater resources for agriculture. Mozambique, in particular, uses 87 per cent of its water for agriculture, while just 2 per cent goes to the industrial sector. Water allocation issues, population and economic growth, the expansion of irrigated agriculture water transfer and climate change are expected to cause use of water runoff to rise to 40 percent by 2025 (Swain et al. 2012). The Zambeze runoff is highly sensitive to variations in climate, as small changes in rainfall produce large changes in runoff. The dependency on water for food production in the basin area affirms concerns that the Zambeze Basin will be strongly affected by climate change (Beilfuss 2012). The hydrology of the basin is very important for hydropower generation, water supply, irrigation and ecological systems. These water dependent sectors are vulnerable to climate change impacts, thus, local climate change scenarios are important for planning and management of water supply and demand. This study aimed at generating scenarios of climate change for precipitation in the Zambeze basin based on GCMs outputs (CanESM2). It will help to provide appropriate information so as to take action for minimizing the negative impacts of climate change in the basin. The SDSM downscaling was done using future emission scenarios of RCP2.6, RCP4.5 and RCP8.5 from CanESM2 GCM outputs.

STUDY AREA AND DATA

Study area: The Zambeze River Basin is the fourth largest river basin in Africa and the largest river basin in the Southern African Development Community (SADC) region with a total drainage area of approximately 1.34 million. The main stream, with a total length of 3,000 km, originates from the Kalene Hills in northwest Zambia at an altitude of 1,500 m and flows eastwards to the Indian Ocean. The river has three distinct stretches: the upper Zambeze from its source to Victoria Falls, the middle Zambeze from Victoria Falls to Cahora Bassa and the lower Zambeze from Cahora Bassa to the delta where the study area is located. It lies between latitudes 10° and 20° south, and between longitudes 20° and 37° east (Fig. 1). The climate of the basin is largely controlled by the movement of air-masses associated with the Inter-Tropical Convergence Zone (ITCZ). Rainfall occurs predominantly during the summer (November to March), while the winter months (April to October) are usually dry. The average annual rainfall over the basin is 990 millimetres (mm), varying from 1,200 mm y^{-1} in the northern parts to 700 mm y^{-1} in the southern and southwestern parts of the basin according World Bank (WB 2010). The Zambeze River is shared by eight countries (Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia and Zimbabwe), and has an estimated population of 30 mil-

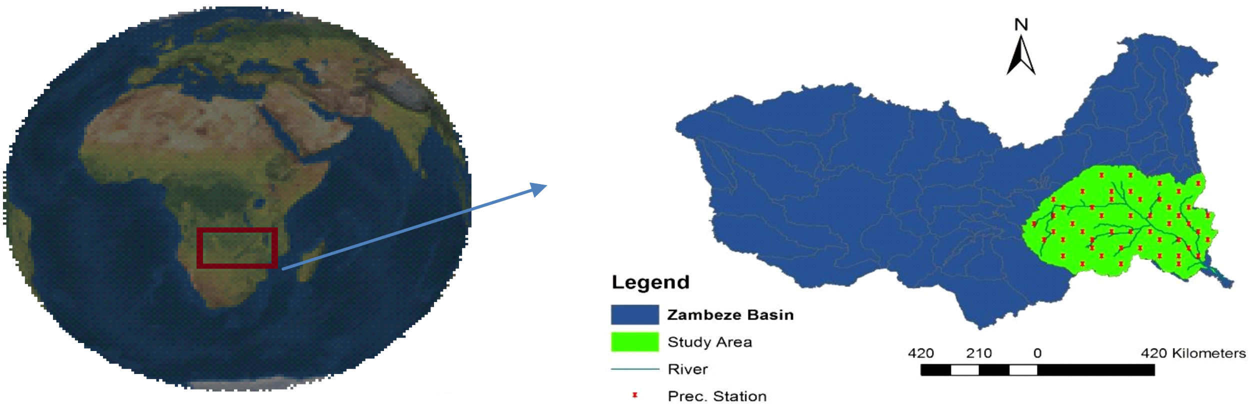

Fig. 1: Overview of Zambeze catchment area.

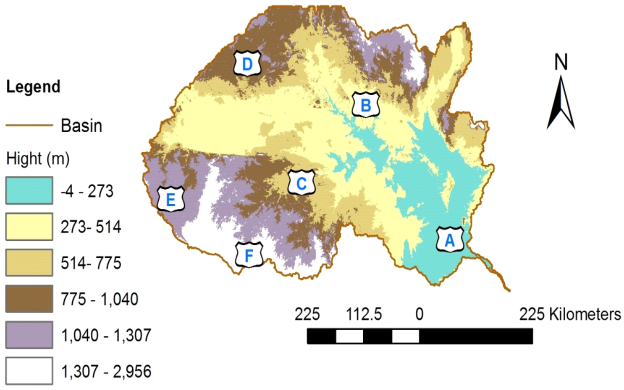

Fig. 2: Study area in Zambeze River Basin.

lion people (Pasanisi et al. 2016). However, rainfall is characterized by considerable spatial and temporal variation throughout the basin. Droughts of several years' duration have been recorded almost every decade (Kane 2009). Mean discharge at the outlet of the basin is estimated to be approximately 3600, but discharge shows large seasonal and intra-annual variations strongly controlled by seasonality in precipitation (Kling et al. 2014).

The historical rainfall data for the study were obtained from the Global Weather Data for SWAT website (https://globalweather.tamu.edu/). The daily observed precipitations of 50 stations with continuous dataset for downscaling were used. The study area was divided into 6 clusters (A, B, C, D, E and F) according to the station elevation (Fig. 2). Where, A is lowest and F the highest elevation (Table 1), having record lengths of 34 years for the period 1980-2013.

The most commonly used predictor variables for the NCEP and CanESM2 GCM experiments are listed in Table 2. These were used as inputs into the SDSM model, and future climate scenarios data were obtained as output from the second generation Canadian Earth System Model (CanESM2) developed by Canadian Centre for Climate Modelling and Analysis (CCCMA) of Environment, Canada. The grid cell size is uniform along the longitude with horizontal resolution of 2.8° and nearly uniform along the latitude of roughly 2.8°. The CanESM2 outputs were downloaded for three different climate scenarios within Representative Concentration Pathways RCP2.6, RCP4.5 and RCP8.5, which were adopted in this study.

METHODOLOGY

Downscaling of climate data to local level was done using SDSM model, which was downloaded at no cost from http://www.sdsm.org.uk. Since most of the time, observed meteorological data are not 100% accurate, before use, quality control was carried out in order to enhance the quality of model output. The selection of predictor variables was based on the strength of correlation between sets of predictors and single predictand, e.g. precipitation (Table 3). The 34 years observed data were divided into two periods, the first half (1980-1996) 17 years of daily data were used for model calibration and the second half (1997-2013) were used for model validation. The weather generator operation was used to produce daily synthetic data for the historical time period by using calibration output and observed NCEP reanalysed atmospheric variables (Wilby & Dawson 2007). The last step involved scenario generator, which is the same as that of the weather generator, considering that both generate synthetic data. However, the major difference between the two being the time period for synthetic data generated. This was done by changing the source data directory of predictor variables and by specifying model time period during the model setting. Future model change in climate was calculated based on the climatological baseline period as a reference period (IPCC 2001).

Statistic downscaling model: The ability of the GCMs to accurately simulate extreme precipitation distributions and trends is of great importance. Generally, studies on precipitation characteristics from climate models have concluded that simulated daily precipitation tends to occur more frequently, but is less intense than observed precipitation (Dai 2006). While these models have improved in terms of accuracy of simulation at a large-scale behaviour of the atmosphere, there are still difficulties in capturing small-scale intermittent processes, for example, local precipitation (Tryhorn & Degaetano 2011). To bridge the gap between the coarse spatial resolution of climate model output and the need for weather information at a higher resolution, downscaling methods have been developed. Downscaling is a process of transforming this coarse information to a finer spatial resolution (Tryhorn & Degaetano 2011). Among downscaling methods, statistical methods are commonly used because they are easy to run and SDSM model is one of the downscaling techniques employed today. It provides a reliable correlation of observational data (predictand) and large-scale daily GCMs climate variables (predictors) using multiple linear regression techniques. The statistical regression is run between predictors and predictand to make spatial scale reduction of the climate data by applying the monthly explained variance and partial correlation coefficient throughout predictand. SDSM model has been developed by Robert L. Wilby and Christian W. Dawson (Wilby 2002). The detailed description of the mathematical and statistical approach of SDSM was explained by Wilby & Dawson (2007) and Wilby (2002). SDSM performance is estimated by validation of calibration result using some

Table 1: List of meteorological stations.

No.	Code	Lat.(°)	Long. (°)	Elevation (masl)	Cluster	No.	Code	Lat.(°)	Long.(°)	Elevation (masl)	Cluster
1	180347	-18	34.7	142	A	26	158344	-15.8	34.4	630	C
2	164350	-16.4	35	52		27	145331	-14.5	33.1	760	
3	170347	-17	34.7	195		28	151325	-15.1	32.5	577	
4	173350	-17.3	35	43		29	167325	-16.7	32.5	578	
5	176353	-17.6	35.3	39		30	173328	-16.1	33.1	530	
6	161338	-16.1	33.8	238		31	155341	-15.5	34.1	686	
7	167331	-16.7	33.1	246		32	161356	-16.1	35.6	648	
8	176347	-17.6	34.7	187		33	155306	-15.5	30.6	590	
9	161347	-16.1	34.7	187		34	164300	-16.4	30	562	
10	167353	-16.7	35.3	42		35	173334	-17.3	33.4	624	
11	167338	-16.7	33.8	308	B	36	170319	-17	31.9	755	
12	148353	-14.8	35.3	482		37	145322	-14.5	32.2	914	D
13	170341	-17	34.1	346		38	151316	-15.1	31.6	840	
14	176341	-17.6	34.1	493		39	158350	-15.8	35	947	
15	161306	-16.1	30.6	376		40	167316	-16.7	31.6	935	
16	158319	-15.8	31.9	343		41	170303	-17	30.3	1112	E
17	161331	-16.1	33.1	365		42	173319	-17.3	31.9	1105	
18	155325	-15.5	32.5	415		43	148341	-14.8	34.1	1000	
19	164313	-16.4	31.3	424		44	176322	-17.6	32.2	1203	
20	164344	-16.4	34.4	289		45	151347	-15.1	34.7	1303	
21	170356	-17	35.6	324		46	167306	-16.7	30.6	1077	
22	158309	-15.8	30.9	331		47	180328	-18	32.8	1664	F
23	151331	-15.1	33.1	493		48	180316	-18	31.6	1345	
24	155334	-15.5	33.4	426		49	170309	-17	30.9	1323	
25	161322	-16.1	32.2	658	C	50	176309	-17.6	30.9	1407	

Table 2: Candidates of atmospheric variables for predictors.

No.	Daily predictor variable	Code	No.	Daily variable	Code
1	Mean temperature	temp.	14	Near surface specific humidity	shum
2	Surface airflow strength	p_f	15	500 hPa airflow velocity	p5_f
3	Surface zonal velocity	p_u	16	500 hPa Vorticity	p5_z
4	Surface meridional velocity	p_v	17	500 hPa Zonal velocity	p5_u
5	Surface vorticity	p_z	18	500 hPa Meridional velocity	p5_v
6	Surface wind direction	p_th	19	500 hPa Wind direction	p5_th
7	Surface divergence	p_zh	20	500 hPa Divergence	p5_zh
8	Mean sea level pressure	mslp	21	850 hPa airflow strength	p8_f
9	500 hPageopotential height	p500	22	850 hPa zonal velocity	p8_u
10	850 hPageopotential height	p850	23	850 hPa meridional velocity	p8_v
11	Near surface relative humidity	rhum	24	850 hPavorticity	p8_z
12	Relative humidity at 500 hPa height	r500	25	850 hPa wind direction	p8th
13	Relative humidity at 850 hPa height	r850	26	850 hPa divergence	p8zh

parameters such as mean monthly precipitation. The calibration is conducted between selected large-scale NCEP predictor variables and the observed precipitation to quantify the accuracy of data modelled. During calibration, mean of downscaled monthly precipitation are adjusted by bias correction to enable the model to replicate the observed data (Saraf & Regulwar 2016, Teutschbein & Seibert 2012).

Re-analysed atmospheric dataset obtained from National Center for Environmental Prediction (NCEP) together with observed data were split into two and used for model calibration, and the remaining datasets were employed for model validation in order to check the statistical downscaled model output from calibration. Both the CanESM2 output and NCEP/NCAR were downloaded from Canadian Climate Data and Scenarios website (http://climate-scenarios.canada.ca/?page=pred-canesm2). The data were downloaded by entering latitude and longitude of the study area, with a large-scale predictor at a spatial resolution of 2.5° longitude and

Table 3: Selected predictor variables for the predictands.

	Station A			Station B			Station C		
Predictand	Predictors	Partial r	p-value	Predictors	Partial r	p-value	Predictors	Partial r	p-value
Precipitation	mslp	-0.162	0.0000	mslp	-0.167	0.0000	mslp	-0.110	0.0000
	p5_f	0.010	0.4162	p8_v	0.027	0.0625	p_z	0.020	0.1687
	p8_z	0.037	0.0085	p8_z	0.052	0.0001	p5_f	0.026	0.074
	prcp	0.164	0.0000	prcp	0.149	0.0000	p8_f	0.014	0.3163
	ptmp	-0.086	0.0000	ptmp	-0.101	0.0000	prcp	0.134	0.0000
	-	-	-	-	-	-	ptmp	-0.064	0.0000
	Station D			Station E			Station F		
	Predictors	Partial r	p-value	Predictors	Partial r	p-value	Predictors	Partial r	p-value
	mslp	-0.156	0.0000	mslp	-0.176	0.0000	mslp	0.020	0.1578
	p_th	-0.013	0.3312	p_zh	0.050	0.0003	p_u	-0.017	0.2272
	P5_zh	0.030	0.356	p8_z	0.053	0.0001	p_th	-0.024	0.0921
	p8_v	0.028	0.051	prcp	0.198	0.0000	P5_v	0.020	0.1616
	p8_z	0.027	0.04221	ptmp	-0.070	0.0000	P8_f	-0.028	0.0457
	prcp	0.174	0.0000	-	-	-	p850	-0.040	0.0035
	ptmp	-0.80	0.0000	-	-	-	prcp	-0.001	0.5631
	-	-	-	-	-	-	shum	0.109	0.0000

Table 4: SDSM performance during the calibration (1979-1996) and validation (1997-2013).

Station	Prec. (R^2 %)	Prec. (SE)
A	13-58	0.5-3.2
B	13-54	0.4-2.7
C	13-56	0.4-2.7
D	17-59	0.4-3.3
E	15-62	0.4-2.5
F	13-58	0.5-3.3

2.5° latitude. Moreover, variables representing the current climatic condition from 1961 to 2005 were obtained from the National Center for Environmental Prediction and National Center of Atmospheric Research (NCEP/NCAR). These predictor variables were used in the downscaling process. The CanESM2 predicator scenarios within Representative Concentration Pathway (RCP 2.6, RCP 4.5 and RCP 8.5) were used for future generation. The future scenario analyses were divided in two periods (2031-2060) near future (NF) and (2071-2100) far future (FF) and were compared with the baseline period.

RESULTS AND DISCUSSION

Selection of Predictor Variables

The best correlated predictor variables were selected for each station's predictands. These variables were then used for calibration of the SDSM (Wilby et al. 2002). The strongest correlation between single predictand and set of predictors was identified. According to Table 3, for precipitation, "mslp" was dominating predictor. However, for the case of precipitation, the correlation (partial r) for individual predictand and a set of predictors was not satisfactory (it is satisfactory when partial r is ±1). This is due to its conditional behaviour of precipitation whereby it is an intermediate process between the regional forcing and local weather (e.g., precipitation amount depends on wet/dry-day occurrence which also depends on regional scale predictors such as humidity and atmospheric pressure) (Wilby & Dawson 2007). Similar results were observed by other scholars (Gulacha & Mulungu 2016).

Calibration and Validation

Similar to most of the applications of SDSM reported, the model was calibrated and validated separately (Huth 1999, Rashid et al. 2014, Wilby 2002, 1997). The performance of models in simulating specific characteristics of any variable such as precipitation is generally validated by comparing the model simulations with the observed data either based on grid values (Mehran et al. 2015) or area averaged values (Dike et al. 2015). In this study, the 34 years baseline (observed) data were used for calibration (1980-1996) and validation (1997-2013) of SDSM, and the spatial and temporal standard error (SE) of predictions and R square (R^2) were used to assess the relative comparison in results of multivariate regression models for each station. In addition, comparing the calibration and validation periods, it is clear that the validation period (Table 4) has better SE and (R^2), and therefore the performance of SDSM can be considered satisfactory for simulation and projection purposes.

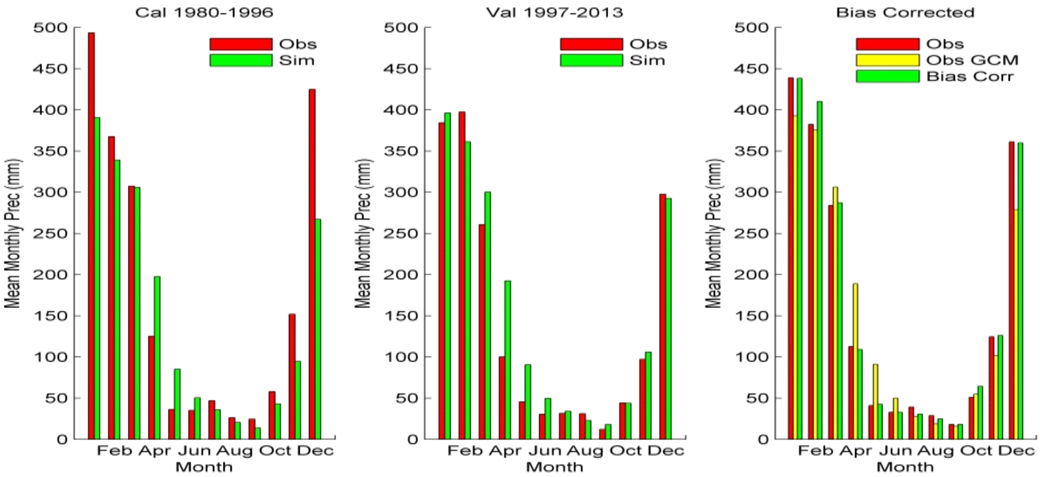

Fig.3: SDSM calibration and validation results.

Table 5: SDSM performer in different studies.

Prec (R^2 %)	Study area	References
28	Toronto	Wilby et al. (2002)
38	Upper Blue Nile basin, Ethiop	Bekele (2009)
13 - 29	Upper Tiber basin central, Italy	Fiseha et al. (2012)
15 - 45	Mountainous regions of Japan	Wilby et al. (1998)
6 - 10	Greater Montreal region	Nguyen et al. (2004)
5 - 13	Upper-Elqui watershed, Chile	Souvignet et al. (2010)
11-35	Wami-Ruvu River Basin (WRRB)	Gulacha&Mulungu (2016)

Similar to most previous studies (Table 5) the calibration outcomes showed that the results of this study are equally of a low performance. This may point to the fact that SDSM may not be the right downscaling model for precipitation in the study area. However, this is subject to the use of longer calibration period (25 years) to account for some of the variability in the observed data (Souvignet et al. 2010).

Fig. 3 illustrate the observed and modelled precipitation at the cluster A in calibration step (1980-1996) and validation step (1997-2013). The calibration results of this study showed that the SDSM may not be the right downscaling model for precipitation in this study because SDSM has no higher accuracy in precipitation, but can be adjusted by bias correction to force the model to replicate the observed data (Saraf & Regulwar 2016).

It is difficult to develop perfect multiple regression equation for precipitation due to its conditional behaviour, because there is an intermediate process between regional forcing and local weather (Wilby & Dawson 2004). Downscaling for precipitation is more problematic than temperature (Hassan & Harun 2011). Figs. 3a and 3b show the comparison of observed and simulated results during the calibration and validation period, and Fig. 3c depicts the GCM historical time series compared with bias corrected one. The analysis was carried out by comparing the generated twenty synthetic weather points with the observed weather data (cluster A) and then the historical GCM observed were compared with bias corrected. The seasonal variation of simulated precipitation presented a trend similar to that of the observed precipitation, but during calibration, there was an overestimation in observed precipitation during all months, except April and May which were underestimated. This indicated the poor performance of SDSM in simulating the peak rainfall in the study area. For the validation step the observed precipitation was well simulated during the period July-December and overestimated for the rest of months. Corrected GCM historical data were compared to the observed climate data (Fig. 3c), and the results showed that the bias correction approach eliminated some biases from the daily time series of downscaled data, and simulations run with bias-corrected GCM variables fitted better with ob-

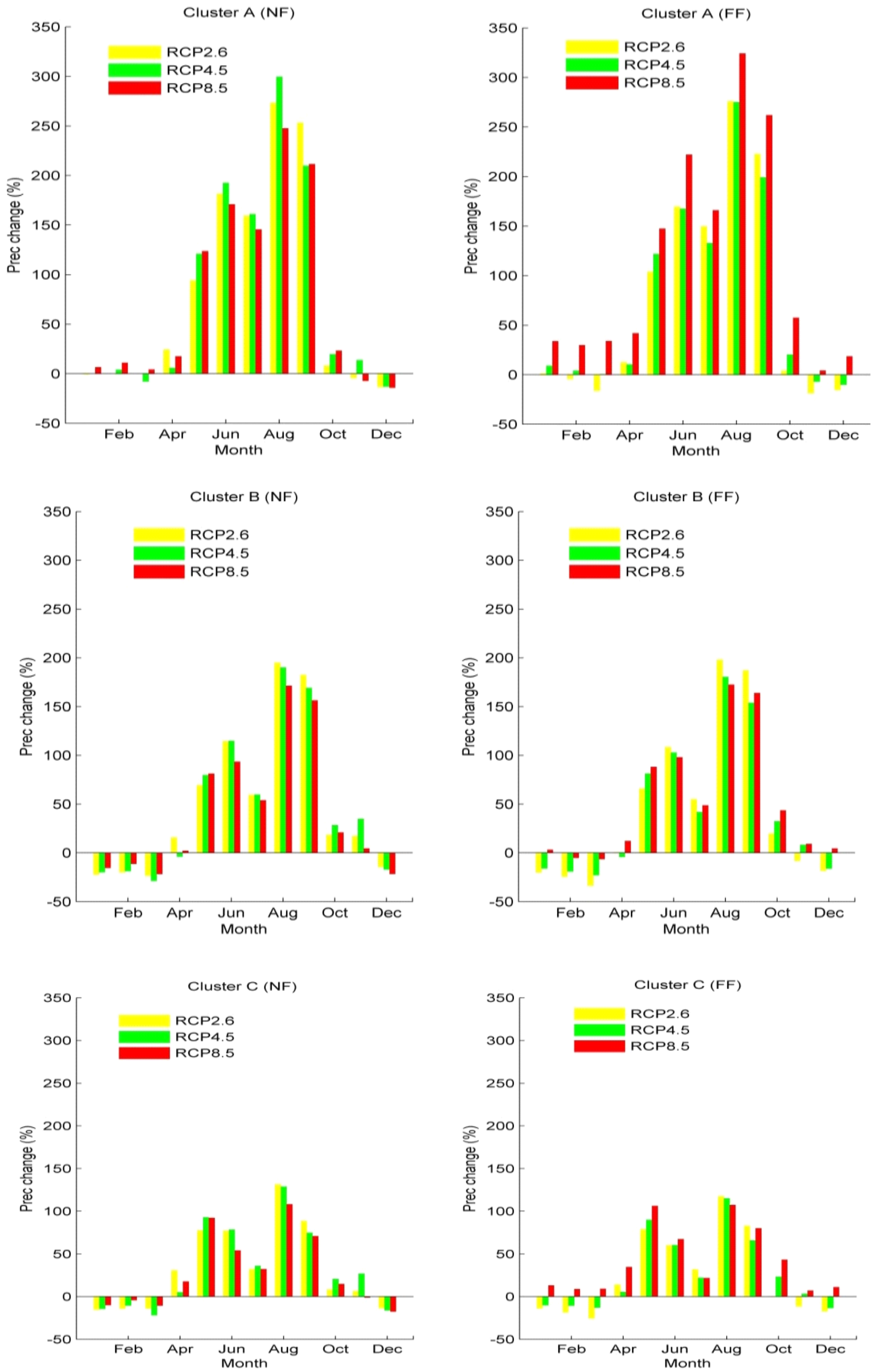
Cluster A (NF)
Cluster A (FF)
Cluster B (NF)
Cluster B (FF)
Cluster C (NF)
Cluster C (FF)
RCP2.6
RCP4.5
RCP8.5
Prec change (%)
350
300
250
200
150
100
50
0
-50
Feb
Apr
Jun
Aug
Oct
Dec
Month

Fig. 4 cont....

...Cont. Fig. 4

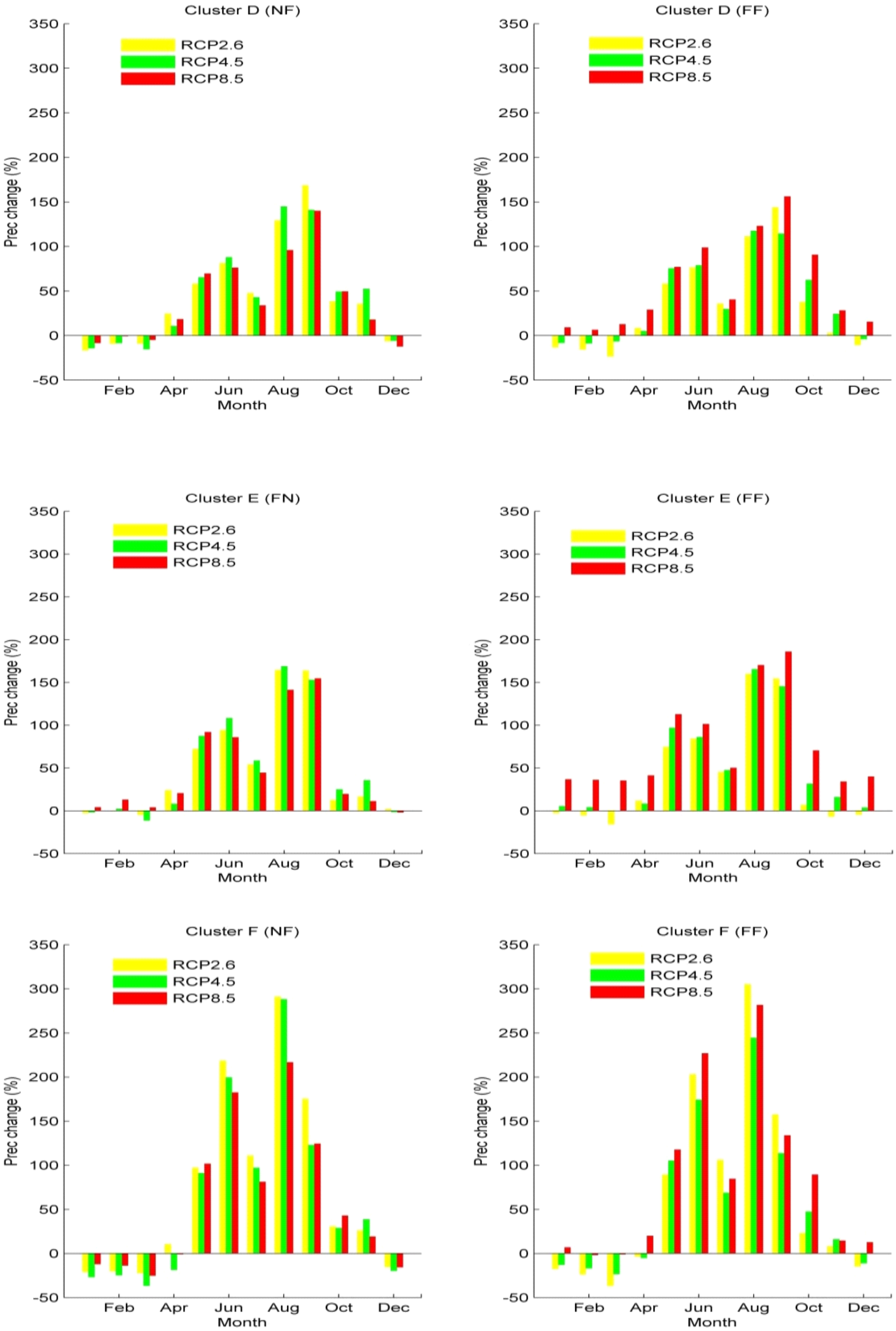

Fig. 4: Monthly precipitation changes during FF (far future) period.

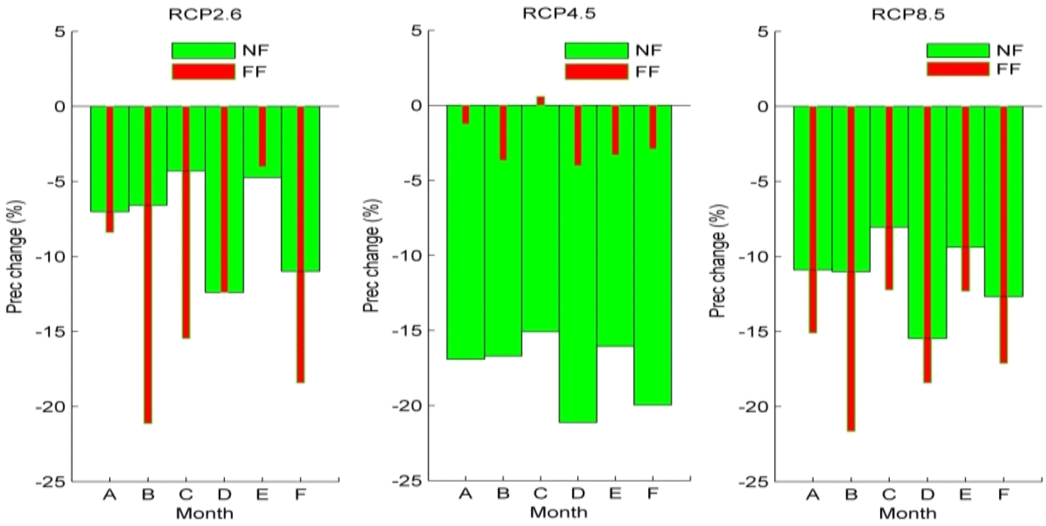

Fig. 5: Annual precipitation changes during NF and FF.

served values than simulations with uncorrected GCM climate variables, moreover, the former had more narrower variability bounds.

Projected Monthly Precipitation

Projected intra-annual variability of precipitation: Monthly statistics analyses are categorized as the suitable form of evaluating the characteristics of change in rainfall patterns (Gulacha & Mulungu 2016). The intra-annual variability results of precipitation were obtained by comparing the future projection with the baseline period and are presented in Fig. 4.

The upward change (%) of precipitation in different months and under different scenarios is presented. It can be found from Fig. 4(a) through to Fig. 4(f) that the difference in increasing and decreasing precipitation change for NF are presented as follows: 273 ~ -13.62%, 299 ~ -13.16%, 247.7 ~ -14.26% for cluster A (Fig. 4a); 195.13~ -23.77%, 190.12 ~ -28.91%, 171.34 ~ -22.03% for cluster B (Fig. 4b); 131.58~ -15.50%, 128.96 ~ -21.94%, 108.20 ~ -17.72% for cluster C (Fig. 4c); 168.83 ~ -16.74%, 144.84 ~ -15.45%, 140.10 ~ -12.40% for cluster D (Fig. 4d); 164.61 ~ -4.87%, 169.01 ~ -11.50%, 154.81 ~ -2.17% for cluster E (Fig. 4e); and 291.23 ~ -22.41%, 288.24 ~ -36.80%, 216.76 ~ -25.35% for cluster F (Fig. 4f) under RCP2.6, RCP4.5, RCP8.5, respectively. The greatest monthly increase and decrease (291.23% and -36.80%, respectively) is observed in cluster F in the month of August and March for RCP2.6 and RCP 4.5 respectively. In the case of this study, the change of 291.23% in the month of August represent a 5 mm change. For this month, it is normal because during this period (dry period) normally there is no precipitation, the maximum precipitation observed in this month during the baseline period (1980-2013) was 12 mm.

For example, (Kane 2009) showed that annual rainfall in southern Africa had considerable year-to-year fluctuations (50% to 200% of the mean), although most studies (Andersson et al. 2009, Hudson & Jones 2002) indicate future reduction in rainfall of up to 50%. Projected future changes in mean seasonal rainfall in southern Africa are less well defined (Wfp 2015).

Comparatively, from Fig. 4(a) to Fig. 4(f) there is a similar range of changes for both NF and FF for all six clusters and scenarios. Generally, a decrease in precipitation is observed during the wet period (October-March) and an increase during the dry period (April- September).

Projected Mean Annual Variability of Precipitation

Fig. 5 shows the average annual precipitation change during NF and FF for RCP2.6, RCP4.5 and RCP8.5 scenarios. It clearly shows that the projected annual precipitation will decrease with time for all scenarios and in all clusters (A, B, C, D, E, and F). RCP4.5 and RCP8.5 exhibit the highest decrease -21.65% for NF and -22.12% for FF, respectively.

Similar result was presented by Beilfuss (2012) which indicated that the Zambeze River Basin is expected to become hotter and drier with 10-15% reduction in rainfall. Besides, many climate change models, predict a 5 to 15% decrease of growing season rainfall in southern Africa (IPCC

2001). Yanda et al. (2011) projected a 3-23% decrease in rainfall attributed to climate change in southern Africa. Projection in precipitation over Europe indicate an increase in northern Europe (5 to 20%) and a decrease (-5 to -30 %) in southern Europe for the period 2080-2099 with the intermediate IPCC SRES A1B (Raisanen et al. 2004). According to Ragab (2004) the annual average rainfall decrease is expected in southern Africa (Angola, Namibia, Mozambique, Zimbabwe, Zambia, Botswana and South Africa) ranges from 5-15% in the south and by 5-10% in the north.

Further, in all the clusters, for both NF and FF there is a consistent decrease in annual precipitation change, which applies to all scenarios, except RCP4.5 (FF) that has a slightly despicable increase. Cluster B shows the largest decrease, while cluster A shows the smallest decrease and it can also be ascertained that, there is no significant relationship between the decrease change and the elevation.

According to Kusangaya et al. (2014), several studies in South Africa showed that rainfall in the region is characterized by high inter-annual variability. Annual rainfall did not have a clear tendency in the last two or three decades, but most concur that dry periods in southern Africa have become longer and more intense (Kusangaya et al. 2014). The basic conclusion from the analysis of rainfall trends is that changes in rainfall are subject to considerable uncertainty, regarding the extent (spatial and temporal) and magnitude of change (Yanda et al. 2011). Part of the basin will experience increase in the mean precipitation and another decrease.

CONCLUSIONS

Generally, in this study, SDSM was applied to simulate and project the future precipitation. The data generated during validation of SDSM showed that the model was not able to replicate observed precipitation very well. This is due to its conditional nature and high variability in space. It has been shown that there is a decrease in precipitation during wet period (October-March) and an increase during the dry period (April-September). The upward monthly increase in projected precipitation expected in August (300%, 325%) with RCP 4.5 and the maximum decrease is recorded in March (38%) with RCP 4.5 for all scenarios in both NF and FF respectively. It also clearly shows that the projected annual precipitation will decrease with time for all scenarios. Furthermore, it was observed that the maximum decrease will range from 7-21.8% for NF and 2-21% for FF. The highest decrease will be observed with RCP4.5 for NF and RCP8.5 for FF.

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