Tanzania CMIP5 Climate Change Projections

[1]Wambura, F., [2]Tumbo, S., [3]Ngongolo, H., [3]Mlonganile, P., and [3]Sangalugembe, C.

[1]Ardhi University (ARU)

[2]Sokoine University of Agriculture (SUA)

[3]Tanzania Meteorological Agency (TMA)

Abstract

This paper presents updated climate change projections for Tanzania based on Coupled Model Intercomparison Project phase 5 (CMIP5) using Mid-Century Representative Concentration Pathway (RCP) 8.5. A total of twenty global circulation models (GCMs) were downscaled based on the eleven Tanzania climatological zones using thirteen synoptic weather stations. For each climatological zone, the skill score test of the 20 GCMs was done against the observed rainfall and the threshold of 80% except for one zone, which used threshold of 75%, to select GCMs for projecting future rainfall and temperature. It was found that in all the climatological zones the number of GCMs which performed above the threshold ranged between five and twelve. Rainfall and temperature of skilled GCMs were then downscaled by Delta method and then evaluated for uncertainty. The skill score test showed that climatological zones in the western part of Tanzania had higher skills and higher agreement compared to zones located in the eastern side. Stations in the bimodal rainfall zones such as Musoma and Same showed high level of uncertainty in the projected future rainfall and temperature. Temperature uncertainty was ± 0.4 ^{o}C for Same, Musoma and Dodoma stations followed by Songea and Mbeya at ± 0.3 ^{o}C. On average, temperature was projected to increase by about 0.9 ^{o}C and also rainfall to increase but mainly in the month of April in the central and southern zones.

Key words: *CMIP5, Delta method, Temperature, Rainfall, Uncertainty.*

1. Introduction

Climate change is recognized as a global problem. Therefore, it is imperative for nations to view the world's climate in broad cooperative perspectives to fully understand its nature and behaviour, and to predict its future course. Predicting future climate well ahead can help to improve decision making in a wide range of activities. More important is perhaps the widely accepted precautionary principle of 'taking measures to anticipate, prevent or minimize the causes of climate change and mitigate its adverse effects' URT, (2003). Climate change is now a global issue posing challenges to the very survival of mankind and sustainable development. The adverse impacts of climate change are now evident almost everywhere URT, (2007).

GCMs are increasing becoming popular in simulation of future climate of Tanzania. Studies by Mwandosya et al., (1999); Matari et al., (2008) used Green House Gas Scenario (GHG) which involves Generic doubling concentration of carbondioxide (CO2) and incremental change in various combinations of temperature and precipitation in the atmosphere by 2100 in simulating the future climate in Tanzania. These projections did not involve GCMs; therefore the complex global circulations were involved in predicting future climate (White et *al.*, 2011). Kilembe *et al.*, 2011 predicted the climate change in Tanzania using CMIP3 climate models, CMIP3 used in the IPCC Fourth Assessment Report; involve the use of Special Report Emission Scenarios (SRES) which are A(s) and B(s) family of scenarios. The SRES(s) are distinguished by their consideration on global population, technology advancement, economic development and world integration to mention the few (AR4, 2007), but the Coupled Model Intercomparison Project Phase 5 (CMIP5) used in the IPCC Fifth Assessment Report (AR5, 2013); coordinated by the World Climate Research Programme in support of the IPCC AR5, is the most recent of these activities, and builds on CMIP3. The efforts for CMIP5 are enormous, with a larger number of more complex models run at higher resolution, with more complete representations of external forcings, more types of scenario and more diagnostics stored (Reto Knutti & Jan Sedláček, 2013).

Although climate has been predicted in various areas in Tanzania, but the performances associated with climate models used in prediction has not been detailed reported especially for the current GCMs (CMIP3 and CMIP5). Notter *et al.*, 2012 studied the hydrological impacts of climate change in Pangani Water basin in Tanzania, with focuses on climate forcings from individual General Circulation Model (s) under the criteria of just being the dries or the wettest. GCM simulated temperature can be relatively consistent between GCMs; the same is not true for rainfall. Indeed, projections of future rainfall from different GCMs often disagree even in the direction of change (Randall et al., 2007). Therefore there is a need to address the important issue of GCM performance score in predicting past climate before it is entrusted to be used in future rainfall prediction. GCM performance test can be done by several methods which compare observed and historical prediction of GCMs; some of these methods are mean and variance method, Root Mean Square Error (RMSE) and a season lag skill score test. Mwandosya *at el.,* (1998) researched on the impact of climate change on stream flows in Ruvu River Sub-basin; GCMs were selected by measuring their performance using the root mean squared error (RMSE) method. RMSE computes the error in the magnitude of GCMs against the observed data, thus the shift in seasons is not captured because the error is lumped in to the final value, but a season lag skill score test measures the relative lag between the GCM seasonal rainfall distributions and the observed data.

If a climate model that has been shown to already simulate seasonal variability that currently exists and will remain in the future (but becomes more likely to occur probabilistically), then we have identified that the model has skill in simulating future seasonal variability. Clearly, this confidence declines as the overlap between the present and future seasonal variability is reduced further into the future. Until the overlap becomes critically small, however, an impacts modeller could use how well a model simulated the whole seasonal variability of a set of variables as criteria for those models to use in future impacts assessments.

However even for the skilled GCM, its projection cannot be used without being downscaled because of the course resolution. Most of the GCMs have a resolution of 1.3^{o} x 2.7^{o} latitude and longitude scale. There are many methods available for downscaling GCM projections to the specific region or study area of interest, for discriminating between mean changes and changes in climatic variability and for ensuring consistency between climate change scenarios. The method ranges from complex procedures like dynamical and statistical downscaling to simple approaches like bias correction methods. However Fowler et al., (2007) reported that simple methods have been used for downscaling and found to be effective. The most common bias correction methods is the simple delta method (SDM), also called linear delta method.

All the skilled bias corrected GCMs; each one has equal chance of predicting future rainfall. However, since each one has its own future rainfall in terms of magnitude and direction thus it is very uncertain to use either of them on its own. Therefore the uncertainty in GCMs' rainfall projections has to be considered. Even the use of the driest and the wettest GCMs represents the uncertainty, but this kind of uncertainty does not include the fact that each skilled GCM has its very right of degree of applicability. The Median Confidence Interval (MCI) from the Median of projection is a convenient approach to estimate the band of uncertainty because it involves all the GCMs in estimating the parameters. In this study the CMIP5 climate were used to predict the mid century climate of Tanzania with incorporation of uncertainties associated with differences in projections among the skilled GCMs.

2. Material and Methods

2.1Materials

The climate of Tanzania (Figure 1) is characterized by two main rain seasons namely the long rains and the short rains which are associated with the southward and northwards movement of the ITCZ (URT, 2011). The long rains (Masika) begin in the mid of March and end at the end May, while the short rains (Vuli) begin in the middle of October and continues to early December. The northern part of the country including area around Lake Victoria Basin, North-Eastern Highland and the Northern Coast experience bimodal rainfall regime, whereby the first maximum occur in the period of March, April and May (MAM) while, the second maximum in the period of October, November and December (OND). Central, South and Western areas have a prolonged unimodal rainfall regime starting from November continue to the endof April. Annual rainfall varies from 550 mm in the central part of the country up to 3690 mm in some parts of south-western highlands (Chang'a et al., 2010).

There are about twelve rainfall zone falling in the two regimes (figure 1), with each rainfall zone having homogeneous rainfall within it zone. Table 1, shows the summary of rainfall amount in the rainfall zones taken from the zone rainfall stations.

Data use in this study were monthly rainfall data of thirteen rainfall stations (for eleven rainfall zones) obtained Tanzania Meteorological Agency (TMA) and GCM precipitation data from the Climate Model Inter-comparison Project Phase 5 (CMIP5) data base.

2.2Methods

Due to large inconsistence in precipitation as compared to temperature, thus only precipitation was used in selection of GCMs. Therefore measurement of the performance of the GCMs in predicting the rainfall seasonality during the control period was done using the skill score equation as shown in Equation 1

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$$SL_{score(jk)} = \sum_{1}^{12} \text{minimum} \left(\frac{GCM_{jk}}{GCM_{MAP_k}}, \frac{OBS_j}{OBS_{MAP}} \right) \quad [1]$$

Where, $SL_{score(jk)}$ is season skill score for month j, GCMk; GCM_{jk} is baseline mean monthly precipitation for month j and GCMk; GCM_{MAPk} is Baseline mean annual precipitation for GCMk; OBS_j is observed mean monthly precipitation for month j; and OBS_{MAP} is observed mean annual precipitation.

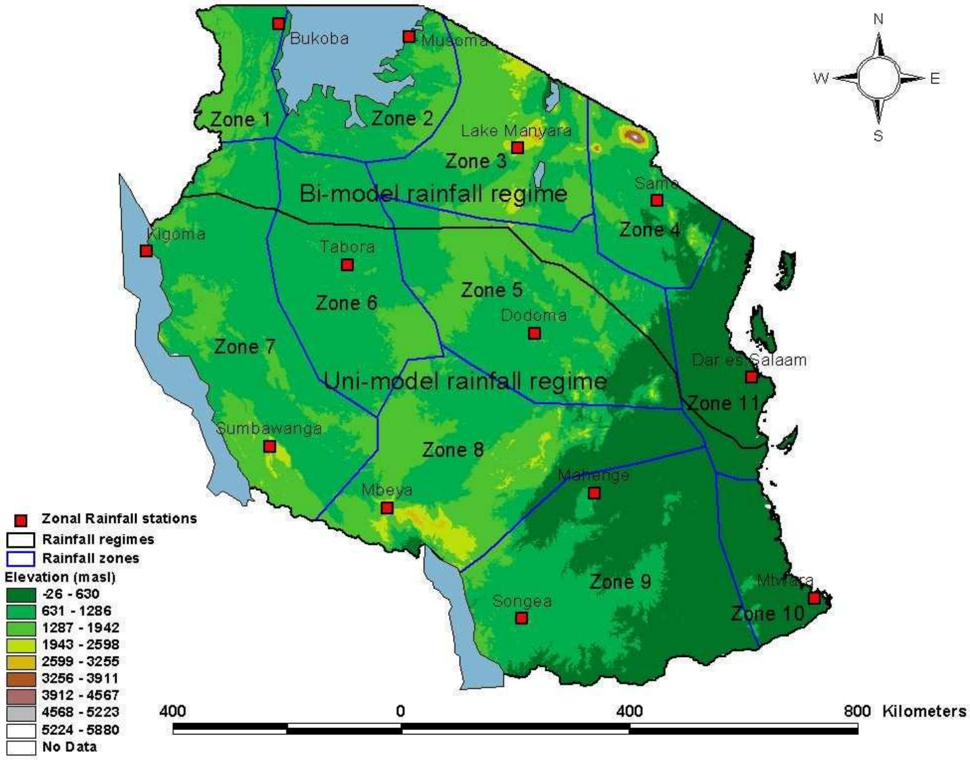

Figure 1: Map of Tanzania rainfall zones

Table 1: Summary of monthly rainfall amount (mm), 1980-2010

Station	Minimum	Average	Maximum
Bukoba	47.5	168.3	333.3
Musoma	15.1	74.5	174.4
Same	3.6	44.3	99.7
Tabora	0.8	79.1	201.3
Lake Manyara	16.2	82.2	213.5
Dodoma	0.0	49.6	136.7
Sumbawanga	2.0	75.0	184.7
Mahenge	9.7	195.3	485.0
Dar es Salaam	0.0	81.3	238.1
Mbeya	0.2	79.3	230.1
Songea	0.8	89.1	263.4
Mtwara	9.4	88.8	220.1

After obtaining the skilled GCMs for future projection of rainfall, the emission scenario of RCP 8.5 was selected for mid and end century terms because, the RCP 8.5 was selected because it has the highest rising rising radiative forcing pathway leading to 8.5 W/m2 (~1370 ppm CO2 equivalent), the highest baseline of greenhouse gas emissions, the highest increase in the use of cropland and grasslands and increase in atmospheric air pollution emissions by 2100. The underlying scenario drivers and resulting development pathways are based on the A2 scenario (CMIP3) detailed in Riahi et al. (2007). Thereafter the baseline (1980 – 2009) was suggested because it incorporates some of the strongest natural variability of climate, including the strongest El Nino Southern Oscillation (ENSO) warm event in 1997/1998 to a strong La Nina cold event in 1999/2000 (Anyamba et al., 2002).

Delta method was used for down-scaling the GCMs. It involved downscaling of GCM by the use of interpolation of the large grid. After the grids have been interpolated to specific point of interest, ratio of means of precipitation between the future projection of GCM and its baseline was applied to the observed data to result into future precipitation. SDM for downscaling precipitation is expressed formally by Equation 2 (Prudhomme et al., 2002).

$$P_{future\ (jk)} = OBS_{past\ (j)} \times \overline{GCM}_{future\ (jk)} / \overline{GCM}_{baseline\ (jk)}$$

Where, $P_{future\ (jk)}$ is the projected future GCM*k* precipitation for month *j*; is the observed precipitation $OBS_{past\ (j)}$ data for month, *j*; $GCM_{future\ (jk)}$ is the mean of future GCM*k* precipitation at month, *j* in the future data set and $GCM_{basline\ (jk)}$ is the mean of baseline GCM*k* precipitation at month, *j* in the baseline record

Downscaling of temperature by SDM (Equation 3) involves interpolation of grids to specific point of interest and then the difference of means between the future and baseline temperature is applied to the observed temperature to obtain the predicted temperature (Prudhomme et al., 2002).

$$T_{future\ (jk)} = TOBS_{past\ (j)} + (\overline{T}_{future\ (jk)} - \overline{T}_{baseline\ (jk)})$$

Where, $T_{future\ (jk)}$ is the projected future GCM*k* temperature for month *j*; $TOBS_{past\ (j)}$, is the observed temperature data for month *j*; $GCM_{future\ (jk)}$ is the mean of future GCM*k* temperature at month, *j* in the future data set and $GCM_{basline\ (jk)}$ is the mean of baseline GCM*k* temperature at month, *j* in the baseline record. The Median Confidence Interval (MCI) from the Median (Equation 4) of projected climate was found to be a convenient approach to estimate the band of uncertainty because it involves all the GCMs in estimating the parameters. For *n* equals one (1), there are no uncertainty bounds; for the case of *n* equals two (2) the bounds are the two values; for *n* equals three (3) the uncertainty bounds are the first and the last values from the ordered sample; but for n greater or equals to four (4), then Equation 5 is the appropriate for computation of uncertainty bounds. Using BPMCI in estimation of MCI, the sample must be ordered. For calculating the confidence interval the median and a distribution-free estimate of the variance of the median are determined. The following are the formulas used in estimation of median and its corresponding uncertainty bounds using MCI from the ordered sample of *n* items (Bonett and Price, 2002). For estimation of median, from a sample space;

$$\tilde{X} = \begin{cases} X_{\frac{(n+1)}{2}} , & \text{for } n = \text{odd} \\ \dfrac{\left(X_{\frac{n}{2}} + X_{\frac{n}{2}+1}\right)}{2} , & \text{for } n = \text{even} \end{cases}$$

For estimation of lower and upper uncertainty bounds, from the sample space;

$$\pm X_b = \tilde{X} \pm Z_{\alpha/2} \sqrt{\left(\frac{X_{\left(n - \left(\frac{n+1}{2} - \sqrt{n}\right) + 1\right)} - X_{\left(\frac{n+1}{2} - \sqrt{n}\right)}}{2\, z_j}\right)^2}$$

Where, the value of z_j from Table 1 in Bonett and Price (2002) depends on the size of the sample in question, and in question, and is the level of significance.

3. Results and discussion

3.1 Skill score test

In this test probabilities were developed for observed data for each zonal climate station and the GCMs' precipitation variables interpolated to that station. Then the skill score tests were done for each station against various GCMs using Equation 1. A threshold of 80% was used as suggested by Perkins, 2007. The same procedure was used for testing the skills of all GCMs against the zonal rainfall stations. Figure 2 show the performance of all the GCMs against each zonal climate station. It was found that most of the rainfall zones have more than a GCM which meet the threshold.

Some of GCMs showed small spatial uncertainty in simulating the past observed precipitation in for all the rainfall zones in the country (Figure 3), but unfortunately they did not have the average or minimum performance equal or above the threshold therefore the option of suggesting the use of some common GCMs for most part of the country did not succeed. Therefore treating each rainfall zone separately with its GCMs (regardless of whether any of the GCM at a rainfall zone appears inferior at another rainfall zone) was the only option left.

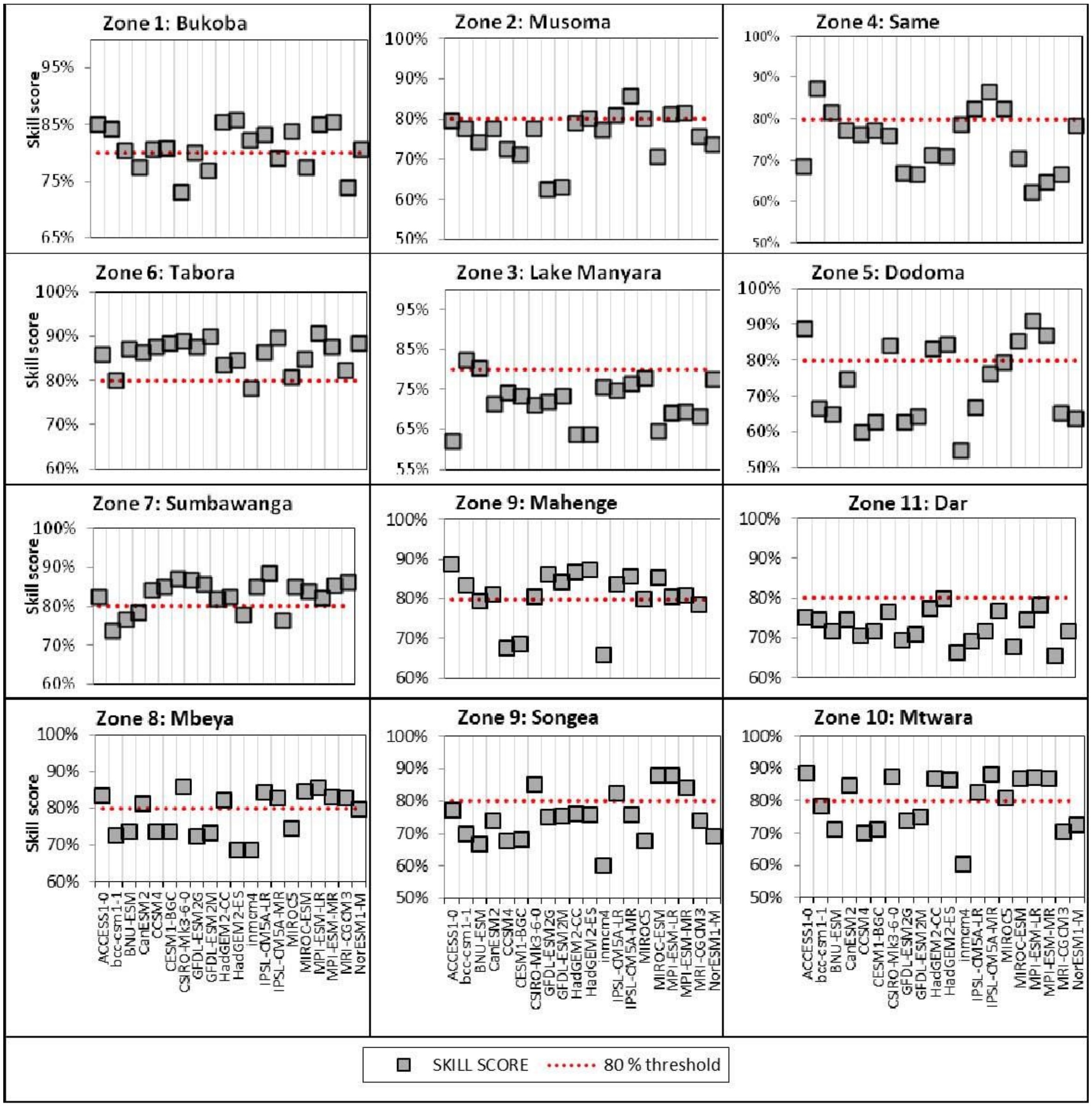

Figure 2: Skill score of GCMs against Observed precipitations

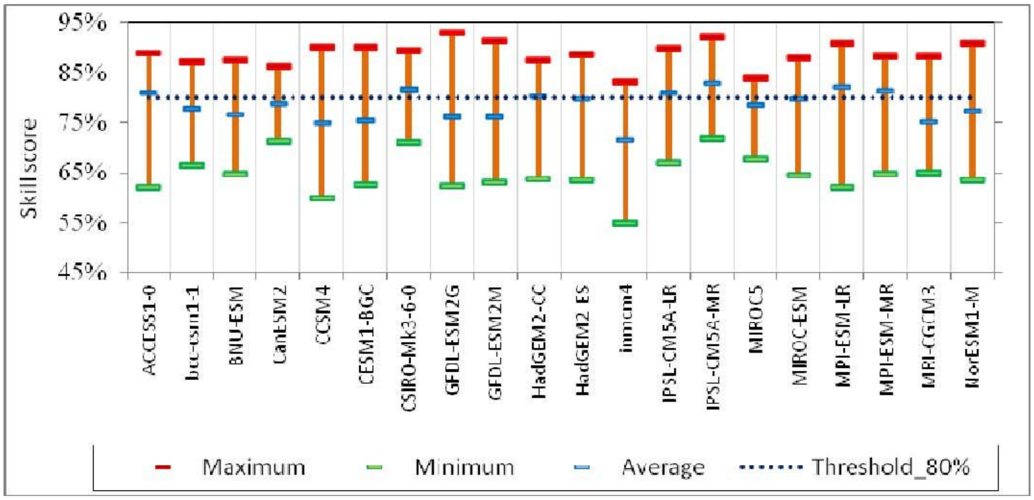

Figure 3: Skill score of GCMs across the country

3.2 Prediction with uncertainty

3.2.1 Temperature across the country

Table 2 shows that all the CMIP5 climate of the country. Although some southern models predicts increase in temperature at and northern parts like Songea shows the an average of 0.9 oC by the year 2050 highest change in temperature, but the across the country; the southern and predicted temperatures are relatively low northern parts of the country (Figure 1) as compared to baseline condition of some shows the highest change of temperature central parts like Dar es Salaam and as compared to the the central part (inland) Mahenge.

Table 2: Annual temperature at mid century period

Station	Baseline (°C)	Prediction (°C)	Change (°C)	Uncertainty (°C)	
Bukoba	21.9	22.7	0.8	±	0.2
Musoma	23.2	24.1	0.9	±	0.4
Same	22.8	23.7	0.9	±	0.4
Tabora	24.0	24.9	0.9	±	0.2
Lake Manyara	19.1	19.9	0.8	±	0.2
Dodoma	25.1	26.0	0.9	±	0.4
Sumbawanga	23.9	24.7	0.8	±	0.2
Mahenge	27.2	28.1	0.9	±	0.2
Dar es Salaam	26.6	27.3	0.7	±	0.1
Mbeya	21.1	22.0	0.9	±	0.3
Songea	22.8	23.8	1.0	±	0.3
Mtwara	26.6	27.5	0.9	±	0.2

3.2.2 Rainfall across the country

The CMIP5 climate models predicts is decrease in rainfall by 26% in the northern part of the country(Same, Musoma and Bukoba) and Dar es Salaam by year 2050 (Table 3). However the uncertainty of GCM's precipitation is also higher in these areas. The central part of Tanzania year predicted to have high increase in rainfall by 9% whereas the southern part is predicted to have increase in rainfall by about 13%.

Table 3: Annual precipitation at mid century period

	Baseline	Prediction	Change		Uncertainty	
	(mm)	(mm)	(mm)	(%)	(mm)	(%)
Bukoba	2020	1943	-76	-4	± 68	± 3
Musoma	894	884	-10	-1	± 147	± 17
Same	532	531	-1	0	± 143	± 27
Tabora	949	1030	82	9	± 17	± 2
Lake Manyara	987	1051	65	7	± 153	± 15
Dodoma	595	658	62	10	± 42	± 6
Sumbawanga	899	1005	106	12	± 11	± 1
Mahenge	2344	2449	105	4	± 80	± 3
Dar es Salaam	1097	1081	-17	-2	± 55	± 5
Mbeya	951	1074	123	13	± 19	± 2
Songea	1069	1258	189	18	± 50	± 4
Mtwara	1066	1155	89	8	± 50	± 4

Figure 4, shows that the level of uncertainty is also higher in the north eastern part of the country as compared to other areas, the uncertainty is highly found in months with rainfall. The southern part of the country also shows presence of uncertainty, but this one expresses the shift of starting of rain seasons.

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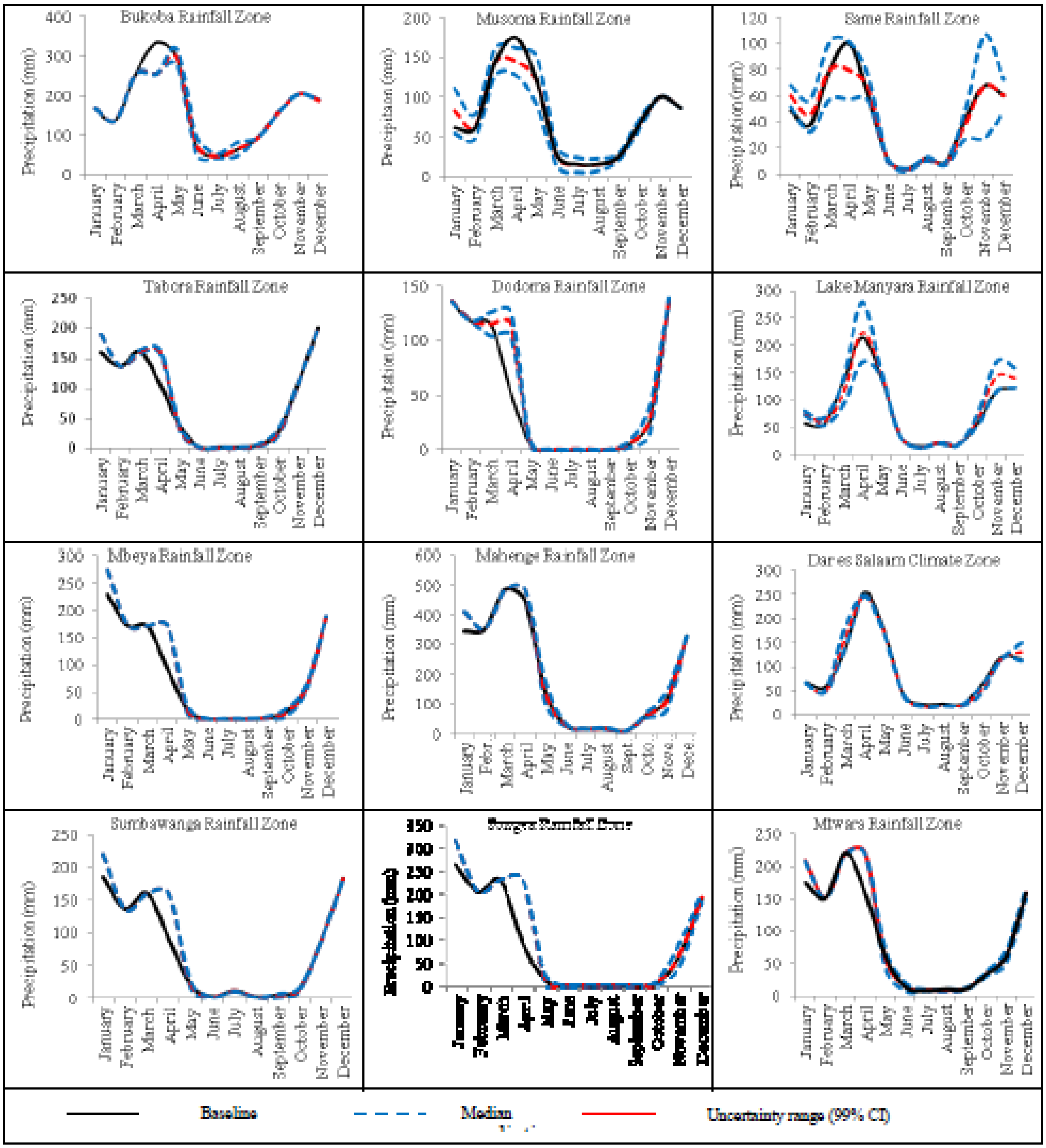

Figure 4: Predicted precipitation with uncertainty

3.3 Comparisons of previous studies against CMIP5 prediction

Mwandosya *et al.*, (1998) predicted rise in mean daily temperature, on average, by 3 to 5$_{o}$C, and a rise in mean annual temperature on average by 2 to 4 $_{o}$C (Table 4) throughout the country. The study by Matari *et al.*, (2008) indicates that the mean annual temperatures are projected to rise by 1.7 $_{o}$C over north eastern areas of the country

The climate projection by Kilembe *et al.*, (2013) expresses that the CNRM-CM3 and ECHAM 5 models projects median increase of 2.1°C. The CSIRO Mark 3 and MIROC 3.2 models also exhibit median temperature increases of around 1.0°C. The MIROC 3.2 model seems to exhibit spatial variability, which ranges from 0.5°C to 2°C across the country (Table 4).

In this study the mean annual temperature is predicted to rise by 0.7 to 1.0°C across the country (Table 4); the study involved the use CMIP5 climate models with emission scenario, RCP8.5. Despite the differences in climatology of projections, but the changes from the baseline temperatures have been reduced as the capacity of modeling the circulation systems increases; from $2CO_2$ to CMIP3 and then CMIP5 (Table 4).

Table 4: Comparison of Climate change prediction in Tanzania

		Mid term (2050)		End term (2100)	
Authors	**GCMs**	**Temperature change (oC)**	**Rainfall change (%)**	**Temperature change (oC)**	**Rainfall change (%)**
Mwandosya *et al.*, (1998)	2CO2	-	-	2.0 ~ 4.0	5 ~ 45
Matari *et al.*, (2008)	2CO2	-	-	1.7 ~ 2.5	-6 ~ 17
Kilembe *et al.*, (2011)	CMIP 3	1.0 ~ 2.1	-100 ~ 300 *	-	-
This study	CMIP5	0.7 ~ 1.0	-4 ~ 18	-	-

* figures in millimetre of rainfall

The rainfall prediction by Mwandosya *et al.*, (1998) indicates that bimodal rainfall pattern will have increased rainfall ranging from 5 to 45% and unimodal rainfall will experience reduced rainfall ranging from 5 to 15% (Table 4). Matari *et al.*, (2008) indicated that there will be increase in annual precipitation over the whole country by 10% (Table 4).

Using CMIP3 climate models, the projected change of rainfall in Tanzania ranges between -100 and 300 mm per year (Table 4). Kilembe *et al.*, (2013) reported that MIROC 3.2 model projects increase in precipitation of around 200 to 300 mm per year. The ECHAM 5 model projects that most of Tanzania will not have significant change in rainfall except around Lake Victoria, where rainfall is projected to increase by between 100 and 200 mm per year. The CRNM-CM3 model predicts rainfall dropping by around 100 mm per year around Lake Victoria; the model also predicts an increase of 50 –100 mm per year for the southern half of the country.

CMIP5 projection of rainfall in this study shows that rainfall will range from -4 to 18 % throughout the country (Table 4); this is equivalent to projection changes from -76 to 189 mm (Table 3) of rainfall. In comparison with $2CO_2$ the prediction of rainfall decrease and increase do not differ much, but CMIP3 results are comparable in the decrease in rainfall but the difference is twice as much for the case of increase in rainfall (Table 4).

4. Conclusion

CMIP5 climate models show that the western part of Tanzania had higher skill scores and higher agreement compared to zones located in the eastern side. Stations in the bimodal rainfall zones showed high level of uncertainty in the projected future rainfall and temperature. On average, temperature was projected to increase by about 0.9°C and also rainfall to increase but mainly in the month of April in the central and southern zones.

CMIP5 climate projections which were developed using a new set of RCPs climate forcing scenarios (van Vuuren *et al.*, 2011) reflect recent advancements in integrated assessment modeling to characterize future developments in global greenhouse gas (GHG) emissions. Therefore, CMIP5 projections represent a new opportunity to improve our predictions of future climate in localized environment in Tanzania.

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7. Appendices

Appendix 1: GCMs performance for each rainfall zone in Tanzania.

Station	**Minimum Score (%)**	**Average Score (%)**	**Maximum Score (%)**	**Number of GCMs (Score >= 80%)**
Bukoba	73	81	86	14
Dar es Salaam	65	73	80	1
Dodoma	55	73	91	7
Kigoma	81	88	93	20
Lake Manyara	62	72	82	2
Mahenge	66	80	89	14
Mbeya	69	78	86	10
Mtwara	60	79	89	11
Musoma	62	76	86	6
Same	62	74	87	5
Songea	60	75	88	5
Sumbawanga	74	83	88	15
Tabora	78	86	91	18

Appendix 2: Rainfall prediction with uncertainty at Bukoba Stations

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	167	167	0	± 0	± 0
February	138	138	0	± 0	± 0
March	255	255	0	± 0	± 0
April	333	255	-24	± 0	± 0
May	297	297	0	± 20	± 7
June	73	73	0	± 23	± 32
July	47	47	0	± 6	± 14
August	64	66	3	± 18	± 27
September	95	95	0	± 0	± 0

August	21	21	0	± 0	± 0
September	19	19	0	± 0	± 0
October	57	63	10	± 11	± 17
November	115	142	24	± 27	± 19
December	122	140	15	± 19	± 13

Appendix 3: Rainfall prediction with uncertainty at Dar es Salaam Station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	67	64	-3	± 0	± 0
February	58	48	-17	± 2	± 5
March	137	160	17	± 21	± 13
April	255	247	-3	± 0	± 0
May	174	168	-3	± 0	± 0
June	40	38	-6	± 1	± 3
July	22	16	-25	± 1	± 8
August	23	18	-22	± 1	± 3
September	22	20	-13	± 2	± 11
October	64	54	-15	± 8	± 14
November	120	116	-3	± 0	± 0
December	115	130	13	± 19	± 14

Appendix 4: Rainfall prediction with uncertainty at Dodoma station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	136	136	0	± 0	± 0
February	118	118	0	± 0	± 0
March	115	115	0	± 12	± 10
April	53	115	118	± 12	± 10
May	5	5	0	± 1	± 27
June	0	0	0	± 0	± 36
July	0	0	nil	± 0	± nil
August	0	0	0	± 0	± 53
September	0	0	0	± 0	± 53
October	5	5	0	± 3	± 53
November	26	26	0	± 12	± 47
December	137	137	0	± 3	± 2

Appendix 5: Rainfall prediction with uncertainty at Lake Manyara station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	58	77	31	± 5	± 6
February	56	60	7	± 7	± 12
March	134	112	-17	± 22	± 20
April	213	223	5	± 55	± 25
May	143	149	5	± 6	± 4
June	33	33	0	± 0	± 0
July	16	13	-20	± 1	± 7

August	21	21	0	± 0	± 0
September	19	19	0	± 0	± 0
October	57	63	10	± 11	± 17
November	115	142	24	± 27	± 19
December	122	140	15	± 19	± 13

Appendix 6: Rainfall prediction with uncertainty at Mbeya station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	230	274	19	± 0	± 0
February	172	172	0	± 0	± 0
March	171	171	0	± 0	± 0
April	92	171	85	± 0	± 0
May	18	18	0	± 5	± 30
June	1	1	0	± 0	± 19
July	0	0	0	± 0	± 0
August	0	0	0	± 0	± 19
September	3	3	0	± 1	± 28
October	14	13	-6	± 6	± 45
November	60	60	0	± 5	± 8
December	189	189	0	± 0	± 0

Appendix 7: Rainfall prediction with uncertainty at Mahenge station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	345	411	19	± 0	± 0
February	352	352	0	± 0	± 0
March	485	485	0	± 0	± 0
April	444	485	9	± 0	± 0
May	138	138	0	± 35	± 26
June	29	29	0	± 5	± 17
July	17	17	0	± 0	± 0
August	18	18	0	± 2	± 11
September	10	10	0	± 0	± 0
October	63	63	0	± 7	± 11
November	115	113	-2	± 31	± 27
December	329	329	0	± 0	± 0

Appendix 8: Rainfall prediction with uncertainty at Musoma station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	62	83	34	± 28	± 34
February	61	63	4	± 15	± 24
March	144	144	0	± 17	± 12
April	174	144	-17	± 17	± 12
May	120	120	0	± 30	± 25

June	26	24	-5	± 12	± 49
July	15	14	-5	± 9	± 63
August	15	15	-4	± 8	± 52
September	25	25	0	± 4	± 17
October	66	66	0	± 6	± 9
November	100	100	0	± 0	± 0
December	86	86	0	± 0	± 0

Appendix 9: Rainfall prediction with uncertainty at Mtwara station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	175	208	19	± 0	± 0
February	151	151	0	± 0	± 0
March	220	220	0	± 0	± 0
April	158	220	39	± 0	± 0
May	61	57	-7	± 15	± 27
June	14	14	0	± 6	± 45
July	9	9	0	± 1	± 13
August	11	9	-17	± 2	± 21
September	12	12	0	± 2	± 14
October	34	34	0	± 4	± 12
November	61	61	0	± 10	± 17
December	159	159	0	± 10	± 6

Appendix 10: Rainfall prediction with uncertainty at Same station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	48	60	24	± 8	± 14
February	38	45	19	± 12	± 28
March	79	79	0	± 22	± 28
April	100	79	-20	± 22	± 28
May	60	66	9	± 10	± 15
June	11	11	0	± 1	± 10
July	4	3	-7	± 1	± 29
August	12	12	0	± 1	± 12
September	10	8	-13	± 1	± 16
October	42	38	-9	± 11	± 29
November	68	68	0	± 40	± 59
December	60	60	0	± 13	± 21

Appendix 11: Rainfall prediction with uncertainty at Songea station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	263	314	19	± 0	± 0
February	204	204	0	± 0	± 0
March	230	230	0	± 0	± 0

April	93	230	148	± 0	± 0
May	12	14	10	± 9	± 63
June	1	1	0	± 0	± 14
July	1	1	0	± 0	± 0
August	1	1	0	± 0	± 35
September	1	1	0	± 1	± 69
October	5	5	0	± 5	± 86
November	65	65	0	± 25	± 38
December	192	192	0	± 11	± 6

Appendix 12: Rainfall prediction with uncertainty at Sumbawanga station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	185	220	19	± 0	± 0
February	136	136	0	± 0	± 0
March	160	160	0	± 0	± 0
April	90	160	78	± 0	± 0
May	21	21	0	± 5	± 25
June	2	2	0	± 0	± 0
July	11	11	0	± 0	± 0
August	2	2	0	± 0	± 0
September	5	5	0	± 3	± 61
October	15	15	0	± 3	± 17
November	90	90	0	± 0	± 0
December	183	183	0	± 0	± 0

Appendix 13: Rainfall prediction with uncertainty at Tabora station

	Baseline	Median prediction		Uncertainty	
	(mm)	(mm)	(%)	(mm)	(%)
January	159	190	19	± 0	± 0
February	137	137	0	± 0	± 0
March	161	161	0	± 3	± 2
April	106	161	52	± 3	± 2
May	38	34	-10	± 4	± 11
June	1	1	0	± 0	± 0
July	1	1	0	± 0	± 0
August	1	1	0	± 0	± 0
September	5	5	0	± 2	± 30
October	28	28	0	± 5	± 19
November	110	110	0	± 0	± 0
December	201	201	0	± 0	± 0