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Examining the Impact of Bias Correction on the Prediction Skill of Regional Climate Projections

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Abstract

Rainfall is crucial for many applications e.g. agriculture, health, water resources, energy among many others. However, quantitative rainfall estimation is normally a challenge especially in areas with sparse rain gauge network. This has introduced uncertainties in rainfall projections by climate models. This study evaluates the performance of three representative concentration pathways, RCP *i.e.* 4.5, 6.0 and 8.5 over Uganda using the Weather Research and Forecasting (WRF) model. It evaluates the model output using observed daily rain gauge data over the period 2006-2018 using Pearson correlation; relative root mean square error; relative mean error and skill scores (accuracy). It also evaluates the potential improvement in the performance of the WRF model with respective RCPs by applying bias correction. The bias correction is carried out using the quantile mapping method. A poor correlation with observed rainfall is generally found (−0.4 to +0.4); error magnitudes in the ranges of 1 to 3.5 times the long-term mean are observed. The RCPs presented different performances over different areas suggesting that no one RCP is universally valid. Application of bias correction did not produce realistic improvement in performance. Largely, the RCPs underestimated rainfall over the study area suggesting that the projected rainfall cases under these RCPs could be seriously underestimated. However, the study found RCP8.5 with slightly better performance and is thus recommended. Due to the general weak performance of the RCPs, the study recommends re-evaluating the assumptions under the RCPs for different regions or attempt to improve them using data assimilation.

Keywords

Representative Concentration Pathways, WRF Model, Rainfall Projections

1. Introduction

Developing countries e.g. Uganda normally suffer from the adverse impacts of extreme climate. Studies on future climates e.g. Tiyo *et al.* [1], Okonya *et al.* [2], Ongoma *et al.* [3], among others have generally projected increasing magnitudes and frequency of extreme weather events. Unfortunately, developing countries have lower adaptive capabilities [4] [5] [6] and less developed early warning mechanism [3] [6] which make them vulnerable to the negative impacts associated with these extreme events. The changes in climate have been attributed to increasing pollution levels and changes in environment due to changes in land cover and land use. Consequently, the concentration of atmospheric pollutants has been conceptualized into Representative Concentration Pathways (RCP) [7]. Four RCPs have been proposed, namely RCP2.6, RCP4.5, RCP6.0 and RCP8.5 [3] [7].

Future climate studies using General Circulation Models (GCMs) e.g. Giannini *et al.* [8], Kisembe *et al.* [9] among others, have projected enhanced wet conditions over East Africa. This is due to the weakening of moisture convergence over the Congo basin [8] [10]. The GCMs are normally used for simulating the climate on different spatial scales, *i.e.* mesoscale, regional and global scale [9] including different time-scales *i.e.* days, weeks, months, years and decades. However, these GCMs have been found to have coarser horizontal resolutions which are not useful for regional high impact studies [5] [9] [11]. An evaluation of selected 10 models within CODEX by Kisembe *et al.* [9] revealed that most regional climate models (RCM) reproduce the inter-annual rainfall variability but present a poor skill in reproducing the rainy seasons especially the March-May rainfall season. Additionally, dry days are normally overestimated and presented as drizzles in these numerical models [10] [12] [13].

An approach normally proposed to address the limitations of the GCM is using bias correction. It has been used in many studies e.g. Sharma *et al.* [14], Ghimire *et al.* [15], Noor *et al.* [7], Cannon *et al.* [16], Monaghan *et al.* [17], Piani *et al.* [13] among others. By carrying out statistical bias correction on daily rainfall, Piani *et al.* [13] found an improvement in the mean and representation of extreme events like droughts. Ghimire *et al.* [15] argue that bias correction results in reduced biases and improves accuracy of simulations. For this reason, Noor *et al.* [7] evaluated the bias correction methods *i.e.* linear scaling, gamma quantile mapping, generalized quantile mapping, and power transformation and noted that the power transformation method was the most suitable for bias correction of the GCM. However, Myo *et al.* [18] and Ghimire *et al.* [15] found the linear scaling method to produce the best performance and recommended it for hydrological studies at river basins. On the other hand, Mahmood & Mukand [19], and Sharma & Kumar [14] recommended the quantile mapping bias correction method. This could suggest that no one method is universally valid.

Additional efforts to improve the projections of GCMs using dynamical downscaling of RCMs have been proposed. This method has also been used in many studies e.g. Ouédraogo *et al.* [5], Kisembe *et al.* [9], Nalukwago *et al.* [20], among others. The RCMs are useful in down-scaling the coarse resolution of the GCMs to a higher resolution which is potentially useful for high impact studies [9] [21]. This is because the RCMs have a better representation of local features e.g. mountains [5] [9], land-cover and water bodies than the GCM [9] [21]. However, these RCMs normally inherit biases from the parent GCM [5] [21] which predisposes them to require robust validation over areas of interest before they can be reliably used.

It is therefore necessary to have a realistic representation of climate fields especially rainfall in climate models for high impact studies [11]. This is because understanding the physical basis of the climate models will help us to advance better prediction as argued by Giannini *et al.* [8]. Equally important is to have deeper understanding of the biases of these climate models at different spatial and temporal scales. For this reason, Piani *et al.* [13] has recommended this to enable high impact studies for improved vulnerability assessment. Additionally, the changing frequency of extreme weather events requires a detailed assessment to build realistic future occurrences [4] [5] [22].

In order to enhance our understanding of the future climatic evaluations, a couple of studies using RCPs/GCMs and experiments e.g. CORDEX have been proposed and widely carried out. For example, Ongoma *et al.* [3] evaluated 22 GCMs under the Coupled Model Inter-comparison Project Phase Five (CMIP5) over East African considering RCP8.5. They used gridded satellite rainfall data-sets from the Global Precipitation Climatology Center. However, this study uses observed rainfall data-sets and contends that the RCPs are not universally valid. This is what motivated the study and it seeks to answer the question: which RCP is realistic for Uganda and how can the uncertainty be decreased for future projections.

2. Materials and Methods

2.1. Data

This study used Lateral Boundary Conditions (LBCs) from the National Center for Atmospheric Research (NCAR) [17] [23]. It validated the model outputs using monthly rain-gauge data-sets from the Uganda National Meteorological Authority for the period 2006-2018. Like many climatic data-sets in developing countries, missing data were found and these were removed from the analyses. The LBCs used were obtained from the global bias-corrected climate model output data of version 1 of NCAR's Community Earth System Model (CESM1) that participated in CMIP5 [17] [24]. These data-sets are interpolated to 26 pressure levels and are provided at six hourly intervals and at $1^\circ \times 1^\circ$ horizontal resolution [23] [24]. The variables have been bias-corrected using the European Centre for Medium-Range Weather Forecasts Interim Reanalysis for fields from 1981 to 2005 [17]. The repository (https://rda.ucar.edu/datasets/ds316.1/) provides three input files, namely the Representative Concentration Pathway (RCP) future scenarios *i.e.* RCP4.5, RCP6.0 and RCP8.5. The study used these RCPs for the period 2006-2018.

2.2. Study Area

This study was carried out over Uganda and used 28 study locations as presented using **Figure 1**. Uganda is located within the latitudes: 1˚29'S to 4˚12'N and the longitudes: 29˚34'E to 35˚29'E [9] [10]. It is a landlocked country found in the eastern part of equatorial Africa [10] [12]. The country is relatively flat in the central with a few highland areas; and having mountains in the East (Mt. Elgon; Mt. Moroto) and west (Mt. Rwenzori). The country is endowed with fresh water bodies, namely Lake Victoria, Albert, Kyoga, Edward, Wamala, George among others and has a good climate condusive for agriculture [4] [20] [25]. Most areas of the country receive a bimodal rainfall distribution *i.e.* March-May and September-November with exception of the northern region whose rainfall distribution tend to be unimodal peaking around August [9] [12] [20].

2.3. Study Design

This study contends that the study carried out by Ongoma *et al.* [3] used GCM in the CMIP5 which were coarse *i.e.* largely coarse greater than 1.5˚ about 150 Km × 150 Km horizontal resolution compared to the horizontal resolution used in this study *i.e.* 30 km (about 0.3˚). Therefore, this study designs and runs a comparatively higher resolution validation experiment of the RCPs over Uganda and uses 28 study locations as presented in **Figure 1**. Additionally, the study carried out by Fotso-Nguemo *et al.* [27] over a comparatively similar region used gridded data-sets but this study uses observed station rainfall data-sets and uses comparatively a longer validation period *i.e.* 13 years (2006-2018).

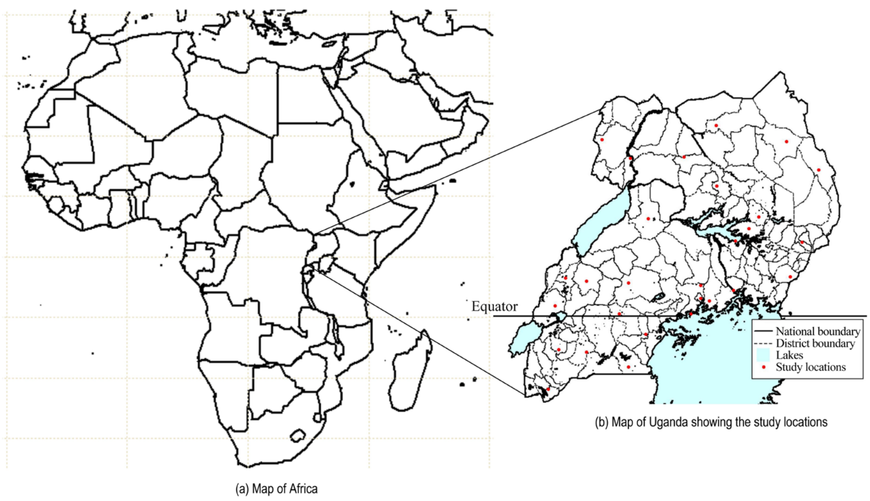

Figure 1. Shows the study area. (a) is the map of Africa showing the location of Uganda. (b) is the map of Uganda showing the study area and study locations. This figure is generated using an R-statistical programming language and the package is provided by [26].

This study first evaluates the performance of the RCPs in reproducing the observed climate patterns over the period 2006-2018 *i.e.* direct model output by running the Weather Research and Forecasting (WRF) model version 3.9 [10] [28] with boundary conditions of the three RCPs *i.e.* RCP4.5, RCP6.0 and RCP8.5 [17]. The direct model outputs are then bias corrected using quantile mapping (Equation (6)) to investigate any possible improvement in the performance as recommended by Sharma *et al.* [14], Ghimire *et al.* [15], Noor *et al.* [7], Cannon *et al.* [16], Monaghan *et al.* [17], Piani *et al.* [13] among others.

In running the WRF model, model the parameterization schemes used are adopted from Mugume *et al.* [29] and are presented using **Table 1**. These parameterization schemes are also used in Ingula *et al.* [30]. The study domain used in this study is shown using **Figure 2**. This study used single domain at 30 Km × 30 Km covering the equatorial Africa but analyses are carried out over Uganda shown with a red box in **Figure 2**.

2.4. Study Methods

The evaluation of the WRF model performance based on the three RCPs (RCP4.5, RCP6.0 & RCP8.5) is done using both continuous scores and categorical scores. The continuous scores comprise of the Pearson correlation coefficient, r, (Equation (1)) for assessing the relationship between observed and simulated; the relative root mean square error, $RMSE$ (Equation (2)) and relative mean error, ME (Equation (3)) for examining the error magnitudes. The categorical skill scores, namely the accuracy (Equation (4)) are obtained from the contingency table (**Table 2**).

$$r=\frac{\sum_{i=1}^{n}\left(p_i-\bar{p}\right)\left(O_i-\bar{O}\right)}{\left[\left(\sum_{i=1}^{n}\left(p_i-\bar{p}\right)^2\right)\left(\sum_{i=1}^{n}\left(O_i-\bar{O}\right)^2\right)\right]^{0.5}} \quad (1)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=n}^{n}\left[\frac{p_i-O_i}{LTM}\right]^2} \quad (2)$$

$$ME=\frac{1}{n}\sum_{i=n}^{n}\left[\frac{p_i-O_i}{LTM}\right] \quad (3)$$

where: p_i, O_i, LTM, and n are the model predicted i^{th} value, observed i^{th}, long-term mean, and number of observations respectively. The relative root mean square error $RMSE$ (Equation (2)) and the relative mean error, ME (Equation 3) presented in this study are as percentage of the LTM which is also used and recommended by Ongoma *et al.* [3]. This study used relative root mean square error and relative mean error in order to compare the performance against long-term mean.

Additionally, in this paper, the accuracy (*i.e.* hit rate) is defined as the proportion of hits (*i.e.* A_{11}, A_{22} and A_{33}) (**Table 2**) to total observations. So in this paper for a given location, i, the accuracy is:

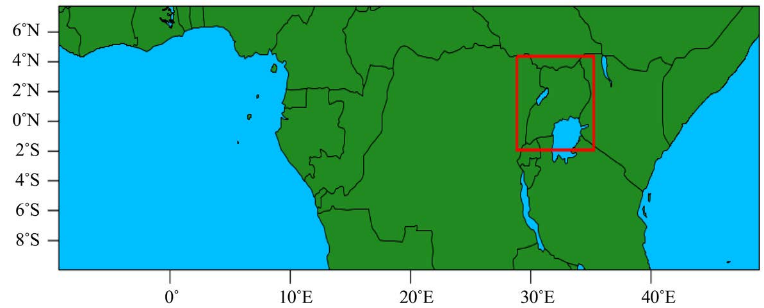

Figure 2. Shows the domain used in the study. While the domain covered the entire equatorial region, the main study was over Uganda, the red box inside the domain. The figure is generated by run an NCL programming code syntax.

Table 1. Shows the experiment set-up and the parameterization schemes in the study.

Set-up/Scheme	Description
Grid	Staggered Arakawa C grid with 33 vertical levels and model top at 100 hPa [10] [31]
Vertical coordinate	Terrain-following vertical coordinate with flexible vertical grid spacing [29] [32]
Integration	Runge-Kutta 2nd order integration option [10] [12] [33]
Cumulus scheme	Kain-Fritsch [31] [33]
Microphysics	WRF single moment-6 class scheme. Recommended by [10] [34]
Longwave	Rapid radiative transfer scheme [32]
Shortwave	Dudhia shortwave radiation [35]
Land surface model	Noah Land-Surface Model [36]
Planetary boundary layer	Yonsei University planetary boundary layer scheme [10] [37]

Table 2. Shows the contingency table as used in the study. "Below normal" is total rainfall less than 75% of the long-term mean; "Normal" is total rainfall within 75% to 125% of long-term mean; and "Above normal" is total rainfall greater than 125% of long-term mean.

		Model prediction		
		Below Normal	Normal	Above Normal
Observed	Below Normal	A_{11}	A_{12}	A_{13}
	Normal	A_{21}	A_{22}	A_{23}
	Above Normal	A_{31}	A_{32}	A_{33}

$$ACC_i = \frac{A_{11} + A_{22} + A_{33}}{n} \tag{4}$$

a hit is defined in this paper as, for example when model prediction is "below normal" and the observed is also "below normal" *i.e.* A_{11}; model prediction is "normal" and observation is "normal" *i.e.* A_{22}; and model prediction is "above normal" and observation is "above normal" *i.e.* A_{33} as illustrated in **Table 2**.

The contingency table used, as presented using **Table 2** is based on three cases, namely "below normal", "normal" and "above normal". These terms are in operational use by UNMA and are defined as captioned in **Table 2**. The long-term mean monthly rainfall used in the study is presented using **Table 3**. This study also used graphical analysis of line graphs and maps obtained using inverse distance weighting interpolation [38] and given by Equation (5).

$$p_i^* = \frac{\sum_{i=1}^{n} p_i w_i}{\sum_{i=1}^{n} w_i} \quad (5)$$

p_i^* is the interpolated precipitation amount from p_i neighboring stations weighted with w_i and n is the total of stations used to derive p^*.

2.5. Bias Correction Methods

A couple of methods for bias correction have been proposed which include:

Table 3. Shows the long-term mean monthly rainfall amount in millimeters (mm) used in the study. It is derived from the different publications e.g. dekadal reports issued by UNMA.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Arua	18	37	91	120	128	146	155	217	173	210	125	30
Buginyanya	45	73	124	217	234	180	190	243	199	217	134	41
Bushenyi	75	110	110	157	80	46	42	81	120	141	143	121
Entebbe	90	96	177	274	258	102	67	83	80	111	162	119
Gulu	17	29	85	166	176	152	169	238	175	187	109	37
Jinja	66	54	118	191	136	78	65	112	111	159	177	94
Kabale	65	81	113	140	98	29	20	54	99	111	117	89
Kakoge	36	41	111	161	137	59	76	101	133	164	128	55
Kamenyamigo	52	46	116	145	104	39	21	51	87	116	113	76
Kasese	31	40	116	152	106	54	31	84	64	123	101	68
Kibanda	52	47	70	137	121	41	19	36	60	82	85	73
Kitgum	25	23	77	138	148	148	136	154	142	166	81	36
Kituza	93	65	142	188	127	70	71	116	142	169	188	144
Kotido	6	33	83	100	105	131	118	84	58	90	7	7
Kyembogo	13	40	172	167	86	79	63	81	130	204	225	99
Kyenjojo	25	49	127	179	92	76	67	144	200	139	190	44
Lira	29	41	91	172	190	126	126	215	168	149	84	43
Makerere	51	62	113	182	140	75	50	86	101	109	114	97
Masindi	32	56	107	162	146	97	109	137	141	147	122	48
Mbarara	45	64	96	123	78	23	20	61	95	105	120	75
Moroto	10	27	72	120	121	71	122	94	51	47	49	25
Mubende	32	70	160	178	89	29	49	87	120	106	82	67
Namulonge	50	61	131	145	116	68	59	90	129	129	111	78
Ntusi	36	53	96	103	97	24	36	105	127	136	152	72
Serere	29	28	115	190	192	72	79	123	149	151	123	48
Soroti	32	56	107	162	146	97	109	137	141	147	122	48
Tororo	55	78	138	225	224	108	96	118	111	125	109	78
wedalai	47	45	165	159	158	137	157	168	184	184	213	160

scaling [7] [18]; gamma quantile mapping [7]; generalized quantile mapping [7] [16] [19]; and power transformation [7], among others. This study has adopted the generalized quantile mapping method to examine any potential improvement in the skill as simulated by the WRF model with different initial conditions based on the different RCPs (*i.e.* RCP4.5, RCP6.0 & RCP8.5). Quantitle mapping has been proposed by [19] and presented using Equation 6. This method is also used and promoted by [14] while assessing the changes in precipitation and temperature over the Teesta River basin in the Indian Himalayan region under climate change.

$$p^* = p_{rcp} \times \left[\frac{\overline{p_{obs}}}{\overline{p_{rcp}}} \right] \tag{6}$$

where p^* is the bias corrected precipitation estimate from the model; p_{rcp} is the direct model output without bias correction and p_{obs} is the observed precipitation and $\overline{p_{obs}}$ and $\overline{p_{rcp}}$ are the mean values of p_{obs} and p_{rcp} respectively.

3. Results and Discussion

3.1. The Temporal Performance of the WRF Model for the Different RCPs

The performance of RCPs on monthly, seasonal and annual time scales is presented using **Figure 3** and **Figure 4**. These figures show the temporal simulation performance of WRF being driven by the different RCPs *i.e.* RCP4.5, RCP6.0 and RCP8.5 compared with the observed patterns. **Figure 3** is for the monthly trends over the study period *i.e.* 2006-2018 and Figure 4 is for the annual (**Figure 4(a)** & **Figure 4(b)**) and seasonal trends *i.e.* March-May (**Figure 4(c)** & **Figure 4(d)**) and September-November (**Figure 4(e)** & **Figure 4(f)**) over the study period.

The performance of the WRF model pre-processed with different RCPs on monthly scale as presented by **Figure 3** is generally poor and shows a negligible overall correlation *i.e.* of magnitudes less than 0.200. Some isolated overestimates are observed especially around 2016 and 2018. The results further show that the RCPs can overestimate the monthly rainfall to magnitudes in excess of about 400% for RCP8.5; RCP4.5 overestimates up to about 360% while RCP6.0 estimated up to 240% of the long-term mean. A critical analysis of **Figure 3** shows that 36.7% of observed monthly rainfall were below long-term mean; 63.3% for RCP4.5; 58.3% for RCP6.0; and 57.5% for RCP8.5. This suggested that the RCPs largely underestimated monthly rainfall over the study period. It is this underestimation that resulted in a smaller overall relative anomaly of −3.956% for RCP4.5; 1.265% for RCP6.0; and 4.870% for RCP8.5. A detailed performance for each of the stations used is presented using **Figure 5**.

Additional analysis of annual rainfall patterns revealed that the RCPs largely underestimate annual rainfall totals (**Figure 4(a)**). This performance however improves slightly with bias correction (**Figure 4(b)**). Further analysis of the results for seasonal performance *i.e.* **Figure 4(c)** & **Figure 4(d)** for the March-May rainfall season reveals that generally RCP4.5 and RCP8.5 underestimated the March-May rainfall over the study period with exception of RCP6.0. A slight increasing trend of the total March-May rainfall amount is observed at about 1.93% over the period and a coefficient of variation of 2.4 is observed. Whereas RCP8.5 reasonably reproduced this trend, it had the largest variability *i.e.* coefficient of variation of 7.3. Additional analysis of the September-November results (**Figure 4(e)** & **Figure 4(f)**) also revealed an increasing trend of about 1.43% over the period. The performance of RCPs during this period largely overestimated the seasonal rainfall. RCP4.5 has the smallest relative anomaly *i.e.* 4.984 but comparatively a higher variability, *i.e.* 12.8. On the other hand, RCP6.0 has the highest anomaly but a comparatively smaller variability, *i.e.* 7.1.

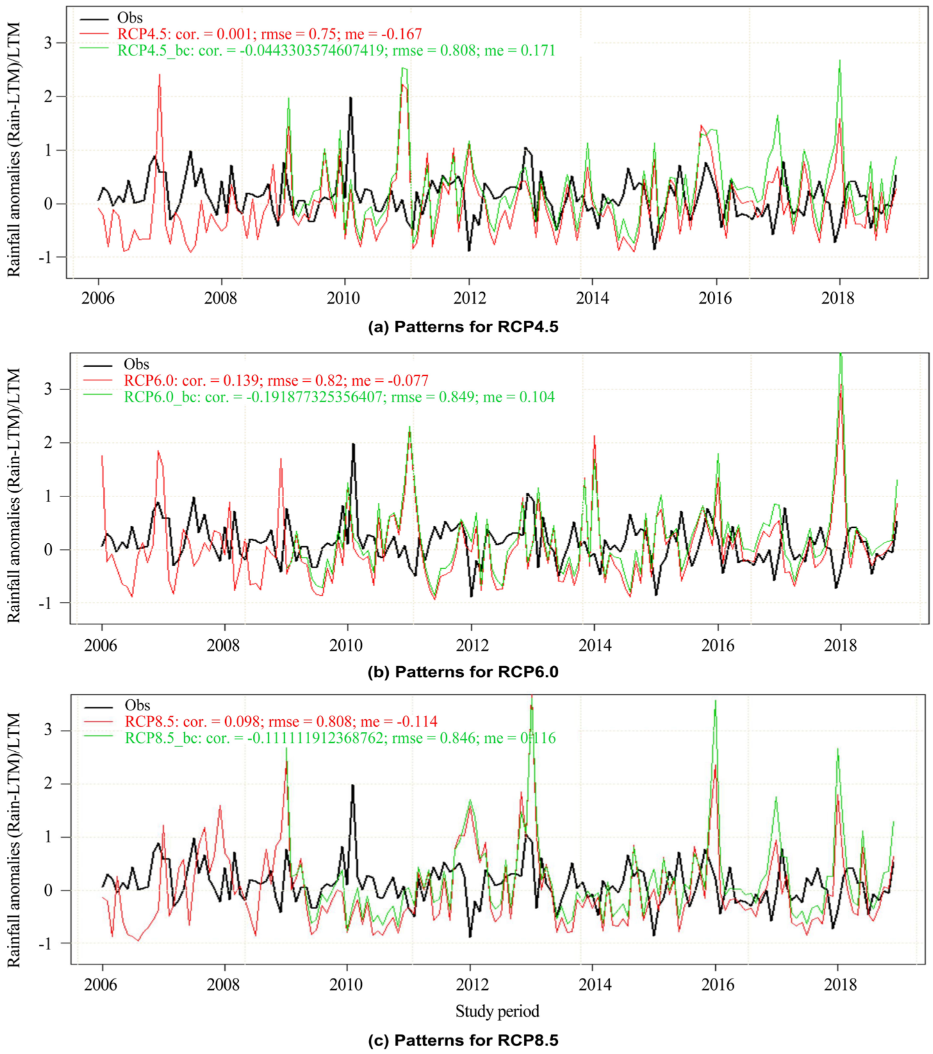

Figure 3. Temporal patterns of RCPs simulated monthly rainfall and observed rainfall. The scale of the vertical axis is for relative rainfall anomalies computed from simulated/observed rainfall less the long-term mean (LTM) and then divided by LTM. Positive values indicate overestimation above the LTM while negative values indicate underestimation of the LTM. They have been presented along with observed rainfall for comparison.

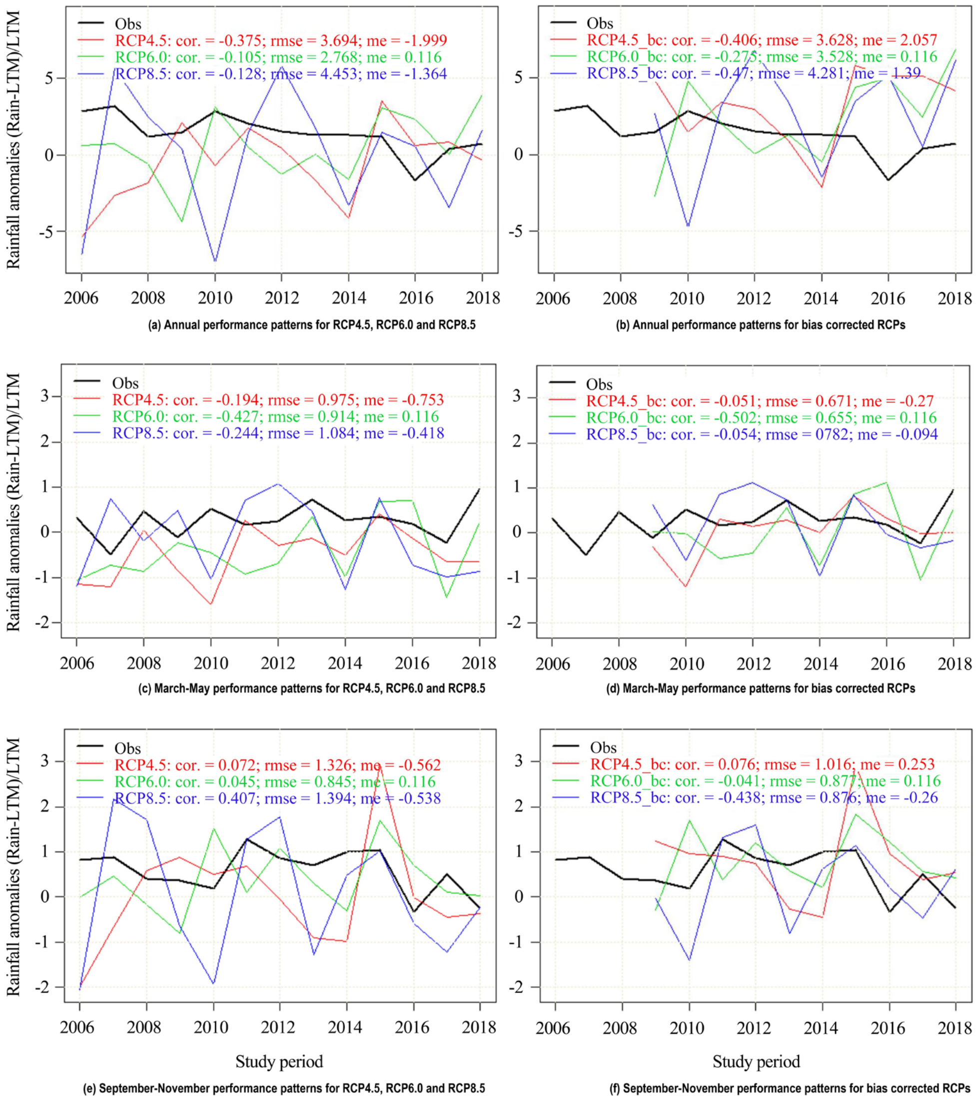

Figure 4. Temporal patterns of RCPs nationally averaged simulated seasonal rainfall and observed rainfall anomalies. (a & b) is for the performance on annual time scales; (c & d) is for the March-May rainfall season while (e & f) is for the September-November Season over the study period.

The results in this study are comparable to the findings of Ongoma *et al.* [3] over East Africa. They evaluated 22 models under the CMIP5 and found the models to have a comparatively lower skill over East Africa while Fotso-Nguemo *et al.* [27] found RCP8.5 to present rainfall magnitudes comparatively lower than the Global Precipitation Climatology Center (GPCC) and Tropical Rainfall Measuring Mission (TRMM). While using RCP4.5 and RCP8.5 and 10 GCMs along with linear scaling as the bias correction method, Myo *et al.* [18] found that these RCPs projected fluctuating average monthly precipitation but found that annual precipitation is likely going to increase. These results are consistent with our findings which make us conclude that the 21st century precipitation is going to be highly variable at monthly scale.

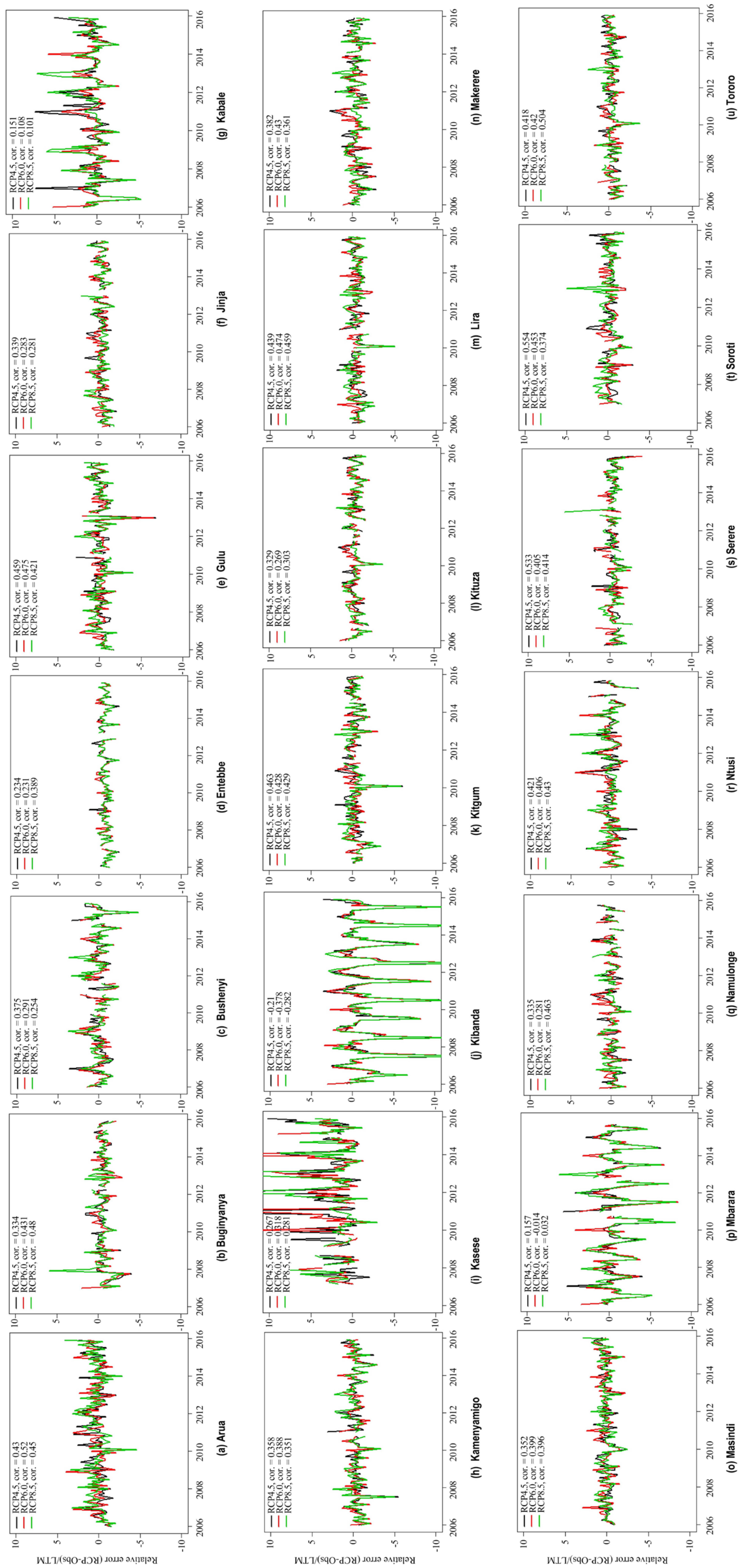

Figure 5. Time series of relative errors comparing the performance of the RCPs.

3.2. Spatial Performance of the RCPs

The spatial performance of WRF model driven by the three RCPs (RCP4.5, RCP6.0 & RCP8.5) considered in this study along with the bias corrected output using quantile mapping is presented using **Figures 6-8**. These figures are for correlation analysis (**Figure 6**); relative mean error (**Figure 7**), and relative root mean square error (**Figure 8**). Additional analysis is presented using **Tables 4-6** which present results per study location for correlation (**Table 4**); relative mean error (**Table 5**) and relative root mean square error (**Table 6**).

Table 4. Shows the correlation values at specific study locations. "Non bc" is direct model output without bias correction.

	Non bc			Bias corrected		
	RCP4.5	RCP6.0	RCP8.5	RCP4.5	RCP6.0	RCP8.5
Arua	−0.07	−0.17	−0.23	−0.08	−0.21	−0.25
Buginyanya	−0.03	−0.12	0.05	0.03	−0.12	0.13
Bushenyi	0.01	0.03	0.03	0.01	0.02	0.03
Entebbe	−0.02	−0.04	0.07	0.04	−0.01	0.15
Gulu	0.12	0.13	0.31	0.37	0.28	0.49
Jinja	0.03	−0.10	−0.04	0.02	−0.17	0.03
Kabale	−0.07	−0.07	−0.01	−0.07	−0.07	−0.01
Kakoge	−0.13	0.27	0.33	−0.40	0.29	0.25
Kamenyamigo	−0.07	0	0.06	−0.11	−0.01	0.10
kasese	0.03	−0.08	0.07	−0.03	−0.12	−0.03
Kibanda	−0.16	−0.23	0	−0.13	−0.16	0.05
kitgum	−0.18	−0.15	−0.16	−0.29	−0.21	−0.17
Kituza	0.03	−0.11	0.02	0.04	−0.10	0.10
Kotido	−0.01	−0.07	0.43	0.06	−0.08	0.45
Kyembogo	0.11	0.01	−0.11	0.09	0.01	−0.14
Kyenjojo	−0.05	0.03	−0.02	−0.06	0.04	−0.03
Lira	−0.10	0.11	0.04	−0.08	−0.04	0.04
Makerere	0.21	0.23	0.29	0.15	0.08	0.19
Masindi	0.16	0.05	−0.10	0.13	−0.02	−0.07
Mbarara	−0.18	−0.20	0	−0.24	−0.26	−0.01
Moroto	−0.06	−0.21	0.44	−0.10	−0.21	0.36
Mubende	−0.08	−0.06	−0.09	−0.08	−0.06	−0.09
Namulonge	−0.02	−0.08	0.21	0.02	−0.13	0.26
Ntusi	−0.07	−0.05	0	−0.12	−0.10	−0.04
Serere	0.14	−0.07	0.16	0.15	−0.03	0.22
Soroti	0.14	−0.06	0.16	0.03	−0.18	0.18
Tororo	−0.13	−0.12	−0.01	−0.10	−0.11	0.03
Wedalai	0.16	−0.10	−0.35	0.22	0.05	−0.36
Average	−0.01	−0.04	0.06	−0.02	−0.06	0.07

Table 5. Shows relative mean error magnitudes as a percentage of the long-term mean. "DMO" is direct model output *i.e.* not corrected for bias.

	Mean Error (DMO)			Mean Error (Bias corrected)		
	RCP4.5	RCP6.0	RCP8.5	RCP4.5	RCP6.0	RCP8.5
Arua	0.09	0.24	0.34	0.31	0.27	0.34
Buginyanya	−0.48	−0.37	−0.36	0.33	0.35	0.24
Bushenyi	0.20	0.15	0.11	0.13	0.02	−0.01
Entebbe	−0.79	−0.76	−0.82	0.24	0.21	0.18
Gulu	−0.43	−0.32	−0.27	0.06	0.02	0.19
Jinja	−0.32	−0.25	−0.32	0.11	0.02	0.03
kabale	0.03	0.04	0.16	0.12	0	0.04
Kakoge	−0.16	−0.18	−0.36	0.08	0.16	0.16
Kamenyamigo	−0.20	−0.16	−0.19	0.08	0.01	−0.06
Kasese	2.00	2.35	2.06	0.15	0.14	0.03
Kibanda	−0.05	−0.07	−0.06	0.22	0.10	0.07
Kitgum	−0.25	−0.10	−0.08	0.36	0.42	0.40
Kituza	−0.59	−0.57	−0.61	0.08	−0.01	−0.03
Kotido	0.89	1.85	0.01	1.51	1.39	0.70
Kyembogo	0.36	0.62	0.51	0.30	0.53	0.66
Kyenjojo	0.53	0.63	0.52	0.16	0.15	0.29
Lira	−1.11	−0.95	−1.00	0.29	0.27	0.32
Makerere	−0.38	−0.33	−0.4	0.17	0.06	0.06
Masindi	−0.29	−0.11	−0.19	0.04	−0.01	0.06
Mbarara	−0.08	−0.09	−0.06	0.20	0.06	0.04
Moroto	−0.38	0.09	−0.4	0.94	0.73	0.82
Mubende	0.59	0.62	0.52	0.14	0.08	0.18
Namulonge	−0.06	0.04	−0.03	0.08	0.01	0.01
Ntusi	0.11	0.21	0.14	0.19	0.11	0.09
Serere	−0.41	−0.36	−0.36	0.23	0.16	0.22
Soroti	−0.28	−0.22	−0.19	0.11	0.08	0.04
Tororo	−0.32	−0.21	−0.25	0.26	0.22	0.20
Wedalai	−0.08	0.01	0.03	0	0.03	0.19
Average	−0.07	0.06	−0.06	0.25	0.20	0.20

Table 6. Shows the relative RMSE over different study locations as a fraction of the long-term mean.

	RMSE (% of LTM)			RMSE (Bias corrected)		
	RCP4.5	RCP6.0	RCP8.5	RCP4.5	RCP6.0	RCP8.5
Arua	1.07	1.17	1.64	1.18	1.2	1.65
Buginyanya	1.14	1.32	1.19	1.49	1.82	1.37
Bushenyi	1.16	0.98	1.04	0.9	0.83	0.86
Entebbe	1.04	1.03	1.03	1.07	1.03	0.89
Gulu	1.26	1.23	1.19	1.24	1.29	1.41
Jinja	0.77	0.79	0.82	0.76	0.76	0.74
Kabale	1.5	1.29	1.56	0.9	0.84	0.84
Kakoge	0.58	0.54	0.51	0.49	0.63	0.60
Kamenyamigo	1.01	0.95	0.96	1.06	1.01	0.96
Kasese	3.82	4.73	3.88	1.23	1.48	1.22
Kibanda	1.24	1.2	1.14	1.28	1.16	1.11
Kitgum	1.3	1.53	1.79	1.57	1.79	2.01
Kituza	0.98	1	1.01	0.91	0.94	0.89
Kotido	2.58	4.61	0.99	3.71	4.31	1.82
Kyembogo	1.2	1.68	1.79	1.15	1.56	2
Kyenjojo	1.18	1.27	1.3	0.9	0.87	1.11
Lira	1.71	1.59	1.65	1.79	1.8	1.92
Makerere	0.96	0.93	0.96	1.02	1.01	0.99
Masindi	0.82	0.91	0.96	0.82	0.88	0.96
Mbarara	1.54	1.38	1.38	1.44	1.31	1.16
Moroto	1.43	2.7	1.3	2.98	3.92	3.01
Mubende	1.25	1.2	1.33	0.91	0.8	1.02
Namulonge	0.86	0.92	0.83	0.8	0.85	0.75
Ntusi	1.13	1.15	1.12	1.05	1.02	1.02
Serere	0.96	1.02	1.02	1.15	1.19	1.24
Soroti	0.88	1	0.98	0.99	1.08	0.96
Tororo	1.14	1.26	1.17	1.22	1.27	1.18
Wedalai	0.43	0.5	0.77	0.48	0.54	1.11
Average	1.25	1.42	1.26	1.23	1.33	1.24

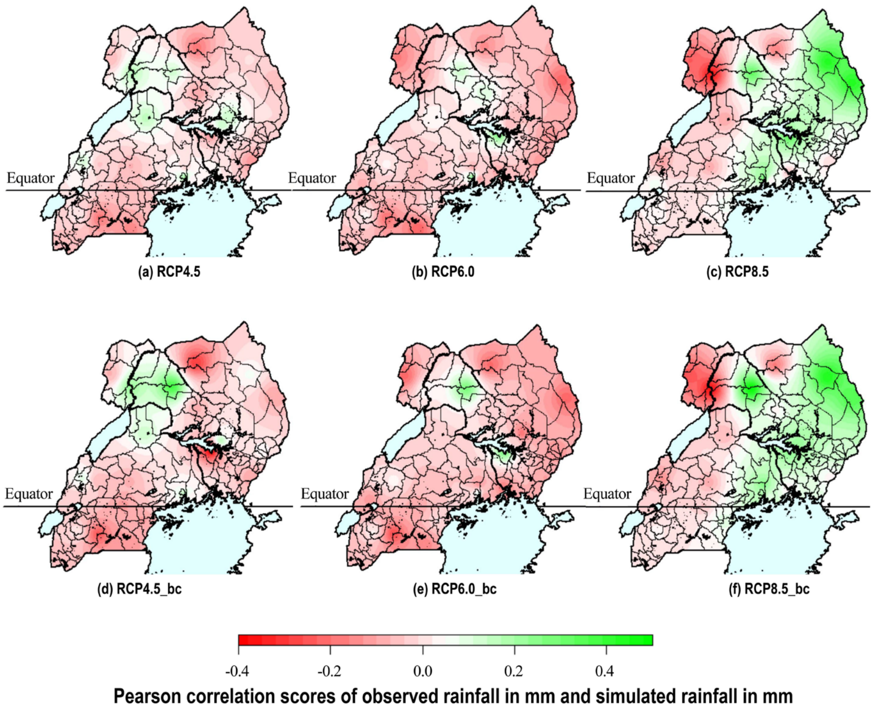

Figure 6. Spatial correlation of RCPs simulated rainfall and observed rainfall. Figures (a-c) are for the direct model output without bias correction while Figures (d-f) are for bias corrected model output.

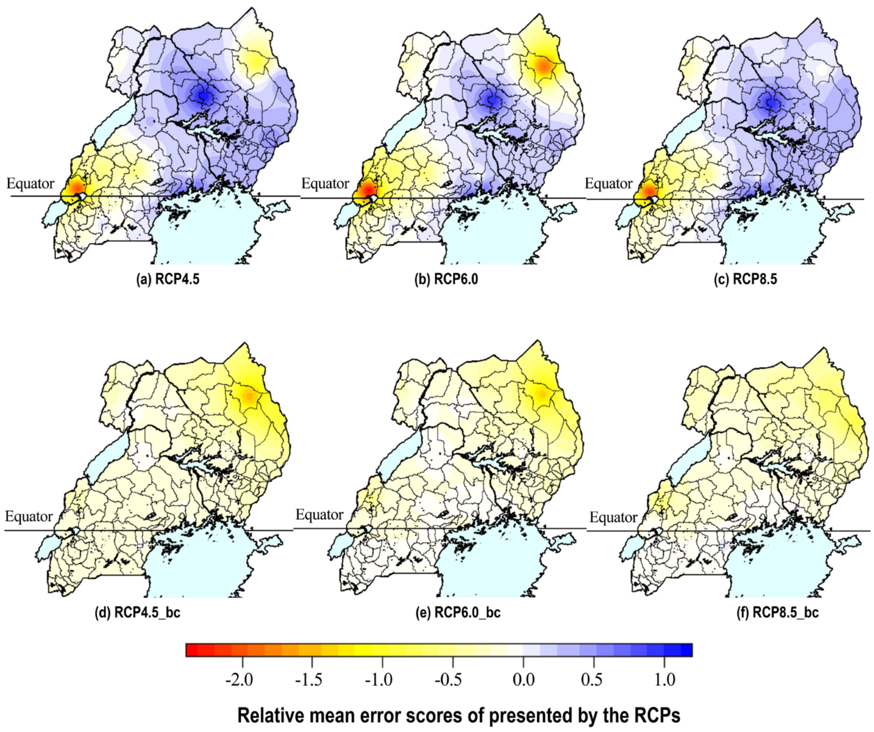

Figure 7. Shows the spatialized relative mean errors presented by the RCPs as a fraction of the long-term mean. Figures (a-c) are the relative mean errors for the RCPs with no bias correction while figures (d-f) are the relative mean errors for the RCPs with bias correction.

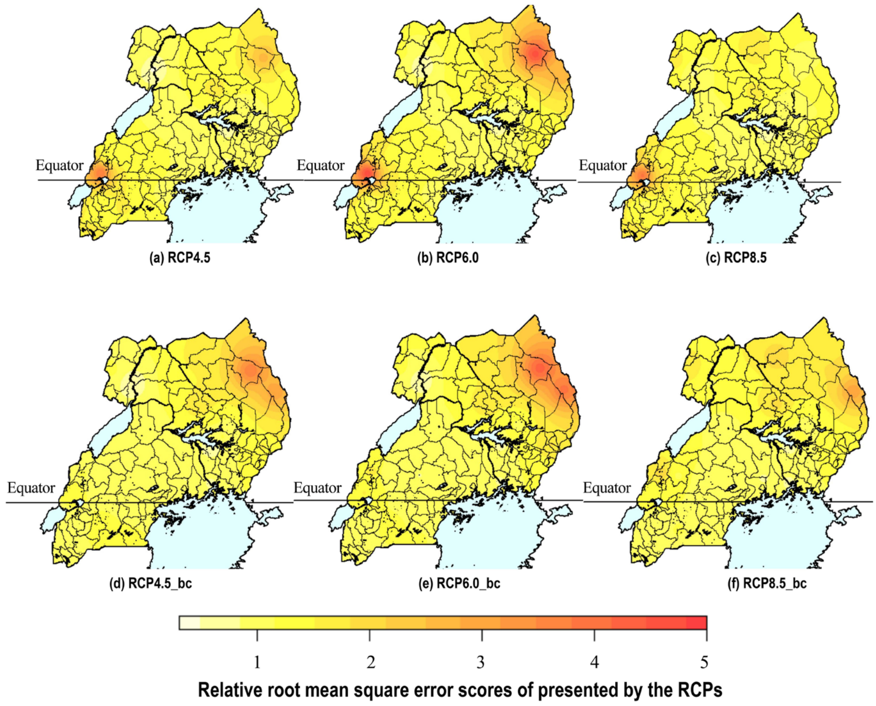

Figure 8. Shows the spatialized relative root mean square errors presented by the RCPs as a fraction of the long-term mean. Figures (a-c) are the relative root mean square errors for the RCPs without bias correction while figures (d-f) are the relative root mean square errors for the RCPs with bias correction.

Analysis of **Figure 6** shows that nearly all the RCPs presented a weak negative correlation over most places of the country. A slight improvement with bias correction is noted over north western with RCP8.5 but largely, RCP4.5 and RCP6.0 presented a negative correction. RCP8.5 had a weak negative correlation on the western part of the country and a slight positive correction on the eastern part of the country. There seems to be no noticeable improvement with bias correction especially for RCP8.5. Additional analysis of the correlation values at specific locations (**Table 4**) reveals generally that RCP4.5 and RCP6.0 largely presented a negative correlation with observed rainfall *i.e.* RCP4.5 (17 cases out of 28 cases as negative correlation values) and RCP6.0 (19 cases out of 28 cases as negative values). Generally, these are very low scores and can not explain the variation in observed rainfall.

Additional analysis is carried out on results presented by **Figure 7** which presents the spatialized relative mean errors. The results show that RCPs with no bias correction had a greater part of the country with a slight overestimate especially RCP4.5 *i.e.* with magnitudes 0 - 1.0 of the long-term mean. For all the RCPs, the southwestern region is underestimated. A further investigation of relative mean errors presented by the bias corrected model output (**Figures 7(d)-(f)**) reveals that largely areas that were originally overestimated are now underestimated. Areas that were originally underestimated have the relative mean errors slightly improved e.g. the case of south western region. Generally the relative mean error magnitudes for both bias corrected and direct model output remain comparatively small largely within −0.9 to 1.0 of the long-term mean. This is also observed from the performance at specific study locations presented using **Table 5**. A detailed analysis of the results presented in **Table 5** reveals that bias correction had a tendency of removing the underestimation to become overestimation over most of locations *i.e.* 23 out of 28; 19 out of 28; and 21 out of 28 for RCPs 4.5; 6.0; and 8.5 respectively. In a related study by Ghimire *et al.* [15], they noted that bias correction reduces the overall error magnitudes. This is why the relative mean error appears positive on average in **Table 5**. This could also be the reason why the bias corrected results presented comparatively better performance in **Figure 3** and **Figure 4**.

A further investigation of the relative magnitudes of errors compared to the long-term mean carried out using the relative root mean square error (Equation (2)) and presented using **Figure 8** confirms the results presented in **Figure 7**. Generally, the magnitude of errors is approximately of magnitude 1.0 to 2.5 with exception of southwestern Uganda where they largely appear greater than 1.5 of the long-term mean especially over Mt. Rwenzori region. Additionally RCP6.0 and the bias corrected RCP4.5 and RCP6.0 appear to present comparatively larger error magnitudes of the north eastern region. A slight improvement in the magnitudes of relative root mean square errors over the south western region especially Mt. Rwenzori area is noted in all bias corrected RCP products. This is also confirmed by the results presented at specific locations in **Table 6** which presents a slight improvement in the error magnitudes. A detailed analysis of the absolute root mean square errors in comparison to the long-term mean is presented using **Table 6**. A poor performance is noted over Kasese, Lira, Moroto and Mbarara (**Table 6**) of order of magnitude generally greater than 1.5 of the long-term mean especially the bias corrected results. Overall the results show that RCP4.5 presented a slightly better performance.

The foregoing results probably indicate that these RCPs may not be realistically valid in low latitudes. However, a study over Central Africa with the domain including Uganda, by Fotso-Nguemo *et al.* [27] noted that the ensemble mean of the 20 GCMs was able to reproduce the rainfall patterns exhibited by the Global Precipitation Climatology Center better than those presented by the Tropical Rainfall Measuring Mission. This suggests different performance scores of RCPs with different data-sets and thus underscores the importance of using station observations as ground truth in validation studies. Nonetheless, the RCPs fairly reproduces the temporal patterns (**Figure 3** and **Figure 4**) albeit with an underestimation. This could suggest that future extreme events being projected by different studies under these RCPs could be underestimated and could actually be severe. To improve the performance of the RCPs, this study proposes data assimilation or review of these RCPs.

3.3. Skill Scores

Figure 9 presents the spatialized accuracy in terms of the hit rate (accuracy) for the RCPs while **Table 7** presents the hit rate levels per study location. The results generally show RCP8.5 presenting a slightly better skill than the rest. Isolated cases of above average skill are observed over the northwestern and northeastern regions. However, generally the skill is largely 20% - 50%. There was no noticeable improvement in skill with bias correction of the RCPs. In some cases over some areas, actually the skill degraded e.g. over the northeastern Uganda. This is in contrast to the findings of Ghimire *et al.* [15], who noted that bias correction improves the accuracy of numerical simulations. This study argues that the weak/no improvement in the performance after bias correction could be because the initial conditions used to initialize this study are already bias corrected as described by Monaghan *et al.* [17], and so additional bias correction is not necessary.

Further to the skill scores (**Figure 9** and **Table 7**), the results are in agreement with Kisembe *et al.* [9], who noted that the climate simulations whereas they reproduce the climate variability, they present a poor skill regarding the rainfall seasons especially the March-May rainfall season over Uganda. In general, this study finds RCP8.5 to present a slightly better performance in terms of the hit rate and is thus proposed for future simulation over low latitudes including Uganda. However it is surprising to note that bias correction did not necessary improve performance and probably considers that this observation could be that because the LBCs used in this experiment are already bias corrected as explained earlier.

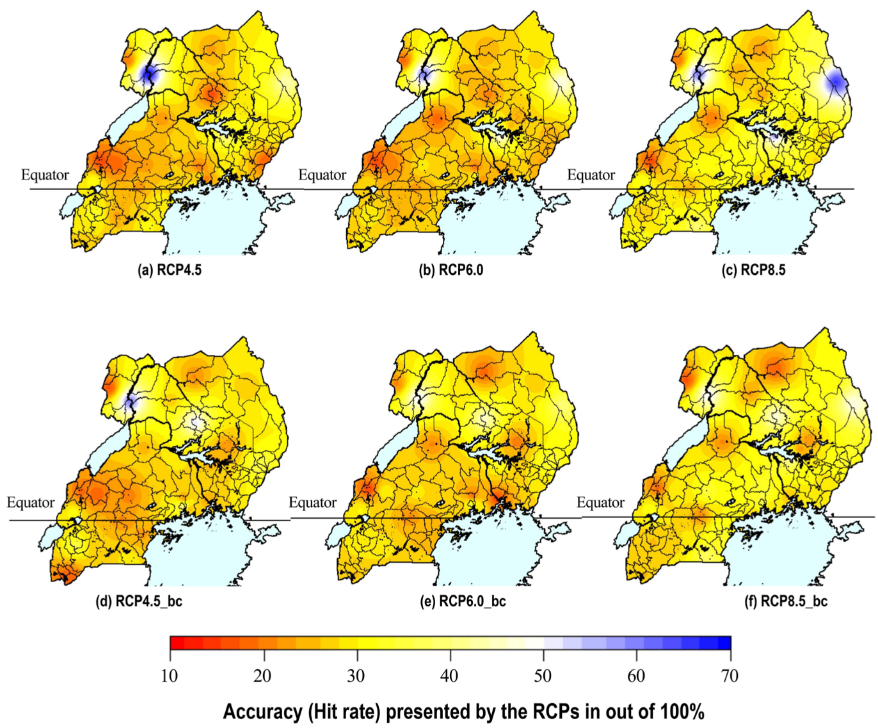

Figure 9. Shows the Spatial accuracy in terms of the hit rate presented by the RCPS. Figures (a-c) are for the direct model output as simulated by the RCPs while Figures (d-f) are for the bias corrected hit rates of the RCPS. The results shown are out of 100%

Table 7. Shows the results of hit rates for the RCPs. "DMO" is direct model output with no bias correction.

	HIT rate, DMO (%)			HIT rate (Bias corrected)		
	RCP4.5	RCP6.0	RCP8.5	RCP4.5_bc	RCP6.0_bc	RCP8.5_bc
Arua	20.00	18.71	19.35	16.81	21.01	16.81
Buginyanya	28.47	24.09	27.01	35.96	34.21	32.46
bushenyi	32.31	29.23	26.15	34.74	29.47	25.26
Entebbe	29.25	27.89	29.25	29.46	25.00	25.89
Gulu	27.52	24.16	23.49	26.55	28.32	23.01
Jinja	29.33	23.33	28.67	23.68	15.79	25.44
Kabale	27.33	28.00	31.33	17.54	25.44	25.44
Kakoge	41.67	50.00	58.33	25.00	33.33	41.67
Kamenyamigo	29.60	25.60	30.4	22.73	23.64	32.73
Kasese	31.37	26.8	32.03	30.77	29.91	30.77
Kibanda	30.46	25.83	38.41	29.06	25.64	37.61
Kitgum	22.97	24.32	22.30	21.24	18.58	17.70
Kituza	19.86	21.92	26.03	25.00	28.57	27.68
Kotido	30.00	26.67	33.33	26.67	26.67	30.00
Kyembogo	15.62	15.62	15.62	18.75	15.62	18.75
Kyenjojo	17.65	20.59	26.47	17.65	29.41	29.41
Lira	16.56	20.53	23.84	50.86	45.69	46.55
Makerere	28.67	31.33	31.33	41.23	33.33	35.96
Masindi	22.22	18.06	19.44	24.77	21.10	21.10
Mbarara	22.88	24.84	30.07	26.05	28.57	26.89
Moroto	43.48	47.83	65.22	30.43	39.13	47.83
Mubende	22.86	28.57	31.43	20.00	28.57	34.29
Namulonge	19.57	19.57	31.88	23.08	19.23	34.62
Ntusi	22.86	22.86	24.29	21.15	21.15	21.15
Serere	30.20	24.83	28.86	23.48	24.35	22.61
Soroti	29.58	23.24	27.46	21.85	19.33	21.85
Tororo	17.81	23.29	27.40	29.82	28.07	28.07
Wedalai	68.75	59.38	59.38	59.38	50.00	50.00
Average	27.82	27.04	31.03	27.63	27.47	29.70

4. Summary and Conclusion

This study was about validating the RCPs and was carried out over Uganda using 28 stations spread across the country for the period 2006-2018. It carried out bias correction for the RCPs over the period 2009-2018. The period 2006-2008 was for training the bias correction algorithm and the study used the quntile mapping method to correct the biases of the three RCPs *i.e.* RCP4.5, RCP6.0 and RCP8.5. In assessing the performance of the RCPs, the study used the Pearson correlation coefficient; the relative root mean square error; relative mean error; and accuracy (*i.e.* hit rate) computed from a 3 × 3 contingency table for the cases of "Below normal", "Normal", and "Above normal". *Below normal* is when the monthly rainfall is less than 75% of the long-term mean; *Normal* is when the monthly rainfall is within 75% - 125% of the long-term mean; and *Above normal* is when the monthly rainfall is greater than 125% of the long-term mean. Trends are presented using line graphs while the spatial patterns are presented using maps derived using the inverse distance weighted spatialization method.

This study summarises the performance of the RCPs using Table 8. The summary shows that RCP8.5 presented comparatively better ranking on correlation score; relative mean error; relative root mean square error and hit rate. This was followed by RCP4.5 and then RCP6.0. However this study observed that there was no significant difference in the performance of all these RCPs and considers that they remain poor in informing us about future changes in climates especially over low latitudes.

The study further noted largely a negligible improvement due to bias correction. It noted that bias correction tended to improve underestimated rainfall cases and on the other hand decreased the overestimated rainfall cases. This did not necessarily improve the skill, nor the error magnitudes and we attribute this

Table 8. Summarizes the performance of the RCPs on different monthly time-scales. "RMSE" is the root mean square error. The values in the parenthesis are the ranking for the given score on the scale of 1 - 3 for the respective RCP. The lower the rank, the better the performance of the RCP. The average ranking is obtained by simple arithmetic average column-wise across different performance scores.

	Scores (%)			Bias corrected		
	RCP4.5	RCP6.0	RCP8.5	RCP4.5	RCP6.0	RCP8.5
Performance score						
Correlation	−0.01 (2)	−0.04 (3)	0.06 (1)	−0.02 (2)	−0.06 (3)	0.07 (1)
Relative mean error	−0.07 (3)	0.06 (1)	−0.06 (1)	0.25 (3)	0.20 (1)	0.20 (1)
Relative RMSE	1.25 (1)	1.42 (3)	1.26 (1)	1.23 (1)	1.33 (3)	1.24 (2)
Hit rate	27.82 (2)	27.04 (3)	31.03 (1)	27.63 (2)	27.47 (3)	29.70 (1)
Average ranking	**2**	**2.5**	**1**	**2**	**2.5**	**1.25**

to the fact that, it could be because the LBCs are already bias-corrected. Whereas this study recommends RCP8.5, it also recommends re-evaluating the assumptions in these RCPs. The other option recommended is to use data assimilation to improve the analysis of these RCPs for future climate scenarios.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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