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Quantile Mapping Bias Correction on Rossby Centre Regional Climate Models for Precipitation Analysis over Kenya, East Africa

Brian Ayugi[1], Guirong Tan[1*], Rouyun Niu [2],Hassen Babaousmail[1,3], Moses Ojara[1,4], Hanggoro Wido[1,5],Lucia Mumo[1], Isaac Kwesi Nooni[1,6], Victor Ongoma[1,7]

[1]Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environment Change (ILCEC)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing, University of Information Science and Technology, Nanjing 210044, China

[2]National Meteorological Center, China Meteorological Administration, Beijing 100081, China

[3]School of Computer and Software, Nanjing University of Information Science and Technology, Jiangsu, Nanjing 210044, China

[4]Uganda National Meteorological Authority, Clement Hill Road, P.O. Box 7025 Kampala, Uganda

[5]Research and Development Center of Indonesia Agency for Meteorology Climatology and Geophysics, Jakarta, Indonesia, 10720

[6]School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing 210044, China

[7]School of Geography, Earth Science and Environment, University of the South Pacific, Laucala Campus Private Bag, Suva, Fiji

*Email: tanguirong@nuist.edu.cn

Abstract

Accurate assessment and projections of extreme climate events requires the use of climate datasets with no or minimal error. This study uses quantile mapping bias correction (QMBC) method to correct the bias of five Regional Climate Models (RCMs) from the latest output of Rossby Climate Model Center (RCA4) over Kenya, East Africa. The outputs were validated using various scalar metrics such as Root Mean Square Difference (RMSD), Mean Absolute Error (MAE) and mean Bias. The study found that the QMBC algorithm demonstrate varying performance among the models in the study domain. The results show that most of the models exhibit significant improvement after corrections at seasonal and annual timescales. Specifically, the European community Earth-System (EC-EARTH) and Commonwealth Scientific and Industrial Research Organization (CSIRO) models depict exemplary improvement as compared to other models. On the contrary, the Institute Pierre Simon Laplace Model CM5A-MR (IPSL-CM5A-MR) model show little improvement across various timescales (i.e. March-April-May (MAM) and October-November-December (OND)). The projections forced with bias corrected historical simulations tallied observed

values demonstrate satisfactory simulations as compared to the uncorrected RCMs output models. This study has demonstrated that using QMBC on outputs from RCA4 is an important intermediate step to improve climate data prior to performing any regional impact analysis. The corrected models can be used for projections of drought and flood extreme events over the study area. This study analysis is crucial from the sustainable planning for adaptation and mitigation of climate change and disaster risk reduction perspective.

Keywords: Quantile Mapping Bias Correction (QMBC), Regional Climate Models (RCMs), Rossby Centre Regional Climate Models **(**RCA4), Drought, Flood, Kenya

1. Introduction

Recently, the changes in the frequency and intensity of extreme events have led to serious climate related disasters across many parts of the world. These extreme events (i.e. floods, droughts, and/or heatwaves) have gained considerable attention by climate scientists and the general public due their devastating impact on ecosystem and different sectors of the society.

Thus, monitoring and forecasting of such extreme events is crucial steps to ensure that the Malabo Goals 2025 and the 2030 Agenda for Sustainable Development of the Sustainable Development Goal 2 (SDG2) are met (FAO, 2019). It is against this backdrop that climate information's availability and accuracy are important for climate change assessment (IPCC, 2014).

From a policy formulation perspective, global climate models (GCMs) and regional climate models (RCMs) are such examples of datasets used in forecasting and projecting studies. Additionally, model outputs from GCMs and RCMs are sometimes used as input data source in the forecasting and projection of the extreme events. However, these model outputs are saddled with uncertainties that arise due to systematic and/or random biases relative to in-situ datasets (Christensen et al., 2008: Teutschbein and Seibert, 2010). For example, Cardell et al., (2019) associated the model random error to intricate topography or atmosphere-biosphere transition along large water bodies. In a different study, Allen et al., (2006) linked systematic errors (model biases) to model coarser resolutions or parameterizations schemes.

Other studies (e.g., Mearns et al., 2012; Cannon et al., 2015), also reported considerable deviations (i.e. over/underestimations) relative to in-situ observations. Thus, within the context of these studies, readers are cautioned when generalizing results from these models outputs. Of great interest, are water resource planners and managers, who are required

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to periodically conduct regional impact analysis to assess the impacts of climate change on watershed hydrology. Thus, to quantify the changes and predict extreme events against the backdrop of warming climate, scientists and policy analyst alike have no option than to use the existing GCM and RCM ensembles, despite report of uncertainties in their climate change assessment (IPCC, 2014).

Meanwhile, different spatial downscaling and bias correction tools have been proposed and applied extensively to remove this inherent errors or biases. Thus, to correct or minimize these biases or errors, scientists use two distinct spatial downscaling and bias correction tools; namely, statistical and dynamic downscaling methods.

In this study, we do not attempt to compare the advantages and disadvantages of these methods since extensive literature review concludes that it is difficult to define the best method as the overall output performance of the two methods are able to reproduce the recent climate (Murphy, 1999; Wilby and Wigley., 2000; Ahmad et al., 2013). From literature, these two methods have been applied to downscale GCM to RCM (IPCC, 2014).

Several RCMs based on dynamic downscaling are now available for many regions across the globe (IPCC, 2014). Example includes the RCM precipitation data sourced from Rossby Centre Climate Model outputs (Samuelsson et al., 2012; Strandberget al., 2014). However, following a phenomenal study of Ahmed et al., (2013) and Wood et al. (2004), it is clear that the spatial resolution of the RCM for regional or local applications, may not be high enough and/or still contain some inherent errors. To use this type of climate data for present and future climate predictions, the two studies recommended bias corrections of RCM data to remove possibly the biases prior to their application. In parallel, this is particularly relevant for the Africa continent as well as her sub-regions where the number of in-situ stations, data availability, and quality have considerably declined and become less reliable (Malhi and Wright (2004).

Thus, to remove biases in RCM, recent studies (Christensen et al., 2008; Terink et al., 2008; Teutschbein and Seibert, 2012; Fang et al., 2015; Cardell et al., 2019) have adopted statistical technique to adjust RCMs simulations and projections of climatic variables using different bias correction methods.

Examples of the bias correction methods include the delta correction (Moore et al., 2008; Rasmussen et al., 2012); Linear transformation (Lenderink et al., 2007); Local Intensity Scaling (Schmidli et al., 2006); Power Transformation (Leander et al., 2008); Distribution mapping (Block et al., 2009; Sun et al., 2011); and the Quantile Mapping Bias Correction

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(QMBC) (Panofsky and Brier, 1968; Piani et al., 2009; Themeßl et al., 2011), just to mention a few.

The conclusions drawn from these studies suggest that QMBC algorithm outperform other methods (Gudmundsson et al., 2012; Teutschbein and Seibert, 2012; Chen et al., 2013). It is important to note that QMBC is also referred as quantile-quantile mapping (Sun et al., 2011), probability mapping (Ines and Hansen, 2006), statistical downscaling (Piani et al., 2010), or histogram equalization (Rojas et al., 2011).

The QMBC method is based on the hypothesis that climate biases that need to be corrected are unchanging hence its features in historical data will persist into the future projections (Maraun et al., 2010, 2012). Although, this study acknowledges that QMBC technique has limitations (see Boé et al., 2007; Cannon et al., 2015), QMBC usage is widely preferred for impact analysis (Maraun, 2013; Hempel et al., 2013; Maurer and Pierce, 2014; Cannon et al., 2015).

Over the East Africa region, recent studies have reported existence of biases in RCMs and GCMs datasets (Endris et al., 2013; Kisembe et al., 2018; Ongoma et al., 2019). To illustrate, Ayugi et al. (2020) demonstrated the manifestation of systematic dry (wet) biases over regions of low (high) altitude characterized by arid and semi-arid lands (ASALs) or complex topography**.** Furthermore, the study highlighted that most mean spatial biases tend to follow the physiographic features in the study domain, which RCMs could not clearly reproduce due to its coarser resolution (~50 km) and physical parameterization.

Despite the observed biases, few studies have attempted to correct systematic distributional biases relative to historical observations, and possible future simulations on the RCMs or GCMs. A number of studies have however improved the quality of satellite-derived estimates using other techniques, such as Bayessian approach (Kimani et al., 2018a,b).

In order to improve the accuracy of projections of extreme events such as drought and flood over East Africa, better performing RCMs and satellite datasets (Endris et al., 2013; Kimani et al., 2018a, b; Ayugi et al., 2019, 2020) ought to be further improved using correctional techniques so as to minimize possible biases and enhance the quality (Maraun et al., 2010).

Thus, as a follow-up from Ayugi et al. (2020), this study focuses on assessing the importance and performance of QMBC on model outputs over East Africa as an intermediate step prior to performing any regional impact analysis. This analysis is crucial from the sustainable planning for adaptation and mitigation of climate change and disaster risk reduction perspective. The objective of this study is to perform bias correction on the RCMs

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over Kenya, using QMBC prior to the assessment and projections of floods and droughts in the mentioned study domain.

The remaining section of the paper are organized as follows: Section 2 highlights data and methods used whilst results and discussions are presented in section 3. The last sections summarize conclusion of the study with possible recommendation.

2. Study Area, Data and Techniques

2.1 Study Area

The region under study is situated in East Africa located along the celestial longitude 34° E-42° E and latitude 5° S - 5° N **(Figure 1).** Diverse physical features that play significant role in climate modulation from one locality to another characterize this region (Bowen et al., 2007). For instance, the maximum thermal heat evidenced over the eastern and northeast parts that are predominantly Arid and Semi-Arid Lands (ASALs) and minimum temperatures over central regions is due to high elevation point. Moreover, the uppermost (lowest) elevation with altitude (>5000 m/<0 m) often leads to random uncertainties in climatic variables during the quantification process (Allen et al., 2006). Consequently, the terrestrial heterogeneous classification influences socio-economic activity with a great inclination to rain fed agriculture (Mumo et al., 2018).

Meanwhile, the region is classified as tropical climate (Kottek et al., 2006) with bimodal patterns of rainfall is experienced during March to May (MAM) and October to December (OND) (Ongoma and Chen, 2017; Ayugi et al., 2019). Looking more closely at the two seasons, the months of May and November record the highest amount of rainfall across the study domain whilst March and October signify the onset of the seasons and record the least rainfall quantity (Ayugi et al., 2016, 2018; Ongoma and Chen., 2017; Mumo et al., 2019).

On the other hand, the highest temperature climatology is observed during January and February (JF) whereas lowest is observed during June to September (JJAS) (Kinguyu et al., 2000; Ongoma et al., 2017; Ayugi and Tan, 2019). Generally, microclimate features over the study area is mostly regulated by the existence of unique geomorphology while synoptic features are influenced by interaction between atmosphere and hydrosphere within the lower troposphere. For example, the changes in Hadley circulation which has an influence in the oscillation of Inter tropical convergence zone (ITCZ), strongly regulate seasonal climate patterns over the study domain (Nicholson, 2008; Hastenrath et al., 2011).

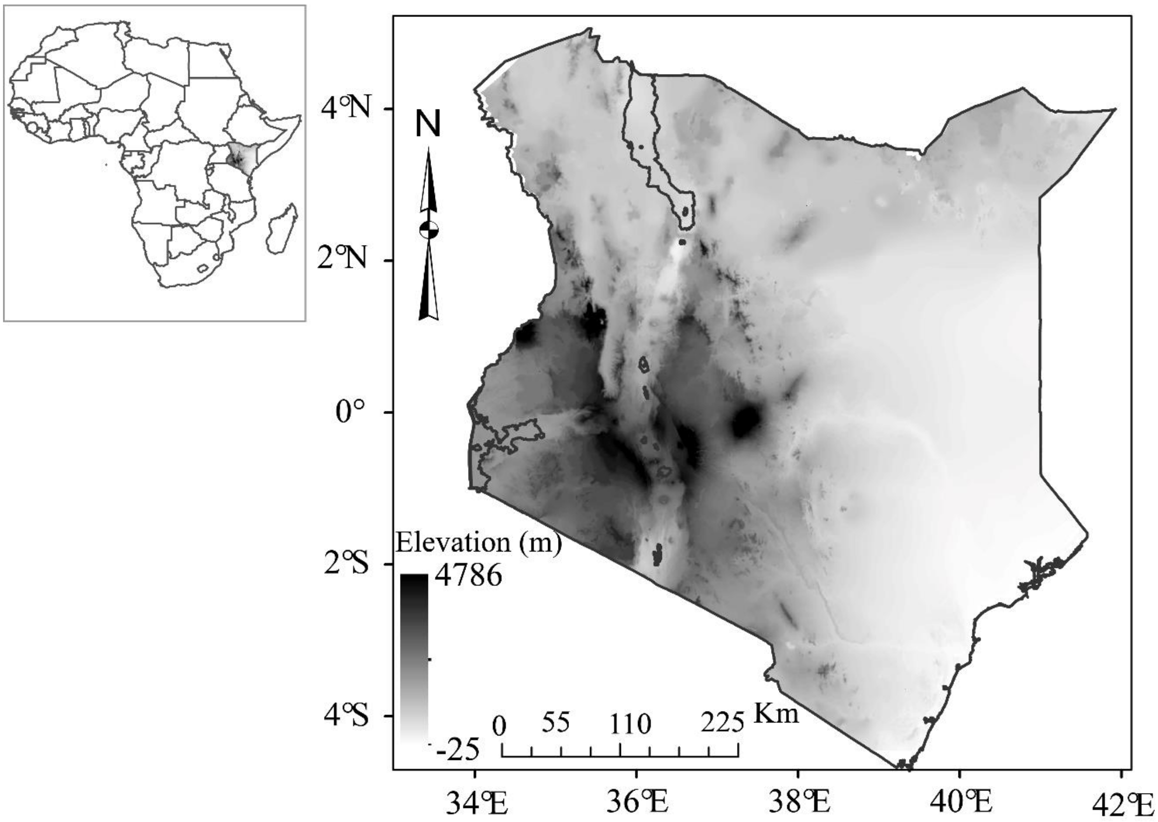

Fig. 1 The study area [34°E–42°E and 5°S–5°N] with topographical elevation (m) in dark color. Enclosed is map of African domain with study domain situated in Eastern region marked with dark color.

2.3 Data and Techniques

2.3.1 Bias correction method

Biases in climate model simulation are commonly detected by validation, (i.e. comparison with observation) through computational of mean, or/and other complex analysis (Teutschbein and Seibert, 2013). A number of correction techniques have been proposed to rectify the existing biases in climate datasets (Lenderink et al., 2007; Leander et al., 2008; Moore et al., 2008; Sun et al., 2011).

The current study employed QMBC algorithm to evaluate monthly RCMs precipitation data sourced from Rossby Centre Climate Model outputs (Samuelsson et al., 2012; Strandberget al., 2014) and their respective Mean Multi-model Ensemble (MME). They are as follows: Model for Interdisciplinary Research on Climate (MIROC5), Commonwealth Scientific and Industrial Research Organization (CSIRO), Institute Pierre Simon Laplace Model CM5A-MR (IPSL-CM5A-MR), Max Planck Institute Earth System Model at base resolution (MPI-ESM-LR) and European community Earth-System (EC-

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EARTH). The RCMs have spatial resolution of resolution of 0.44° × 0.44° (~50 × 50 km) with a historical coverage spanning from 1951 to 2005 for the simulations run whilst projections has temporal span from 2006 to 2100 for both RCP 4.5 and 8.5. The datasets were retrieved from Deutsches Klimarechenzentrum GmbH (DRKZ) website (CERA-WDCC. https://cera-www.dkrz.de).

Recent version Climatic Research Unit (CRU TS4.02) datasets were employed as observed datasets during the validation period. Harris et al. (2014) detailed more on this dataset. The CRU datasets utilized in this study has temporal scale ranging from 1901-2017 and spatial coverage of ~50 km. The RCMs datasets were evaluated in a recent study (Ayugi et al., 2020) and elucidated the listed models as better performing from the ten GCMs that were dynamically downscaled based on RCA4 model. Despite the skillful simulation of observed rainfall as compared to other models, the datasets still reported glaring biases (**Figure 2;** Ayugi et al., 2020). Most models exhibit the overestimation during OND season and underestimation throughout MAM season (**Figure 2**). This has prompted the need for minimizing the biases in order to employ the models for drought and flood projections in a region that is vulnerable to occurrence of extreme events.

The QMBC constructs cumulative distribution functions (CDFs) of the model and observations using a transfer function, which in turn translates the raw model outputs into corrected output. Thus, the CDF of the corrected model are transformed to match that of the observed datasets (Piani et al., 2009; Sun et al., 2011; Teutschbein and Seibert, 2012). Mathematically, quantile mapping is constructed using Eqn 1;

$$y = F_{obs}^{-1}\left(F_{RCM}(x)\right) \tag{1}$$

where *y* is the corrected rainfall value, while *x* is the value of precipitation to be corrected. On the other hand, F_{obs}^{-1} is the inverse of the CDF of the observation and F_{RCM} is the CDF of the RCM employed. The likelihood of detecting x (mm/month) or less in the model is then transferred to the quantile of the observed CDF, matching very similar to observed probability. The QMBC was conducted using available *qmap* package on the R software (Gudmundsson et al., 2012).

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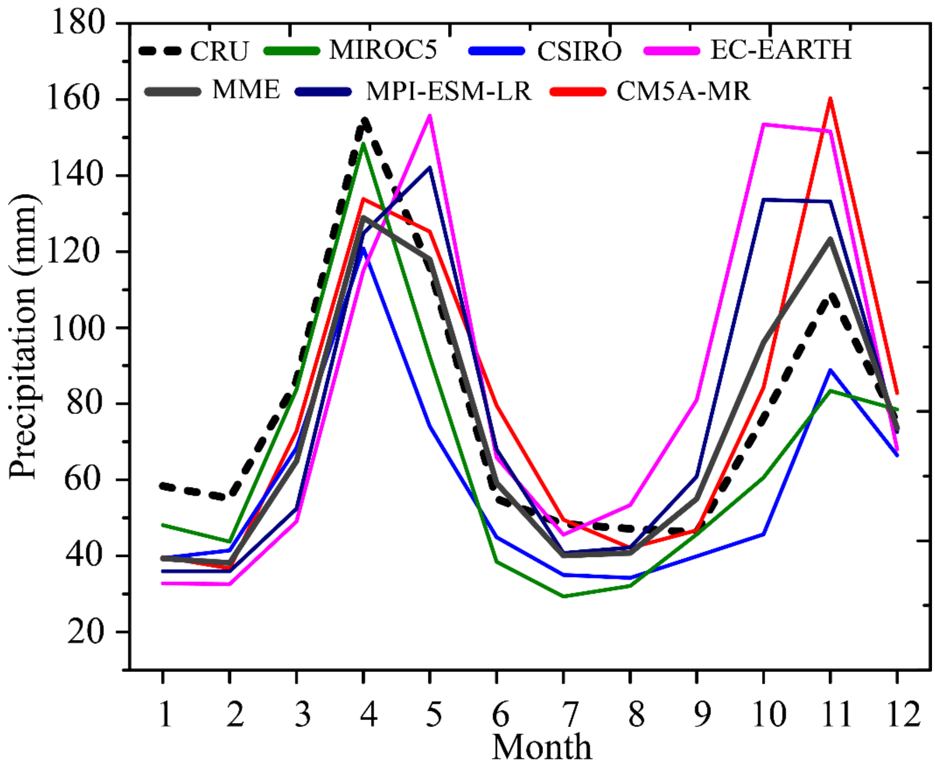

Fig. 2 Monthly precipitation for the period 1951-2005 as simulated by 5 individual models of RCA4 over Kenya, depicting underestimation or overestimation of observed precipitation. Observation (black dotted line) and RCMs Multi-Model Mean (MME) ensemble (gray line) are displayed as well.

2.3.2 Testing the reliability of model correction approach

A number of approaches are utilized in a bid to affirm the reliability of the model correction approach. The present study uses a split sample testing (SST) to examine how effective QMBC algorithm work under different conditions. More information regarding this approach is presented in Klemeš (1986). Meanwhile, SST technique involves splitting the data into two, preferably equal size segment in order to use one as calibration and the one for validation.

In the current study, the SST approach was conducted by first training data for 29 years, (1951-1979), to derive biases field for monthly averages in model and observed precipitation simulations. The monthly biased field were then used to correct independent RCMs during the next 26-year validation period (1980-2005). Additionally, projections estimates were corrected for the whole period, i.e., 2006-2100. The hypothesis for SST technique is the temporal consistency of average errors. **Figure 3** shows a summary flow of the SST approach used in this study.

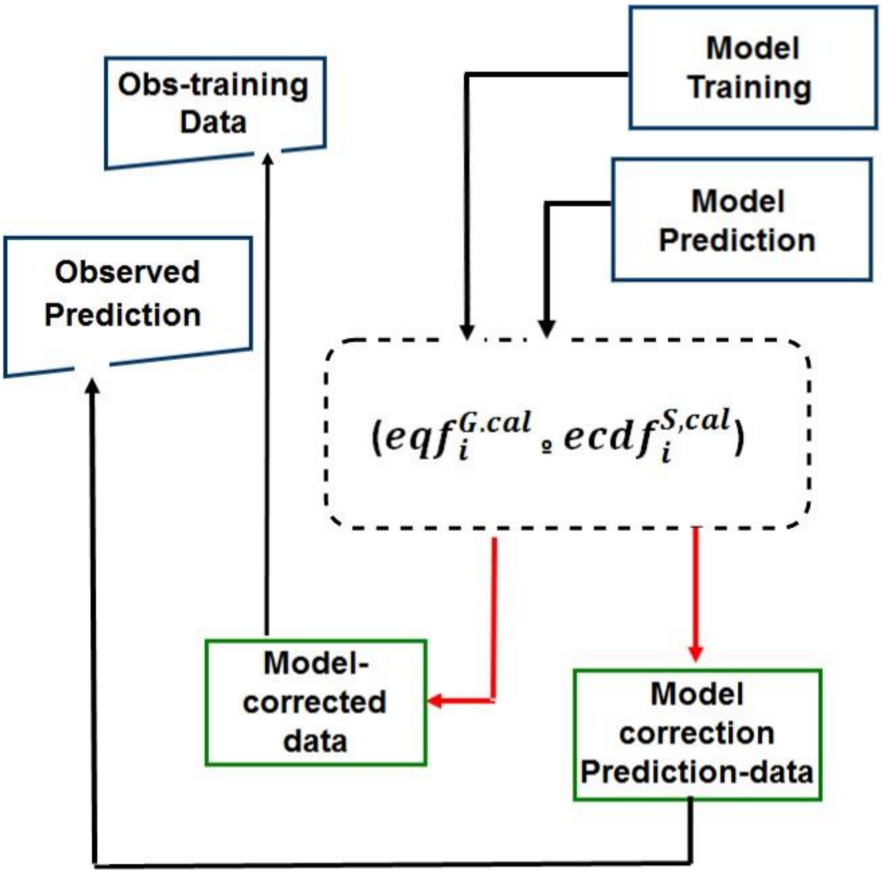

Fig. 3 Flowchart of model bias correction procedure

2.3.3 Evaluation of bias correction approach

Evaluation of bias corrected RCMs; historical simulations, and projection estimates was conducted using raw and bias corrected RCMs related to the observed gridded precipitation datasets on monthly and year basis. Statistical metrics such as the Mean Bias, Mean Absolute Error (MAE), and customized RMSE to a space and time scenario, were employed to compute their relationships. The mathematical formulas of the aforementioned metrics are given in Eqns 2 – 4;

$$BIAS = n^{-1}\sum_{i=1}^{n}(M_i - O_i) \tag{2}$$

,

$$MAE = n^{-1}\sum_{k=1}^{n}\left|P_{M_k} - P_{R_k}\right| \tag{3}$$

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$$RMSE = \sqrt{n^{-1}\sum_{i=1}^{n}\left(P_{M_k} - P_{R_k}\right)} \qquad (4)$$

where P_{M_k} is the model estimate for the considered data point k. P_{R_k} is the observed value for the considered data point k, and N is the length of the distribution of the data point being analyzed. For graphical displays, the study used Empirical quantile mapping distribution (ECDF) and spatial maps to demonstrate the effectiveness of QMBC algorithm.

3. Results and Discussions

3.1 Evaluation of Bias-corrected RCMs Simulations.

3.1.1 Temporal assessment

Figure 4 presents ECDF analysis for 5 GCMs dynamically downscaled with the Rossby Centre Regional Climate Model (RCA4), as well as their ensemble average. The plots (a-b) represent March-May (MAM) season, (c-d) October-December (OND), and (e-f) annual before and after corrections, abbreviated with 'BC' and 'AC', respectively. The MAM period experiences substantial amount of rainfall in terms of magnitude, intensity and frequency, thereby exhibiting large biases (Yang et al., 2015; Nicholson et al., 2017). The observed biases were noted from a recent studies (Endris et al., 2013; Ayugi et al., 2020) that evaluated the performance of RCMs in simulating precipitation climatology over the Great Horn of Africa domain. The aforementioned studies demonstrated the under/overestimations of MAM rainfall in regions mostly associated with complex physiographical features. Compared to the observed datasets (CRU TS4.02; dotted line in Figure 4), it is apparent that QMBC technique significantly improved the accuracy of most models and their ensemble after the corrections. Specifically, there was a remarkable reduction in Mean Bias, RMSD and MAE in most models with significant performance depicted during May (**Table 1**).

Majority of the models show insignificant improvement after correction during MAM. For example, the mean absolute error (MAE) was generally large in MME-AC (24 mm/month) as compared to MME-BC (18.77 mm/month) (**Table 1).** Interestingly, CSIRO and EC-EARTH show a remarkable enhancement during the wet months as compared to other models that exhibited variations from one month to another. Overly, these results show that the algorithm improved the model accuracy despite the noteworthy variation based on the magnitude of rainfall experienced over the study domain. For instance, there are large

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279 incidences of biases noted in May as compared to model underestimations during March and

280 April.

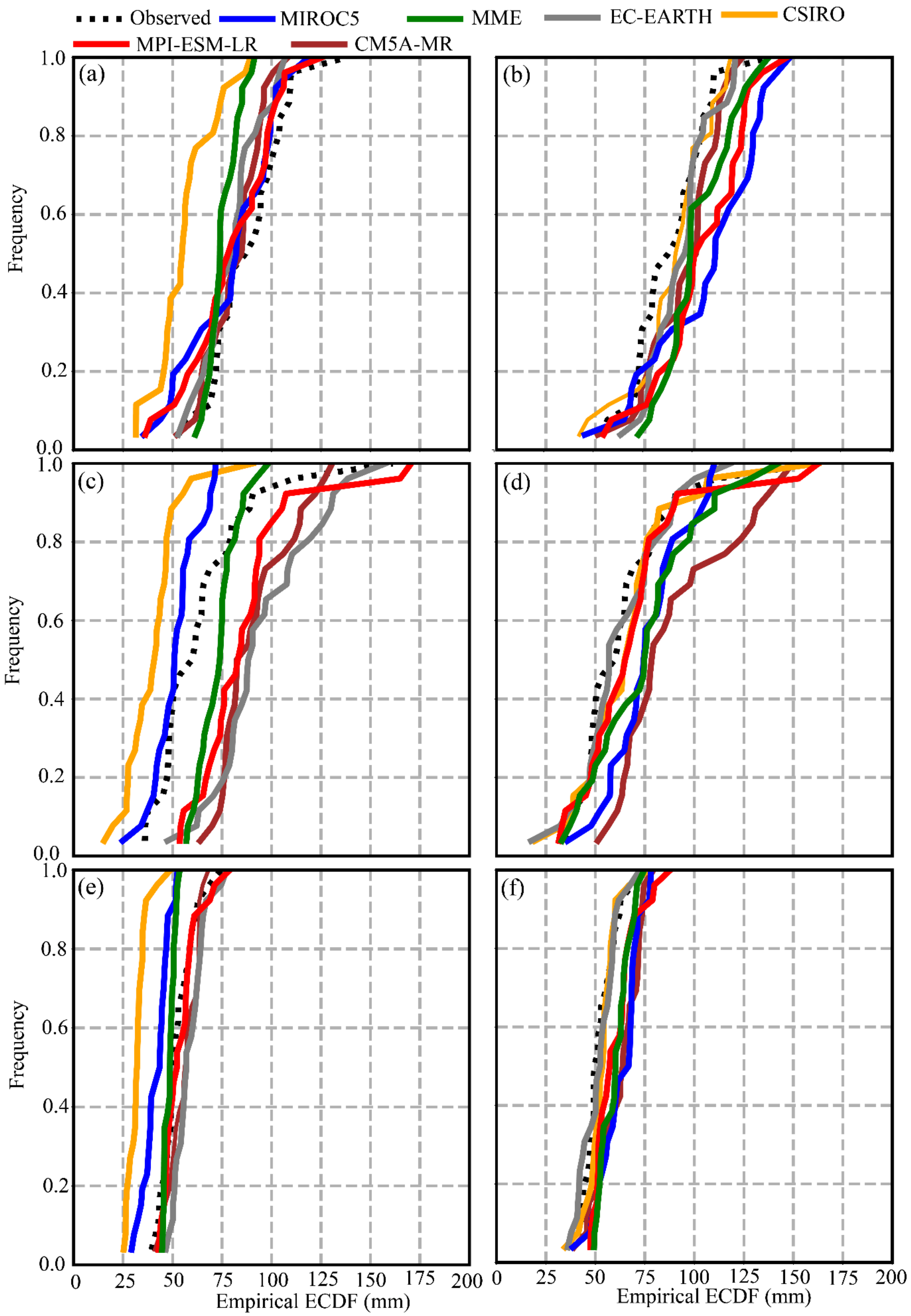

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Fig. 4 The ECDF plots for 5 GCMs dynamically downscaled with the Rossby Centre Regional Climate Model (RCA4), as well as their ensemble average. The plots (a-b) represent March-May (MAM) season, (c-d) October-December (OND), and (e-f) annual before and after corrections.

In OND season **(Figure 4c-d),** a number of models show large biases before corrections that are mostly associated with orographic processes and related teleconnections thus influencing rainfall variability and trends (Camberlin and Okoola, 2003; Ogwang et al., 2014). Most biases increased with increase in rainfall magnitude with some models exhibiting considerable biases even after correction (**Figure 4c-d and Table 1**). In general, the results of this analysis show consistent notable improvement by most models during OND season.

Table 1. Comparison of different RCMs using summary statistics against the observed data for the validation. The effect of bias correction on other statistics (Correlation coefficient), in this case, very small, and the results not reported.

	RCMs validation						
	RCMs	Mean Bias	Bias (bc)	RMSD	RMSD (bc)	MAE	MAE (bc)
MAM	CM5A-MR	6.52	-8.54	24.38	27.84	20.95	22.42
	CSIRO	31.98	-2.58	40.20	26.93	32.75	22.16
	EC-EARTH	8.57	-6.04	25.33	25.11	18.46	16.96
	MIROC5	8.48	-17.31	29.21	47.51	24.21	37.61
	MPI-ESM-LR	8.11	19.66	28.75	36.20	20.94	29.98
	MME	12.73	-16.28	23.61	31.12	18.77	24.37
OND	CM5A-MR	-26.68	-27.32	38.11	46.49	31.86	36.77
	CSIRO	24.23	0.53	38.22	40.82	27.92	28.38
	EC-EARTH	-31.01	2.90	47.75	36.69	40.22	26.18
	MIROC5	13.15	-15.29	30.81	37.88	22.69	31.91
	MPI-ESM-LR	-22.52	-6.70	45.53	44.54	34.80	31.87
	MME	-8.56	-14.64	28.58	42.04	22.15	32.48
Annual	CM5A-MR	-3.49	-11.53	11.07	17.85	9.11	14.46
	CSIRO	20.94	-1.37	22.94	13.29	20.56	9.55
	EC-EARTH	-6.14	1.38	12.68	15.36	10.64	11.07
	MIROC5	10.59	-11.21	15.77	19.05	12.23	16.00
	MPI-ESM-LR	-1.58	-8.93	8.92	14.99	6.66	11.14
	MME	3.89	-9.60	9.23	16.09	7.04	12.89

**Bold values denotes models that exhibited notable improvements*

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This concurs with a study Kimani et al. (2018b), that similarly observed the bias dependence on rainfall amounts over larger domain of East Africa using satellite derived precipitation estimates. In fact, Eden et al. (2012) and, Cannon et al. (2015) demonstrated that persistent biases even after model corrections are as a result of systematic errors in model outputs from diverse sources. For instance, these studies reported that biases field observed are originating from either unrealistic response to climate forcing or unpredictable internal variability that differs from observations. Hence, such biases cannot be corrected by most correction algorithms. The conclusions from these studies highlighted that only errors in convective parameterizations and unresolved sub grid-scale orography can be corrected using univariate statistical bias correction techniques like QMBC employed in the present study.

Nevertheless, Teng et al. (2015) proposed a mitigation measure of enhancing the quality of the datasets that could not be corrected on first attempt by further calibrating the post processing corrections on adequately long historical records.

Further analysis of model bias correction at annual level **(Figure 4e-f)** show upgrading of most models, most specially the EC-EARTH and CSIRO. However, despite the corrected model, underestimation of annual rainfall continues to persist even in the corrected model output. The performance of the algorithm in enhancing the quality of model data affirms the view of Ehret et al. (2012). To illustrate this view, the study pointed out the possibility of less value added to models after corrections in situations of complex modelling chain when considering other sources of uncertainties (Muerth et al., 2013). The persistent biases in **Figure 4e-f** (AC) could be associated with dry biases, originating from the ASAL regions, characterized by moisture outflow over the study region (Kisembe et al., 2018; Ayugi et al., 2020). In addition, the high underestimation of wet season (MAM), could have contributed to overall underestimation of annual rainfall, despite the correction.

A summary of performance of bias correction method during the wet season and annual is shown in **Figure 5**. As noted earlier, most models show improvement after correction across the diverse timescales. For instance, significant improvement is exhibited during MAM season as compared to OND. It is worth noting that CM5A-MR had least improvement during the OND, while substantial improvement is demonstrated by EC-EARTH during similar season. This confirms the need to improve the models before employing them for climate change impact studies (Sillmann et al., 2013).

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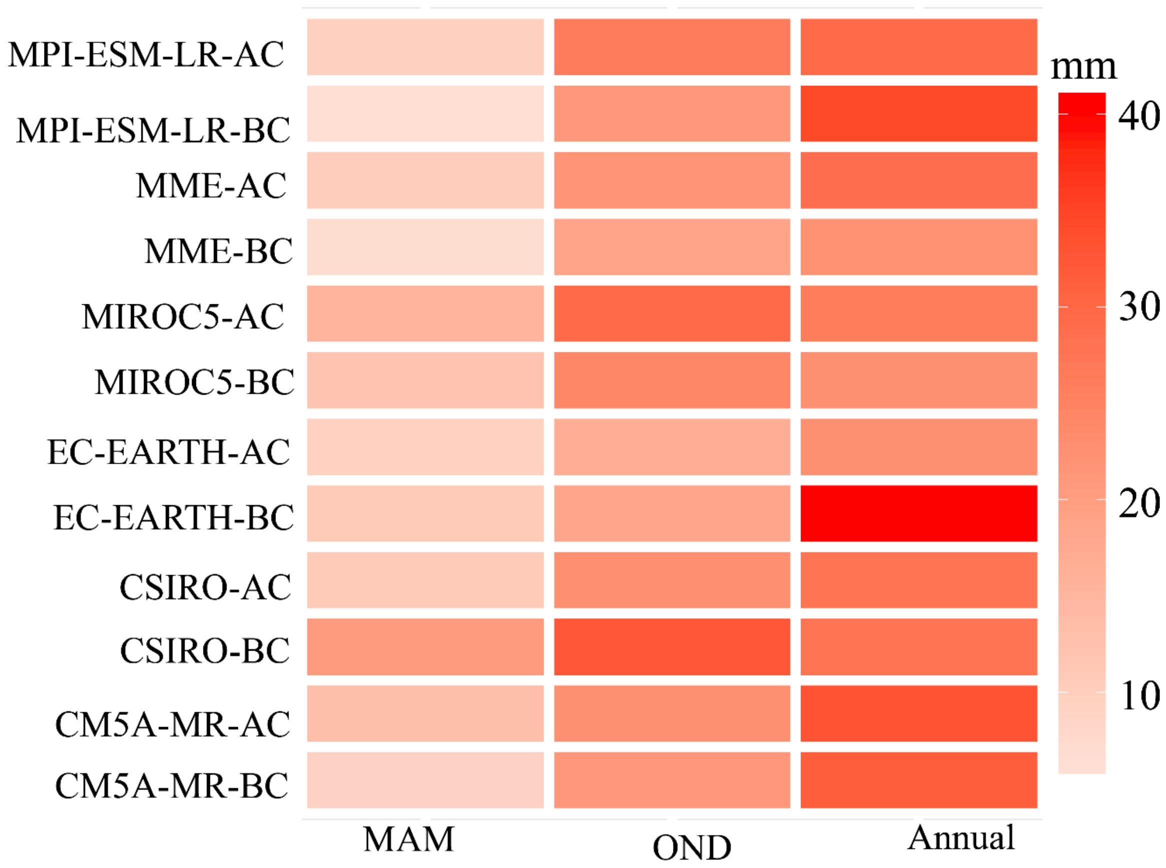

Fig. 5 Heat plot of seasonal and annual Mean Absolute Error (MAE) relative to each model during (1980-2005). A lighter color denotes better results whilst deep color represents unsatisfactory biased corrected value during the wet season and yearly basis.

3.1.2 Spatial bias correction estimates

Figure 6 presents spatial patterns of mean annual root mean square difference (RMSD) during the period 1980-2005 derived from five RCMs as well as their ensemble average. Also shown in the plots are corresponding bias corrected (abbreviated as AC) RCMs from Rossby Centre Regional Climate Model (RCA4), as well as the corrected multi model ensemble (MME). The models were corrected relative to climatic research unit (CRU TS4.02) datasets. The spatial plots depict regions of underestimations and overestimations and respective areas of enhancement after employment of quantile mapping technique.

It is apparent that significant biases simulated by the models corresponded with the regions that experience highest rainfall amount. This agrees with observed west to east gradient demonstrating heavier to lighter rainfall events over the study domain (Kimani et al., 2018a; Ayugi et al., 2019). As a result, the highest RMSD is noted in central and western sections of the study area whilst lowest biases (< 22.1 mm/month) is exhibited in the eastern

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and north western areas. The observed values of RMSD are mostly as a result of complex terrains such as high-altitude topographies. The central and western parts of Kenya has a varying topography explained by the presence of mountains like Mount Kenya and Mount Elgon, respectively. The areas are generally wet and humid, explained by large water bodies notable Lake Victoria.

As result, most models exhibited satisfactory performance after corrections with EC-EARTH, MPI-ESM-LR, and MME demonstrating exemplary improvement as compared to other models. The results concur with recent study that noted linear relationship between increased rainfall values and subsequent increase of systematic uncertainties (Kimani et al., 2018b). The overall monthly reduction in RMSD after correction ranged between 27 mm/month < RMSD < 11.0 mm/month.

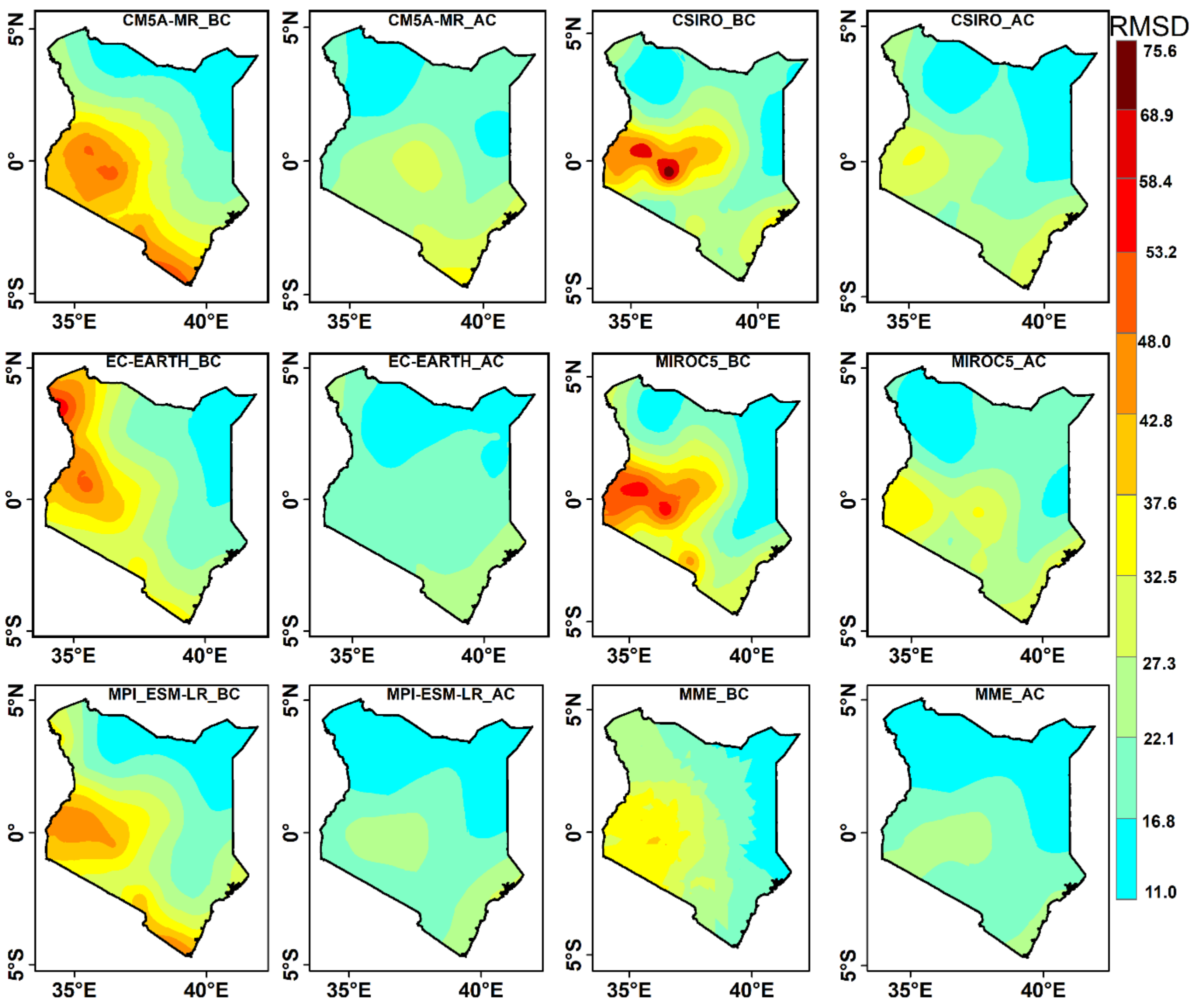

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Figure 6. Spatial pattern of mean annual RMSD (before correction [BC] and after correction [AC] for five global climate models (GCMs) dynamically downscaled with the Rossby Centre Regional Climate Model (RCA4), as well as their ensemble average.

Further analysis was conducted in an effort to evaluate how correction algorithm improves the model projections under RCP4.5 'stabilization scenario' and RCP8.5 'business as usual scenario'. **Figure 7** provides spatial patterns of mean rainfall for seasonal and annual based on Multi-model ensemble (MME) of five RCMs. The model's simulations were corrected using observed data while model projections entailed the simulations and observations as an input variable. It is apparent that historical simulations after corrections improved remarkably across various timescales to resemble the spatial patterns of observed data. Systematic biases appeared to reduce in regions that depicted strong biases, especially during the MAM rainfall season. Moreover, there was a strong evidence of improvement in both projections under medium emissions and strong emission scenarios in all the seasons. However, the regions characterized by complex topography tend to exhibit unsatisfactory reductions in biases, especially during the OND seasons. For instance, the model corrected under RCP8.5 depicts strong wet biases over central and western regions as compared to other timescales. Interestingly, the algorithm tends to show robust performance during the mean annual cycle that exhibits reduced rainfall occurrence.

These results agree with recent reports over broader study domains that have showed decreasing trends in rainfall patterns towards the end of twentieth century (Yang et al., 2015; Ongoma and Chen, 2017; Ayugi et al., 2018; Mumo et al., 2019). Further, these studies demonstrate a continued declining annual rainfall trends for different future scenarios over the study domain (Rowell et al., 2015; Tierney et al., 2015; Ongoma et al., 2018). On the contrary, the observed increment patterns during OND season concur with studies that have reported overestimations of OND, also referred as 'short rains' over the study region (Shongwe et al., 2011; Liebmann et al., 2014; Ongoma et al, 2018). Yang et al. (2015) highlighted the aspect of challenges associated with simulations of atmosphere-ocean-monsoon interaction over East Africa region as the major cause of observed bias in models during OND and MAM projections. According to Liebmann et al. (2014), the warming of western Indian Ocean continues to play a significant role in simulated and projected patterns during seasonal rainfall cycle

These results clearly depict that the QMBC can satisfactorily improve the models under different scenarios and timescales hence its relevance for correcting RCMs outputs. Its application will in effect minimize possible biases, therefore it is suitable for evaluation of extreme events such as drought and flood that continue to pose threat to livelihoods and socio-economic infrastructure over the study domain. Teleconnection patterns responsible for influencing the rainfall during the OND is likely to be amplified during the business as usual model. This scenario could explain the systematic biases that are persistent in models even after the corrections. This calls for a cautious view of the possible limitations of correction techniques during the future projections (Cannon et al., 2015).

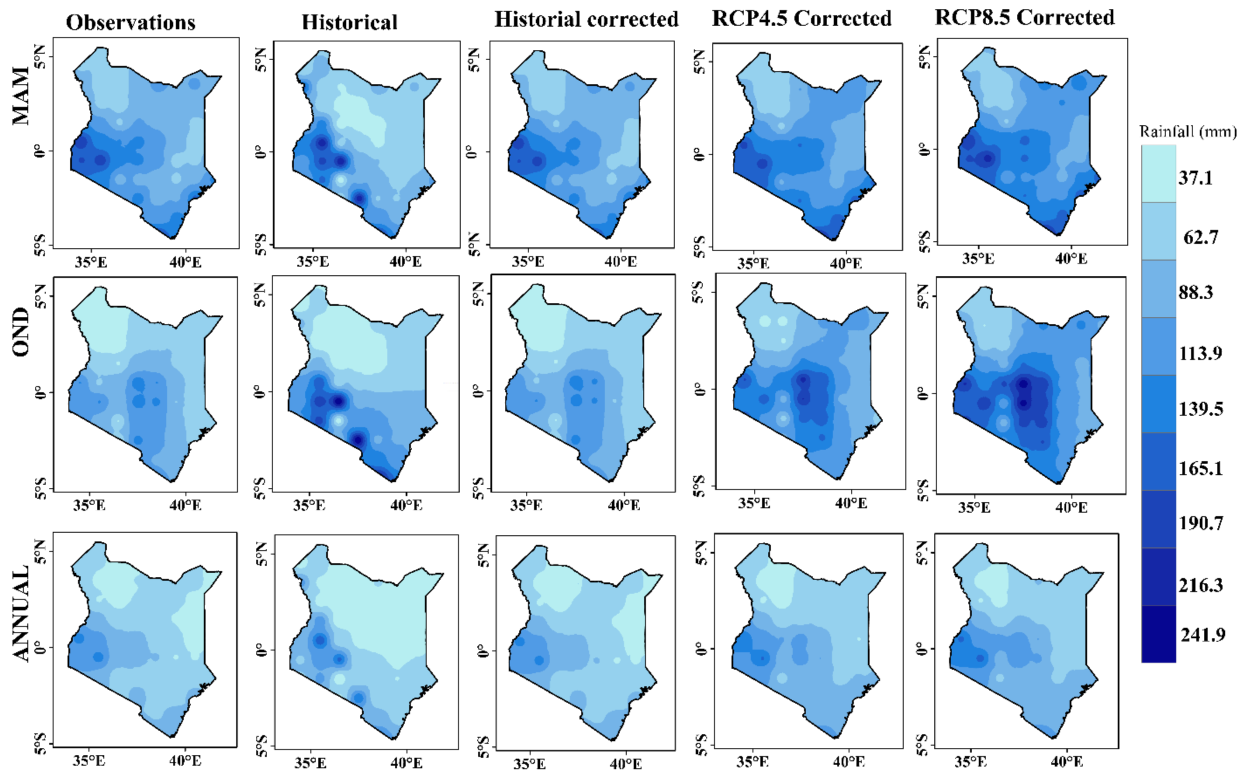

Figure 7. Spatial pattern of mean rainfall for seasonal and annual for observation, simulated, simulated corrected and model corrected projections based on MME of 5 global climate models (GCMs) dynamically downscaled with the Rossby Centre Regional Climate Model (RCA4).

4. Conclusion and Recommendation

The current study examined the effectiveness of quantile mapping bias correction on Rossby Climate Models (RCA4) for drought and flood analysis. The study is a follow-up study by Ayugi et al., (2020) on the recent assessment of performance of RCA4 models over the study domain. Ayugi et al., (2020) elucidated existence of unsystematic and systematic biases in the better performing models across the region. Thus, the current study was conducted within this

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backdrop. Correction to both mean annual and seasonal variance was conducted by employing The Split Sample Testing (SST) approach. The correction was conducted by first training data for 29 years (1951-1979) to derive biases field for monthly averages in model and observed precipitation simulations. The monthly biased field were then used to correct independent RCMs during the next 26-year (1980-2005) validation period. The models corrected are as follows: MIROC5, CSIRO, IPSL-CM5A-MR, MPI-ESM-LR, EC-EARTH, and MME. Broadly, RCMs simulations depicts significant biases that are mostly associated with regions of complex terrains such as high altitude or wet humid regions within the study area. The QMBC demonstrates varying performance from one model to another on both spatial and temporal scales. However, most models exhibit significant improvement after corrections on both seasonal and annual timescales. Specifically, the models EC-EARTH and CSIRO portray exemplary improvement as compared to other models. On the other hand, the model CM5A-MR model show weak enhancement across various timescales. i.e. MAM and OND. The corrected models can be employed for projections of extreme events; drought and flood over the study area. The outputs will aid in appropriate policy formulation for effective and reliable adaptation techniques. The models showing persistent unsatisfactory improvement after employing correction approaches should utilized with caution due to the existence of hidden non-linearity and complex dynamical processes that are uncorrectable.

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Compliance with ethical standards

In a unanimous agreement, all authors declare no conflict of interest in the study.

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