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Extreme Rainfall Assessment using Global Climate Models over the Greater Horn of Africa

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Abstract

The October to December (OND) is a major rainfall season over the Greater Horn of Africa (GHA) with strong El Niño Southern Oscillations (ENSO) signals and high rainfall variability leading to drought and floods. One of the major efforts to address these climate extreme challenges is the use of the Global Producing Centers (GPCs) models for seasonal forecasting. These extremes can be studied better by the use of individual models than ensemble for early warning and preparedness. This paper focuses on the evaluation of the eight individual models for seasonal rainfall forecasting over this region. The OND season is considered because it is a major season which exhibits high rainfall variability in the region. Gridded observation and model outputs from 1983 to 2001 were used and the methodologies employed include; regression analysis, correlation and error analysis techniques.

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The El Niño/La Niña years were correctly simulated by Washington, Montreal and Moscow models over the Equatorial sector. Significant correlation coefficients (0.76) were observed over this sector. Reduced mean errors across the Equatorial sector for Washington and Montreal models were observed. Rainfall onset to peak periods was clearly identified; however, few models dragged the peak rainfall to either early or mid December. The use of individual models for extreme precipitation studies is very crucial in decisive action for early warning and preparedness for disaster risk reductions.

Key words: Climate Extremes, El Niño Southern Oscillations, Model physics, Equatorial Sector

1. Introduction

The Greater Horn of Africa (GHA) region's climate is highly variable geographically making it most frequented by catastrophes associated with recurrent hazards. The region mostly experiences bi-modal rainfall patterns; with long rains occurring between March-April-May (MAM) and short rains occurring between October-November-December (OND). The climate system like Inter-Tropical Convergence Zones (ITCZ) swaps the region twice resulting to bimodal rainfall season (Anyah and Semazzi 2006; Yang *et al.,* 2015). The current trend of declining rainfall and climate variability poses economic and predictability challenges to the region (Eguru *et al.,* 2014).

Whenever an extreme event occurs, the impact and economic losses is always great especially to regions that rely heavily on rainfall for Agriculture activities (Nicholson 2014).Lyon and De Witt (2012), points out that the failures of some of the climate models to issue correct forecasts leads to high vulnerability of the region to the disasters; the reliability and predictability nature of any such systems is key for regional socio- economic stability (Diro et al., 2012).

The current regional efforts geared towards addressing these extremes relies on statistical, dynamical and in some cases a hybrid. Landman et al. (2009) argues that statistical method is still the best way of forecasting climate systems. The complex nature of climate systems makes statistical method still lacking in addressing some uncertainties in the climate forecasts. Dynamical models which is a mathematical representations of the interactions between the atmosphere, oceans, land surface, ice – and the sun provides a better representation of climate systems especially where the statistical fails to represent rainfall processes around the mountainous and lake region (Chang et al., 2013). The hybrid systems take care of both statistical and dynamical methods. In the dynamical approach, the use of high resolution models for simulation processes is desired.

The General Circulation Models (GCMs) though course in resolution, are still capable of providing climate information that are physically consistent to the climate systems. They are robust in regional climate assessment and provide boundary conditions that are lacking in the regional climate models. The model comparison with the observations is still the best way to assign confidence in the climate models (Yang et al., 2014). Over the GHA region, the World Meteorological Organization (WMO) has designated Global Producing Centers (GPCs) provide climate forecast products to alleviate the adverse impacts caused by these events (Stockdale *et al.,* 2010). This study focused on evaluation of individual eight models skill as way of assigning confidence on each model. The individual assessment of the models using systematic and consistent methodologies helps to understand the spatial strength and weaknesses of each model.

The GHA comprises of eleven countries namely Kenya, Uganda, Tanzania, Ethiopia, Burundi, Rwanda, Sudan, South Sudan, Eritrea, Djibouti and Somalia. The region lies between 21°N and 12°S and 23.5°E and 52°E and is characterized widely by diverse climatic conditions ranging from dry to humid equatorial climate conditions. The presence of the water bodies, mountains and valleys generates land-sea/land-lake breezes and slope winds introduce regional and local modifications of the general circulation. Lake Victoria, for instance, has a strong circulation of its own with a semi-permanent trough, which migrates from land to lake and lake to land during the night and day respectively (Bowden, 2004; Anyah and Semazzi 2006).

The General Circulation Models (GCMs) from Global Producing Center (GPCs) currently in operation must be evaluated against the observation in order to assign confidence for their use. The multi-model ensemble approaches reduce model errors and produce more skillful forecasts than the single models (Wang et al., 2008, Krishnamurti et al., 2008 and AchutaRao et al., 2006 and Otieno et al., 2014). The multi-model ensemble however cannot be used to study the extreme precipitation patterns in the individual models because of its averaging tendency (Kang and Jin Ho 2006). Opijah et al. (2014) pointed out that model performance over GHA region is still a challenge due to the tendency of the climate models to average climate processes especially for meso-scale processes. The Equatorial sector of the GHA region shows high predictability skill during the OND season for ENSO events (Muhati *et al.,* 2007). The study therefore evaluated the skill of individual eight models for extreme precipitation analysis during the OND.

Past studies have shown that seasonal climate prediction skill is higher during OND months and ENSO events (Dutra *et al.,* 2013a and Mwangi *et al.,* 2013) due to the strong relationship between the OND season rains, Sea Surface Temperatures and ENSO parameters dominant during the season (Ogallo *et al.*, 2008; Bowden and Semazzi 2007; Omondi *et al.*, 2012; Lanman *et al.*, 2012; Anyah and Semazzi 2006). The study therefore concentrated on a pilot ENSO period of 1997 and 2000 when a strong El Nino event of 1997/98 shifted to strong La Nina event in the years 1999/2000 with far reaching implication when climate anomalies over most of GHA region shifted from extreme floods in 1997/98 to extremes droughts 1999/2000 years.

2. Materials and Methods

The last phase of the study used eight climate models from GPC centers (Table 1). The models were used to provide hindcast datasets over the GHA region during the ENSO years 1997 to 2000. These were compared with observed rainfall data used in this study including the University of East Anglia gridded observed rainfall data from the Climate Research Unit (CRU), together with data from point rainfall stations over GHA based on homogenous zones and correlations between inter-stations (Ogallo, 1989).

Table 1: Characteristics of the WMO Global Producing Centers

Model	Center	Ensemble size	Resolution
Beijing (Bei)	BCC	Coupled (48)	T63/L16
Melbourne(Melb)	Australian Bureau of Meteorology	Coupled (33)	T47/L17
Montreal(Mont)	Meteorological Service of Canada	2-tier (40)	T32/T63/T95/2.0° × 2.0° (4- model combination)
Seoul	KMA	2-tier (20)	T106/L21
Tokyo(Tok)	JMA	Coupled (51)	TL159/L40
CPTEC	CPTEC	2-Tier(15)	T62/L28
Washington(Wash)	NCEP	Coupled (41)	T62/L64
Moscow (Mosc)	Hydromet Center of Russia	2-tier (10)	1.1° × 1.4°/L28

Table 2: A 3 by 3 Contingency Table

		FORECAST			**TOTAL**
OBSERVED		Below Normal	Normal	Above Normal	
	Below Normal	A	B	C	M
	Normal	D	E	F	N
	Above Normal	G	H	I	O
TOTAL		J	K	L	T

Table 3: Computation of Skill Scores Based on Table 2

	Below Normal (BN) Rainfall Category	**Normal Rainfall Category(N)**	**Above Normal(AN) Rainfall Category**
Bias	J/M	K/N	L/O
PoD	A/M	E/N	I/O
FAR	1-A/J	-	1-I/L

The spatial and temporal distributions of observed and predicted rainfall anomalies over the study domain were plotted, showing the areas with biases. The relationship between the model estimates and observed rainfall output was developed using the regression technique. Correlation analysis involved determining the Spearman's correlation coefficients and the computed coefficient value tested for significance at the 95% confidence interval using student T-test. Categorical statistics employing a 3 by 3 contingency table (Table 2) was used to assess the skill of model output.

Table 3 shows the formulation for computing various scores used in the study. The Bias score indicates whether the forecast system has a tendency to under forecast (Bias<1) or over forecast (Bias>1) rainfall events, and ranges from 0 to∞, with a perfect score of unity. The categorical statistics derived from Probability of Detection (PoD) give a simple measure of the proportion of rainfall events successfully forecast by the model with the perfect score is 1 (Wilks,2006).

3. Results and Discussion

Figure 1 shows the spatial distribution of rainfall observed from CRU estimates and 8 model rainfall output for El Niño Episode 1997. High rainfall amount was mainly around the Equatorial sector, mostly in the western part of the GHA and southern part of the coastal strip of Kenya. The observed rainfall distribution is attributed mainly to the influence of the ITCZ, ENSO parameters and local forcing which agrees with the previous findings. These findings are consistent with previous studies by Indeje et al. (2000). Low rainfall occurred in the Northern and Southern sectors of the study region. The distribution of the observed rainfall from CRU was closest to the spatial patterns from the Washington, Melbourne, Moscow, Montreal, Seoul, and CPTEC.

Figure 2 shows the spatial distribution of observed and modeled rainfall for the La Nina episode of 2000. Drought condition dominated most parts of the GHA a part from some western Equatorial sectors. The distribution of rainfall was observed during the 1999/2000 La Nina period show relatively low rainfall values in models CPTEC, Montreal, Seoul and Tokyo models. The stations that depicted low distribution of rainfall around the Equatorial sector were from central Kenya and northern Part of Tanzania. These findings are consistent with studies by Cholette et al. (2015) who reported that with the advancement in computing facility and, some GCMs still experience challenges in simulations of climate processes around the mountainous areas. The distribution of observed low rainfall for the La Nina period was closest to the products from Moscow, Montreal, Soul, Tokyo and CPTEC. Comparatively, Figures 1 and 2 show the opposite rainfall anomaly signals during El Nino and La Nina periods signal. These results agree with previous studies by Ogallo et al. (2000) and Yang et al. (2014).

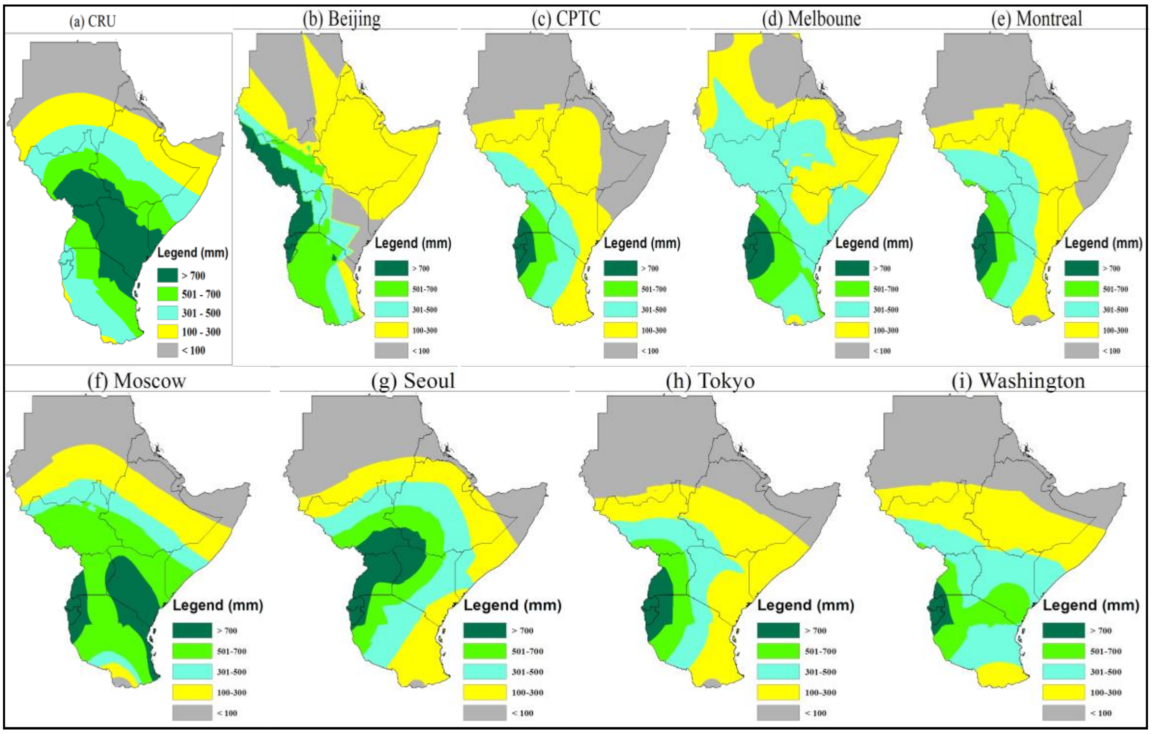

Figure 1: Spatial distribution of observed and 8 model rainfall output for the El Niño Episode of 1997

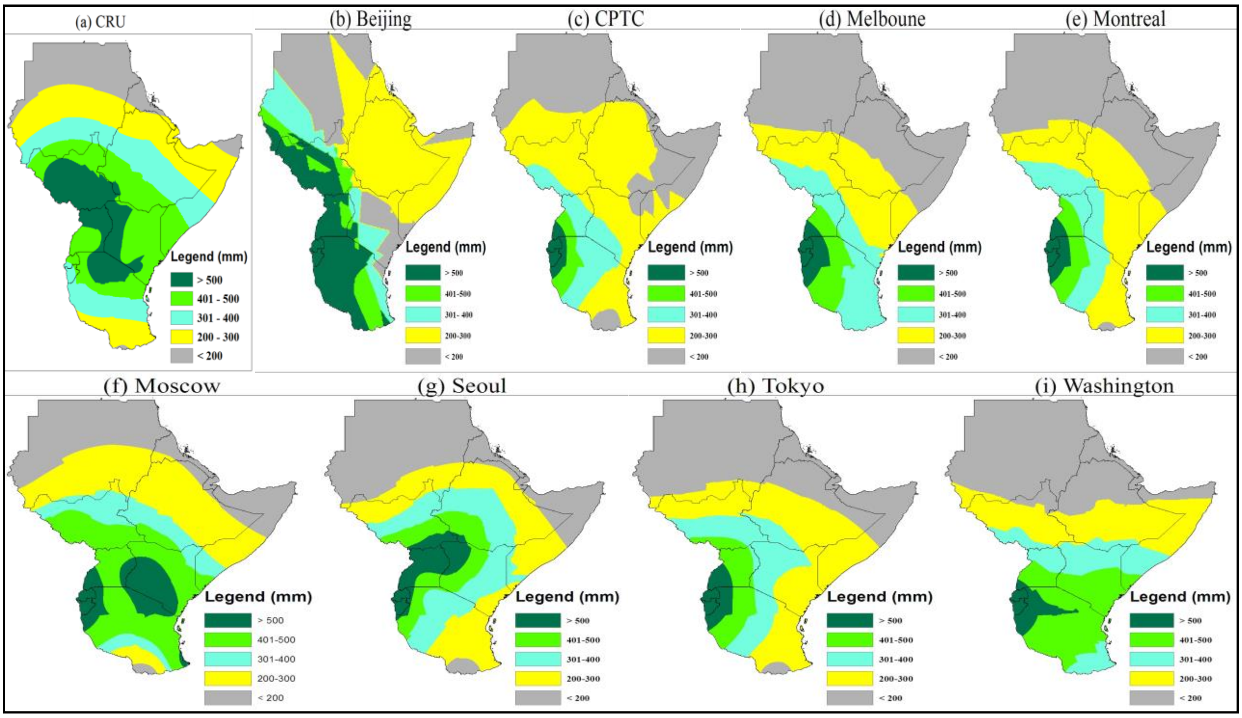

Figure 2: Spatial distribution of observed and model rainfall for the La Niña episode of 2000

Table 4 shows the values of correlation coefficients obtained between the model output and the observed rainfall over the Equatorial sector during the OND season. The green shadings indicate significant correlations. Statistically significant correlation coefficients equal to or greater than 0.43 were observed in many areas, with highest values of 0.76 is some areas. This represents an explanation of total maximum variance ranging from 18 – 42%. Most significant correlations were concentrated across the Equatorial sector of the GHA region. This is attributed to the influence of the ITCZ and meso-scale forcing during the OND season. This finding is consistent with studies by Ogallo et al. (2000) and Muhati et al. (2007) that revealed strong correlation between rainfall and model estimates over Equatorial sector during OND season due to the strong influence of ENSOSea Surface Temperatures (SSTs) and large scale climate systems.

Table 5 shows the results of the regression analysis of the individual model outputs based on their R-squared and P-values at 95% confidence interval. Most stations around the Equatorial region had R-squared values of above 45% and P-values below 0.1. These results indicate that the models had skill over this region.

Table 4: Correlation Coefficients between CRU and Model Estimates

CRU Data	Beij	CPTEC	Melb	Mont	Mosc	Seoul	Tokyo	Wash
Abuhamad	-0.38	0.07	-0.38	-0.39	0.44	0.16	-0.23	0.35
Bujumbura	0.33	-0.15	0.39	0.17	0.31	-0.03	-0.44	0.35
Combolcha	0.41	0.11	-0.37	0.12	0.12	-0.17	0.29	0.37
Dagoreti	0.05	0.43	0.10	-0.18	-0.14	-0.14	0.44	0.66
Djibouti	0.15	-0.26	0.35	0.58	0.50	0.37	0.38	0.64
Entebbe	0.04	0.49	0.18	0.19	0.52	0.23	0.21	0.75
Gulu	0.35	-0.20	-0.18	0.07	-0.02	0.08	0.49	0.43
Juba	0.12	-0.23	0.12	-0.18	-0.14	0.13	0.33	0.51
Kabale	0.38	0.21	-0.56	0.36	-0.45	-0.01	0.18	0.27
Kericho	0.13	0.11	-0.04	0.08	-0.61	0.06	0.39	0.22
Khatoum	0.07	-0.16	-0.06	-0.08	-0.11	0.02	0.28	0.55
Lamu	0.12	-0.22	0.15	-0.16	-0.15	0.14	0.34	0.53
Lodwar	0.12	-0.22	0.15	-0.16	-0.15	0.14	0.34	0.53
Makindu	0.05	-0.57	0.01	-0.22	0.03	0.08	0.16	0.48
Mtwara	-0.06	-0.43	-0.19	0.70	0.09	0.06	0.76	0.66
Mwanza	0.03	-0.23	-0.11	-0.28	-0.01	0.19	0.32	0.37
Narok	0.49	-0.17	0.03	-0.23	0.03	0.11	0.40	0.43
Wajir	0.07	-0.16	-0.23	-0.06	-0.43	0.07	0.08	-0.08

Table 6: Regression Analysis for Selected Stations

Stations	Regression Equations	R-Square	P-value
ABUHAMAD	0.304*BEI +0.596*MONT+0.705*MOSC	72	0.012
BUJUMBURA	-0.983*TOK-0.43*MELB	54	0.024
DJIBOUTI	0.564*WASH	26	0.289
ASMARA	-0.234*BEI-0.467*CPTEC	58	0.025
COMBOLCHA	0.989*WASH	46	0.021
LODWAR	0.53*WASH	37	0.049
KERICHO	-0.674*MOSC+0.369*MONT	36	0.205
LAMU	0.021*WASH+0.111*MONT	53	0.012
DAGORETI	-0.561*MONT	27	0.123
MTWARA	-0.281*MONT+0.744*WASH	53	0.13
JUBA	-0.308*MONT+0.75*WASH	51	0.117
KHARTOUM	0.833*WASH	48	0.032
ENTEBBE	-0.184*CPTEC+0.777*WASH	68	0.09
GULU	0.716*TOKYO	31	0.075
KABALE	-0.581*MELB	41	0.035

4. Categorical Skill Scores

Table 6 gives a summary of skill scores for the stations that showed strong correlation between the observed rainfall and model outputs. Most stations in the Equatorial sector had over 47% correct forecasts. The skill of the individual models was better over the Equatorial sector than other sectors of the study region.

In the analysis of bias, 40% of the forecasts were perfect for the models considered; 60% of the forecasts were almost nearing to perfect scores. From the results of the probability of detection, 87% instances predicted above 50% for the normal rainfall category; 70% instances predicted above 50% for the above normal category and 53% instances predicted above 50% for below normal category. Over 50% of the stations within the Equatorial sector had a score above 50%, while stations in the Northern and Southern regions recorded scores less than 50%.

In the analysis of the False Alarm Ratio, stations within the equatorial region recorded scores less than 50% for the below and above normal rainfall categories while those in the northern and southern sectors of the region recorded scores of more than 50%.

5. Conclusions

The models were able to simulate the ITCZ rain-bearing system and the rainfall distribution over the GHA during the OND season during both El Nino and la Nina episodes. The models correctly showed higher quantities of rainfall in the Equatorial belt. The models however tended to under-predict the amount of rainfall over the region; the rainfall was also displaced.

The models realized better skill over the Equatorial sector of the GHA than over the northern and southern sectors of the GHA during the OND season. The study revealed that Washington, Moscow and Montreal models gave the best representation of the observed rainfall pattern over the Equatorial sector of the Study domain. The correct model physics representation is a precursor for any realistic climate simulations. The ability of climate models in simulating regional rainfall within the GHA is important for socio-economic planning and risk reduction associated with climate extremes.

The extreme precipitation patterns can be studied better by the use of individual models than ensemble modeling; this assists in decisive action for early warning and preparedness for disaster risk reductions. Further studies needs to be done on better ways to represent small scale processes like cloud convection, soil moisture, Radiation amongst others in the climate models.

Table 6: Summary of Various Skill Scores

Station	Model	PC	POD			FAR		BIAS		
			BN	N	AN	BN	AN	BN	N	AN
Abuhamad	Beij, Mon and Mos	53	33	57	66	60	0	83.3	142	66
Bujumbura	Tokyo and Melb	53	50	16.7	86	50	40	100	50	140
Asmara	Bei and CPTEC	47		57	83	0	50	0	129	167
Combolcha	Washington	42	50	28	50	50	62	100	70	130
Dagoretti	Montreal	42	50	29	50	25	67	70	86	150
Djibouti	Washington	68	33	86	83	0	37	33	130	133
Entebbe	Washington & CPTEC	52	33	57	67	0	50	33	133	133
Gulu	Tokyo	31	33	71	67	33	20	50	150	80
Juba	Montreal& Washington	68	67	71	67	20	43	80	100	100
Kabale	Melbourne	42	57	86	33	33	35	0	200	50
Kericho	Moscow and Montreal	63	67	71	50	20	40	80	130	80
Khartoum	Wash	37	50	14	50	50	57	100	90	100
Lamu	Wash and Mon	63	83	43	67	29	43	120	70	120
Lodwar	Washington	47	33	43	67	33	50	50	110	130
Mtwara	Mon and Mel	63	33	100	50	0	0	30	200	50

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