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Full Length Research Paper

Seasonal rainfall forecasting using the Multi-Model Ensemble Technique over the Greater Horn of Africa

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This study evaluated the skill of forecasting seasonal rainfall over the Greater Horn of Africa (GHA) using Ensemble Model Technique from a cluster of four General Circulation Climate Models (GCMs) from Global Producing Centers (GPCs). The spatial distribution of rainfall anomalies of the observed models output during extreme events showed that the ensemble model was able to simulate El-Niño (1997) and La-Niña (2000) years. The ensemble models did not show good skill in capturing the magnitude of the extreme events. The skill of the ensemble model was higher than that for the member models in terms of its ability to capture the rainfall peaks during the El-Niño Southern Oscillation (ENSO) phenomena. The analysis for the correlation coefficients showed higher values for the ensemble model output than for the individual models over the Equatorial region with the stations in the northern and southern sectors of the GHA comparatively giving low skill. The ensemble modeling technique significantly improved the skill of forecasting, including the sectors where individual models had low skill. In general, the skill of the models was relatively higher during the onset of the ENSO event and became low towards the decaying phase of the ENSO period. Generally, the study has shown that the ensemble seasonal forecasting significantly adds skill to the forecasts especially for October-December (OND) rainy seasons. From the study, ensemble seasonal forecasting significantly adds skill to the forecasts over the region. Blending dynamical ensemble forecasts with statistical forecast currently being produced during Regional Climate Outlook Forums (RCOFs) would add value to seasonal forecasts. This significantly reduces the impacts and damages associated with climate extremes over the region.

Key words: Climate extremes, El-Nino, La-Nina, skill, El-Niño Southern Oscillation.

INTRODUCTION

The frequent hazards and disasters like drought and floods over the Greater Horn of Africa (GHA) each year have led to high economic losses (Omondi et al., 2013; Ogallo et al., 2000; Bowden, 2007; Mwangi et al., 2014). The availability of accurate predictions mechanism with adequate lead time would be very essential strategy to address these challenges. The Global Producing Centers (GPCs) designated by the World Meteorological Organization (WMO) (Timothy et al., 2009; WMO, 2010; Graham, 2010) provide climate forecast products to alleviate the adverse impacts caused by these events. These model products over the region need to be

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evaluated in terms of their skill using systematic and consistent methodologies (Krishnamurti et al., 2008).

The region of the study was the Greater Horn of Africa (GHA) which comprises 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, 2007).

The regional seasonal forecasts currently relies on the statistical outputs obtained from historical archived datasets and dynamical model outputs from GPC models (Otieno, 2013; Ogallo et al., 2008; Mwangi et al., 2014). The applications of these models have been extended to GHA but the skill of such models in the region has not been extensively tested. A study by Otieno (2013) on the suitability of GPCs for seasonal forecasting found an appreciable level of skill over the Equatorial sector. However models registered biases in the forecasts especially over the Northern and southern sector of the GHA.

The multi-model ensemble are some of the techniques currently operational over the region that reduces model errors and produce more skillful forecasts (Wang et al., 2008; Krishnamurti et al., 2008; AchutaRao et al., 2006; Palmer et al., 2004). This study sought to assess the skill of ensemble models from a cluster of 4 models in simulating regional rainfall characteristics over the GHA.

Past studies have shown that seasonal climate prediction skill is higher during OND seasons and ENSO events (Dutra et al., 2013; Mwangi et al., 2014). This has been attributed to the strong relationship between the OND season rains, Sea Surface Temperatures (SSTs) and ENSO parameters which are dominant systems influencing rainfall during the season (Ogallo et al.,, 2008; Bowden et al., 2006; Omondi et al., 2012; Lanman et al., 2012). This study therefore concentrated on ENSO period of 1997 and 2000 when a strong El-Nino event of 1997/1998 shifted to strong La-Nina event in the years 1999/2000.

DATA AND METHODOLOGY

This study used four models out of eight GPCs models to generate ensemble models for seasonal climate prediction over the region. Table 1 shows the summary of the characteristics of the four models while Table 2 shows the models performance based on R-square and regression weights calculated for each of the four models.

Composite Analysis method was used to calculate the model weights. The simple composite for the first ensemble model forecast (ENSE 1) is shown in Equation 1:

$$ENSE\ 1 = \frac{1}{n}\sum_{i=1}^{n} mi \quad \text{..(1)}$$

where, *mi* is the rainfall output for the i^{th} model and *n* is the total number of years used for the prediction.

The second ensemble (ENSE 2) model was developed as an improvement to the first ensemble from the four models that had high skill (Equation 2):

$$\bar{y} = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_k x_k \quad \text{.......................(2)}$$

where b_k is the k^{th} regression weight for the model, x_k is the k^{th} number of models used to generate the ensemble model, and $\bar{y_i}$ is the predictand. The regressions coefficients and the R-square explained by the individual models were multiplied and then divided by their totals to generate the weights. The best most skillful model got higher weight and the less skillful model amongst the four got the least weight.

The data were obtained from model hindcast datasets from four models 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.

The spatial distributions of observed and predicted rainfall anomalies over the study domain were plotted. 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. The regression analysis method was used for the individual models to determine the weights of each of the individual models to generate the ensemble models. 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 or over forecast rainfall events. The categorical statistics derived from Probability of Detection (PoD) gives a simple measure of the proportion of rainfall events successfully forecasted by the model (Table 4).

RESULTS AND DISCUSSION

The four global forecasting models from Washington, Montreal, Melbourne and Moscow GPCs were subjected to further analysis since they had better skill (Table 5).

Table 1. Characteristics of the WMO global producing centers.

Model	Center	Ensemble size	Resolution
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)
Washington (Wash)	NCEP	Coupled (41)	T62/L64
Moscow (Mosc)	Hydromet Center of Russia	2-tier (10)	1.1° × 1.4°/L28

Table 2. Model ranked based on R-square and regression coefficients.

Model	R-Square	Coefficient
Washington	47	0.74
Montreal	41	0.63
Melbourne	17	1.29
Moscow	16	1.00

Table 3. Contingency table.

		Forecast			Total
		Below Normal (BN)	Normal (N)	Above Normal (AN)	
Observed	BN	A	B	C	M
	N	D	E	F	N
	AN	G	H	I	O
Total		J	K	L	T

Table 4. Computation of skill.

	BN	N	AN
Bias	J/M	K/N	L/O
PoD	A/M	E/N	I/O
FAR	1-A/J	-	1-I/L

Table 5. Model weights developed for the four models.

Model	Weight
Washington	0.36
Montreal	0.27
Melbourne	0.20
Moscow	0.17
Total	1.00

Figure 1 shows the results of the spatial analysis of the first model ensemble (ENSE 1), second model ensemble (ENSE 2) and observed rainfall distributions from CRU for the years 1983 to 2001. The spatial distribution pattern of rainfall for ENSE 1 and ENSE 2 show that most rainfall was over the Equatorial Sector (Figure 1a and b). The distribution pattern of ENSE 2 model output was very close with the observed rainfall pattern (Figure 1c).

Figure 2 shows the spatial distribution of the observed rainfall, ENSE 1 and ENSE 2 model rainfall output over the study domain. The rainfall distribution pattern is concentrated on the western sector of the GHA. ENSE 2 depicted high simulation of observed rainfall pattern than ENSE 1 (Figure 2a, b, c). During El-Niño year for the OND season, the distribution of rainfall pattern was on the Equatorial sector of the study domain. These results are consistent with those of similar previous works over the region (Owiti, 2004; Conway et al., 2007; Muhati et al., 2007; Endris et al., 2013). The observed rainfall distribution is attributed mainly to the influence of the ITCZ, ENSO parameters and local forcing during the OND season.

The rainfall distribution pattern was concentrated on the

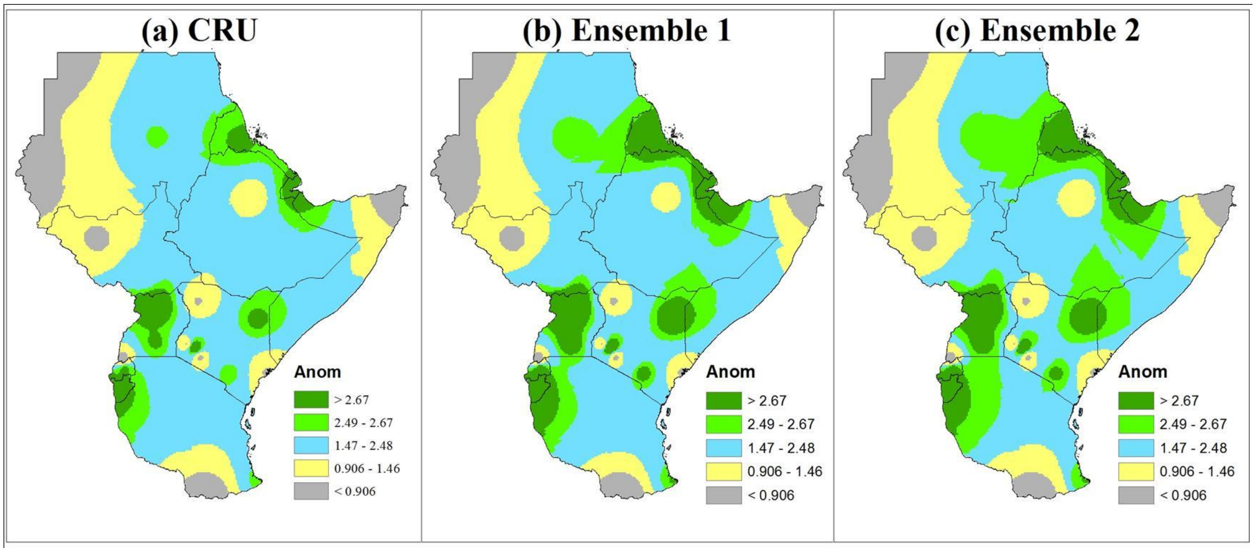

Figure 1. Spatial distribution of: (a) CRU, (b) ENSE 1 and (c) ENSE 2 for 1983-2001.

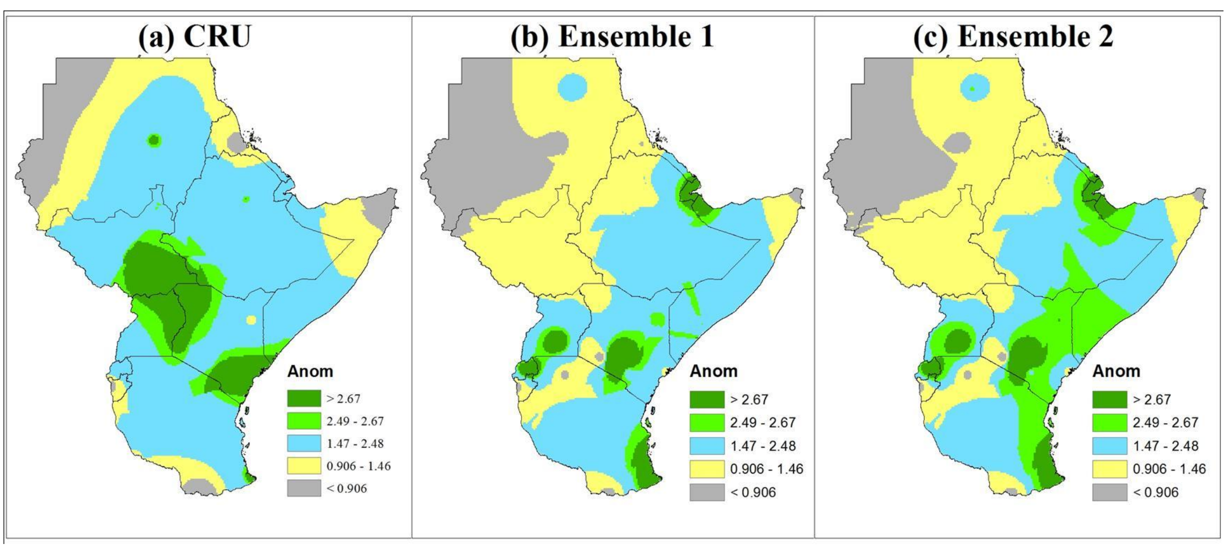

Figure 2. Spatial distribution of (a) CRU, (b) ENSE 1 and (c) ENSE 2 models output for 1997.

western sector of the GHA over the study domain during La Niña episode 2000 (Figure 3). The distribution pattern of rainfall was better in ENSE 2 than ENSE 1 models output as shown in Figure 3. The distribution of rainfall pattern was on the Equatorial sector of the study domain.

Table 6 shows the correlation coefficients for the individual models while Table 7 shows the correlation coefficients calculated for the ensemble models output. The coefficients increased especially for stations around the Equatorial sector. For example in Table 6, stations like Dagoreti, Entebbe, Gulu, Kericho and Kabale, the correlation coefficients are in the range of -0.5 to 0.6. In Table 7, the coefficients are in the range of 0.3 to 0.7. The improvements in the coefficients were also realized from the ENSE 1 to ENSE 2 model output. For example the coefficients for the stations: Abuhamad, Khartoum, Asmara and Juba for the ENSE 1 are 0.21, -0.7, 0.56 and 0.68 respectively. For the ENSE 2 models output, the correlation coefficients are 0.23, 0.75, 0.56 and 0.73 respectively.

For the stations in the Equatorial sector, that is, Dagoreti, Entebbe, Gulu, Kericho and Kabale, the coefficients for ENSE 1 are 0.63, 0.61, 0.76, 0.71, 0.62 and 0.33. For ENSE 2, the coefficients from the same

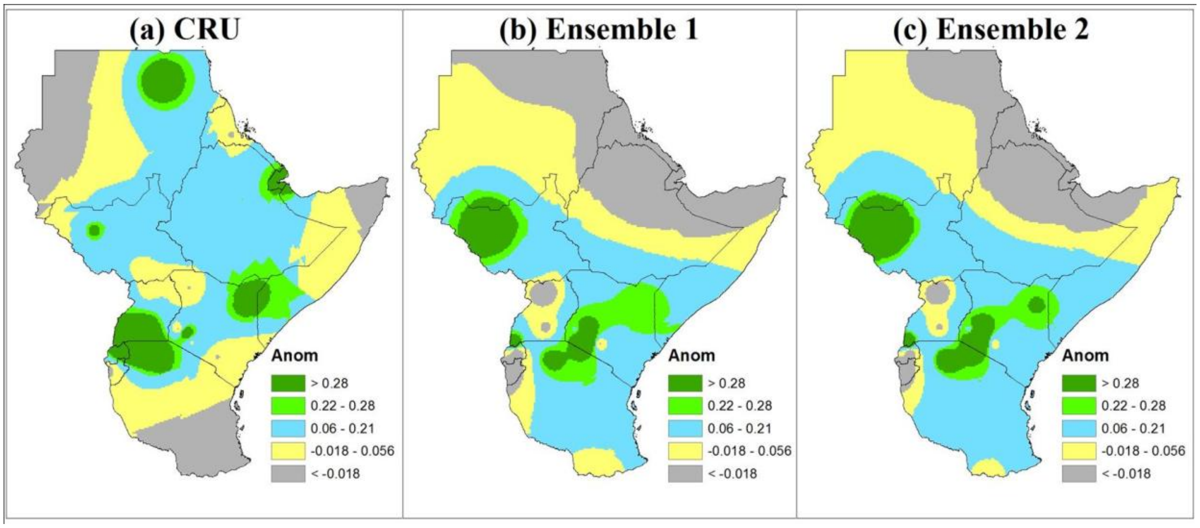

Figure 3. Spatial distribution of (a) CRU, (b) ENSE 1 and (c) ENSE 2 models output for 2000.

Table 6. Correlation coefficients between CRU data at various stations and individual GPCs product.

CRU Data	Melbourne	Montreal	Moscow	Washington
Abuhamad	-0.38	-0.39	0.44	0.35
Bujumbura	0.39	0.17	0.31	0.35
Combolcha	-0.37	0.12	0.12	0.37
Dagoreti	0.10	-0.18	-0.14	0.66
Djibouti	0.35	0.58	0.50	0.64
Entebbe	0.18	0.19	0.52	0.75
Gulu	-0.18	0.07	-0.02	0.43
Juba	0.12	-0.18	-0.14	0.51
Kabale	-0.56	0.36	-0.45	0.27
Kericho	-0.04	0.08	-0.61	0.22
Khatoum	-0.06	-0.08	-0.11	0.55
Lamu	0.15	-0.16	-0.15	0.53
Lodwar	0.15	-0.16	-0.15	0.53
Makindu	0.01	-0.22	0.03	0.48
Mtwara	-0.19	0.70	0.09	0.66
Mwanza	-0.11	-0.28	-0.01	0.37
Narok	0.03	-0.23	0.03	0.43
Wajir	-0.23	-0.06	-0.43	-0.08

stations are 0.65, 0.55, 0.78, 0.64, 0.62 and 0.37. The above findings are consistent with those of previous work by Ogallo et al. (2008). These results could be attributed to the influence of the rain bearing system like ITCZ and mesoscale forcing (Muhati et al., 2007).

Figure 4 shows the spatial distribution of correlation coefficients for ENSE 1 and ENSE 2 models output over the GHA. This shows where the correlation indices were high and those regions where they were low during the OND season. High correlation values were concentrated around the Equatorial sector. Other regions that showed high correlation with the ensemble models were central Ethiopia and the Kenyan Coastal strip. Correlation values ranging between 0.4 and 0.5 were evenly distributed over most sectors of the study region (Figure 4b). Low coefficients were observed on the northern part of Kenya,

Table 7. Correlation between Observed, ENSE 1 and ENSE 2 model output rainfall anomalies respectively.

Stations	ENSE 1	ENSE 2
Abuhamad	0.21	0.23
Asmara	0.56	0.26
Bujumbura	0.59	0.64
Combolcha	0.29	0.43
Dagoretti	0.63	0.65
Djibouti	-0.35	0.55
Entebbe	0.61	0.66
Gulu	0.76	0.78
Juba	0.68	0.73
Kabale	-0.35	-0.37
Kericho	0.62	0.62
Khartoum	-0.70	0.75
Kigali	0.64	0.64
Kisumu	0.71	0.76
Lamu	0.71	0.76
Lodwar	0.71	0.76
Makindu	0.69	0.73
Mtwara	0.71	0.70
Mwanza	0.29	-0.54
Narok	0.55	0.61
Wajir	-0.39	-0.59
Wau	0.32	0.30

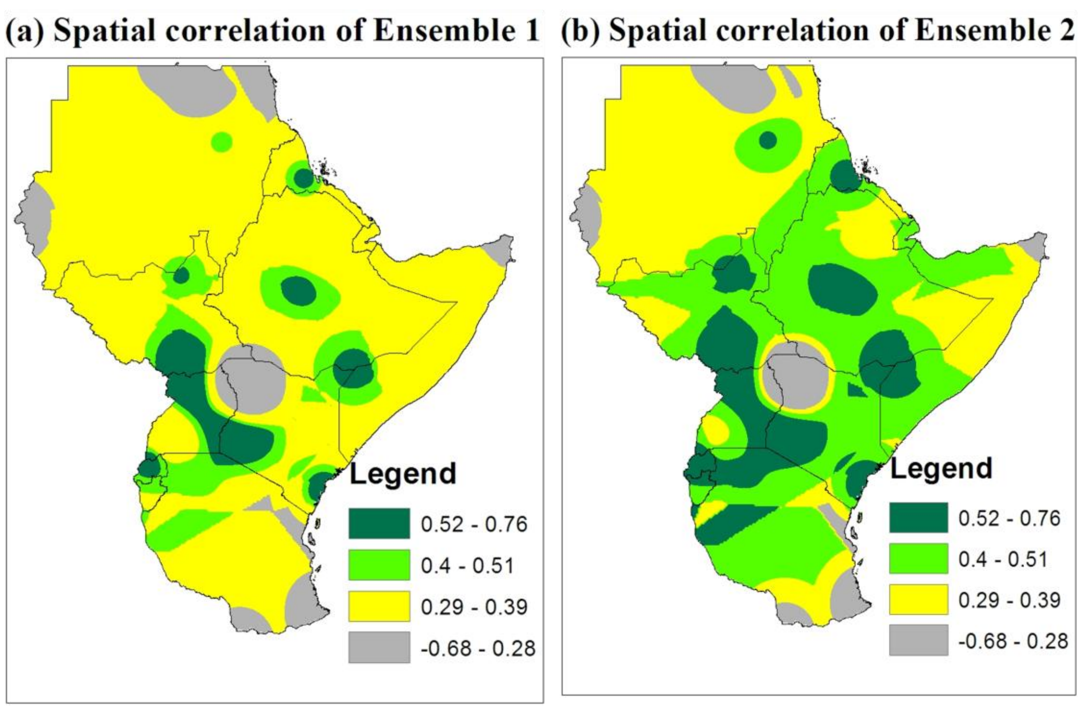

Figure 4. Distribution of correlation coefficients for (a) ENSE 1 and (b) ENSE 2 models output over the study domain. The indices ranged between -0.68 and 0.76.

Table 8. Summary of various skill scores.

Stations	Ensemble	Percent correct	POD			FAR		BIAS			HSS
			BN	N	AN	BN	AN	BN	N	AN	
Abuhamad	ENSE 1	58	50	57	67	40	42	83	100	117	30
	ENSE 2	58	50	57	67	40	42	83	100	117	42
Bujumbura	ENSE 1	47	33	71	86	43	40	67	50	83	28
	ENSE 2	51	17	71	80	41	37	50	50	83	43
Asmara	ENSE 1	47	67	43	67	32	42	83	100	117	31
	ENSE 2	59	50	43	67	29	41	100	100	100	39
Combolcha	ENSE 1	36	50	43	50	50	62	100	71	130	36
	ENSE 2	37	47	43	51	50	61	67	86	120	42
Dagoretti	ENSE 1	26	50	29	50	25	67	70	86	1	36
	ENSE 2	42	47	42	53	21	63	71	93	130	47
Djibouti	ENSE 1	47	33	86	83	12	37	83	71	150	52
	ENSE 2	47	33	67	82	13	33	100	78	150	55
Entebbe	ENSE 1	52	33	57	67	15	33	33	133	133	35
	ENSE 2	51	32	56	63	15	30	50	123	110	41
Gulu	ENSE 1	31	42	71	50	33	20	83	100	117	31
	ENSE 2	32	42	50	61	29	21	83	129	83	40
Juba	ENSE 1	26	67	71	67	20	43	83	57	100	51
	ENSE 2	31	59	50	68	32	40	100	43	123	53
Kabale	ENSE 1	37	0	57	50	33	23	50	130	100	32
	ENSE 2	42	0	57	60	32	31	50	121	100	37
Kericho	ENSE 1	58	57	71	50	20	40	67	103	83	36
	ENSE 2	58	59	33	86	50	25	67	100	67	45
Khatoum	ENSE 1	37	50	14	50	47	54	83	90	100	45
	ENSE 2	39	50	23	51	63	50	83	43	120	49
Kigali	ENSE 1	36	50	14	50	29	33	117	57	50	36
	ENSE 2	42	67	50	67	21	32	103	57	52	47
Lamu	ENSE 1	37	83	43	67	29	43	100	43	120	41
	ENSE 2	45	50	50	67	30	41	100	57	130	51
Lodwar	ENSE 1	47	33	50	67	30	47	83	57	130	28
	ENSE 2	49	33	57	69	31	40	100	53	1.2	37
Mtwara	ENSE 1	37	33	57	50	0	0	133	71	100	49
	ENSE 2	63	47	59	50	12	10	133	71	100	52
Mwanza	ENSE 1	37	33	43	33	60	33	83	100	160	24
	ENSE 2	42	33	43	33	25	29	100	71	133	37
Wajir	ENSE 1	32	17	33	43	50	83	83	114	100	55
	ENSE 2	33	17	33	43	33	25	100	100	100	58
Wau	ENSE 1	53	33	71	50	50	25	67	129	100	32
	ENSE 2	53	33	71	50	40	30	67	129	100	37

Sudan; north eastern part of Somalia; and southern part of Tanzania of the study domain. The results could be attributed to large scale systems like ITCZ which are the main drivers of seasonal rainfall over the Equatorial sector. The results revealed an improvement in the ability of the ensemble models to replicate the climate features around these sectors better with high skill and accuracy than the individual models.

Table 6 shows the results for skill score evaluation of the individual models while Table 7 shows the skill analysis for the ensemble model. The skill score of ENSE 1 and 2 in various regions is summarized in Table 8. The number of correct forecasts significantly increased compared with those from the individual model output (Table 8). For example, the number of cases where the models predicted rainfall events correctly was above 50%

Table 9. PC (%), POD (%), FAR (%), BIAS (%) and HSS (%) for the ENSE 1 and ENSE 2 models for BN, N and AN categories.

Station	Model	PC	POD			FAR		BIAS		
			BN	N	AN	BN	AN	BN	N	AN
Abuhamad	Mon and Mosc	53	33	57	66	60	0	83.3	142	66
Bujumbura	Melb	53	50	16.7	86	50	40	100	50	140
Combolcha	Wash	42	50	28	50	50	62	100	70	130
Dagoretti	Mon	42	50	29	50	25	67	70	86	150
Djibouti	Wash	68	33	86	83	0	37	33	130	133
Entebbe	Wash	52	33	57	67	0	50	33	133	133
Juba	Mont and Wash	68	67	71	67	20	43	80	100	100
Kabale	Melb	42	57	86	33	33	35	0	200	50
Kericho	Mosc and Mont	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	Wash	47	33	43	67	33	50	50	110	130
Mtwara	Mon and Mel	63	33	100	50	0	0	30	200	50

in 42% of the stations for the individual models (Table 7). The number of percent correct forecasts above 50% was observed in 52% of the stations for the Ensemble models (Table 8). Improvement in terms of correct forecasts was also noted in ENSE 2. The models performance improved for stations in the northern sector from 32-53% to 37-58%, as shown in Tables 7 and 8 respectively. This shows the ability of the Ensemble models to improve the resolution of the systems influencing rainfall over the region.

For the ensemble models, the HSS values improved across some stations with at least 37% of the stations obtaining values above 50% in the Equatorial sector (Table 8). This is compared to only 26% of the stations getting above 50% for the individual models (Table 7). From the analysis of Bias score for BN, N and AN categories, the perfect score of 100% was achieved in 63% of the stations for the model Ensembles (Table 9). The cases of ensemble model giving forecast nearing almost perfect score was achieved in 53% of the stations.

The analysis of PoD score for the ensemble models output indicates that 63% of the stations predicted above 50% for the normal category, 79% of the stations predicted above 50% for the above normal category and 42% instances predicted above 50% for below normal category. Most of the stations around the Equatorial sector recorded score above 50%, while stations in the northern and southern regions obtained values above 50% in most instances indicating an improvement in the skill of the forecast using ensemble approach (Table 8).

ENSE 2 model over these regions successfully forecasted more than 50% of the rainfall events. The improvement in the forecast skill by ensemble model shows the model ability to resolve correctly the systems that influence rainfall over the Equatorial, Northern and Southern sectors of the study domain well.

The results for FAR score for the below normal and above normal categories indicate that most stations around the Equatorial region recorded score less than 50% while those in the northern and southern sector of the region slightly scored below 50% in few cases. Stations that recorded score more than 50% reduced in the ensemble models than for the individual ones (Tables 7 and 8). The Ensemble models across the stations recorded less than 50% in most instances except for a few stations to the north of the GHA.

The Ensemble models had better score than the individual model output (Table 8) with ENSE 2 models having better skill than the ENSE 1 model. From Table 7, cases of over forecasting and under-forecasting were many in individual models output especially for most stations in the Northern and Southern sectors. The ENSE 1 and ENSE 2 models had close to 48% of the stations of perfect score, though ENSE 2 had many instances where the score was above 50% (Table 8).

There are at least 53% instances when the PoD score is above 70%. These stations like Bujumbura, Gulu, Kericho and Djibouti are those in the Equatorial and Northern sectors. The score is low for some stations in the Southern sector of the GHA (Tables 8 and 9), implying the models inability to detect the signal of rainfall over these sectors.

SUMMARY AND CONCLUSIONS

Assessment of the ability of GPC models in simulating regional rainfall within the GHA is important for socio-economic planning and risk reduction associated with climate extremes. The evaluation of the performance of an ensemble model from a cluster of 4 GPCs models in modeling GHA rainfall was done using graphical plots, correlation, regression, skill scores analysis, composite analysis and weighted method.

The ensemble model was 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 ensemble models correctly showed higher quantities of rainfall in the Equatorial belt than the individual models. The individual models tended to under/over-predict the amount of rainfall over the Northern and Southern sectors of the GHA region; the rainfall was also displaced. However, the ensemble modeling improved the skill over these sectors by correcting the biases from the individual models.

There is need for more diagnostic studies on the representation of the local processes like land processes, soil moisture, convection, vegetation, mountainous regions, lake and water bodies in the GPC climate models. The study has demonstrated that combinations of clusters of models are potent tools for predicting the rainfall distribution over certain parts of the GHA. Regression equations developed from models with the highest correlation can be used to improve dynamical prediction. Ensembles technique should be applied to the best model clusters to enhance the accuracy and skill in the forecasts over the GHA.

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REFERENCES

AchutaRao KM, Sperber KR (2006). ENSO Simulation in Coupled Ocean Atmosphere Models: Are the Current Models Better? Clim. Dyn., 27, 1-15.

Bowden JH (2004). Recent and Projected Climate Variability during the Seasonal Rains of the Greater Horn of Africa. MSc. Thesis, Marine, Earth, and Atmospheric Science, North Carolina State University, 213 pp.

Bowden JH, Semazzi FHM (2006). Empirical Analysis of Intra-seasonal Climate Variability over the Greater Horn of Africa. .North Carolina State University Department of Marine, Earth and Atmospheric Sciences Raleigh, North Carolina North Carolina State University Department of Marine, Earth and Atmospheric Sciences.

Conway D, Hanson E, Doherty R, Persechino A (2007). GCM simulations of the Indian Ocean Dipole Influence on East African rainfall: Present and future. Geophysical research letters, 34, L03705, doi: 10.1029/2006GL027597

Dutra E, Magnusson L, Wetterhall F, Cloke HL, Balsamo G, Boussetta S, Pappenberger F (2013). The 2010–2011 drought in the Horn of Africa in ECMWF reanalysis and seasonal forecast products. Int. J. Climatol., 33, 1720–1729, doi:10.1002/joc.3545.

Endris HS. Omondi P, Jain S, Lennard C, Hewitson B, Chang'a L, Awange J, Dosio A, Ketiem P, Nikulin G, Panitz H, Buchner M, Stordal F, Tazalika L (2013). Assessment of the Performance of CORDEX Regional Climate Models in Simulating Eastern Africa Rainfall. J. Climate, 26**,** 8453-8475.

Indeje, M. and Ogallo L A (2000). ENSO signals in East African Rainfall and their predictions potentials. .Int. J. Climatol. 20; 19-46.

Krishnamurti TN, Basu S, Sanjay J, Gnanaseelan C (2008). Evaluation of several different planetary boundary layer schemes within a single model, a unified model and a multimodel Super-ensemble. *Tellus*, 60A, 42-61.

Landman WA, Dewitt D, Dong-Eun BA, Lotter D (2012). Seasonal Rainfall Prediction Skill over South Africa: One- versus Two-Tiered Forecasting Systems. Council for Scientific and Industrial Research, Natural Resources and the Environment, Department of Geography, Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa and International Research Institute for Climate and Society, Columbia University, Palisades, New York.

Muhati F, Opijah FJ, Ininda J (2007). Relationship between ENSO Parameters and the Trends and Periodic Fluctuations in East African Rainfall. J. Kenya Meteorol. Soc.1 (1), 20-43.

Mwangi, E. Wetterhall F, Dutra E, Di G F, and Pappenberge F(2014). Forecasting droughts in East Africa. Hydrol. Earth Syst. Sci., 18**,** 611–620.

Ogallo, L A (1989). The spatial and temporal patterns of East African- rainfall derived from principal component analysis; Int. J. Climatol., 9**,** 145–167.

Ogallo LA, Pierre B, Jean SM, Stephen JC (2008). Adapting to climate variability and change: The Climate Outlook Forum process WMO bulletin 57 (2).

Ogallo LA, Semazzi HM, Indeje M (2000). ENSO signals in East African rainfall seasons. Int. J. Climate. 20**;** 19–46.

Omondi P, Awange JL, Ogallo LA, Okoola RE, Forootan E (2012). Decadal rainfall variability modes in observed rainfall records over East Africa and their relations to historical sea surface temperature changes. J. Hydrol., 464–465, 140–156.

Otieno GO (2013). Assessing the Skill of the Seasonal Rainfall Prediction over the Greater Horn of Africa Using Global Models as Multimodel Ensemble. Msc.

Thesis, Department of Meteorology, University of Nairobi, Kenya

Owiti ZO (2004). Use of Indian Ocean Dipole as a Predictor of East African Rainfall Anomalies. Msc. Dissertation, Department of Meteorology, University of Nairobi, Kenya.

Schreck CJ, Semazzi FHM (2004). Variability of the Recent Climate of Eastern Africa. Int. J. Climatol., 24*:* 681 – 701.Doi: 10.1002/Joc.1019.

Timothy NS, Oscar A, Boer G, Michel D, Yaqui D, Arun K, Krishn K, Willem L, Simon M, Paulo N, Adam S, Ose T, Yun WT (2009). Understanding and Predicting Seasonal to Interannual Climate Variability-the producer perspective.

www.wmo.int/wcc3/sessionsdb/documents/WS3_WP_capability.pdf

Wang B, Lee JY, Kang IS, Shukla J, Park CK, Kumar A, Schemm J, Cocke S, Kug JS, Luo JJ, Zhou T, Wang B, Yun WT, Alves O, Jin EK, Kinter J, Kirtman B, Krishnamurti T, Lau NC, Lau W, Liu P, Pegion P, Rosati T, Chubert S, Stern W, Suarez M, Yamagata T (2008). Advanced and prospectus of seasonal prediction: Assessment of the APCC/CliPAS 14-model ensemble retrospective seasonal prediction (1980-2004), Climate Dyn., 33, 93-117.

Wilks DS (2006). Statistical methods in Atmospheric Sciences.2nd Ed. Int. Geophys. Series, 91, Academic Press, 592.

Yang W, Seager R, Cane MA (2013). The East African Long Rains in Observations and Models. Columbia University, Palisades, New York. USA Int. Res. Inst. Climate Soc.