ASSESSMENT OF THE SKILL OF ECHAM 4.5 IN SIMULATING RAINFALL ON SEASONAL TIME SCALES OVER THE GHA REGION

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DECLARATION

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ABSTRACT

This study assessed the skill of ECHAM 4.5 in simulating rainfall on seasonal time scales over the GHA region for the period Jan 1961- Dec 2008. The rainfall seasons considered were, March -April-May (MAM) and October- November- December (OND).

The data used in the study included the observed seasonal rainfall totals for January 1961-December 2008 obtained from IGAD Climate Prediction and applications Centre (ICPAC), Nairobi and ECHAM 4.5 model hindcast data sets for the same period obtained from International Research Institute for Climate and Society (IRI). The model has 24 members, where each member represents an ensemble run. The ensemble runs are based on similar initial physical conditions but different initial atmospheric conditions. The atmospheric initial conditions for the 24 members differ because they are generated by adding different small noise perturbations to the same atmospheric state several months before the starting dates.

The methods for analysis included spatial distribution comparison, correlation analysis, root mean square error analysis, categorical statistics and the two-sample Kolmogorov-Smirnov test.

The spatial distribution patterns of the observed rainfall did not wholly match with patterns from any of the 24 members or with the pattern of the mean of all 24 members. However, the patterns of some individual members only had small differences with the observation.

The results from correlation analyses indicated bigger coefficients for the equatorial sector (5°N to 5°S) in both seasons. Root Mean Square Error (RMSE) values were also small in the equatorial sector. The northern sector of the region had small coefficients and big RMSE values in both seasons. Large correlation coefficients were obtained for the OND season. RMSE values were also low for the OND season. Similarly, Two-Sample Kolmogorov-Smirnov test results had higher P values for most of the region in the OND season and in areas with features that enhance convection. Categorical statistics that included Bias, False Alarm Ratio and Probability of Detection confirmed the higher skill for the OND season.

For all the analyses made the mean of all 24 members did not show much skill in predicting rainfall, indicating that not all members are appropriate for forecasting in the GHA region. Some individual members, namely, 15, 18, 21, 22 and 24 performed better than the mean of all 24 members in most instances. Comparing the skill of the mean of the 5 members and that of the mean of the 24 members, the mean of 5 members has more skill.

When considering individual members and the mean of all 24 members. The analyses show that the model has higher accuracy and skill in the equatorial sector of the region and the OND season. This shows that the model simulates rainfall better for the OND season and the equatorial sector. When fewer members were used there was considerable improvement of model accuracy and skill in both seasons and mostly in the northern sector of the region.

The simulation of seasonal rainfall over the GHA region by ECHAM 4.5 is better when a few members which showed higher skill individually are averaged. The study therefore recommends that the mean of the 5 members could be used for seasonal forecasting in the GHA region. The use of 5 members would help to reduce the computing time and the long waiting time for releasing early warning climate products that are required to reduce the negative impacts of the climate extremes over the region. Improvement of early warning will reduce negative effects of climate extremes on agricultural production, hydropower generation, water use, and water availability at household level caused by floods and droughts.

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ACRONYMS AND WHAT THEY REPRESENT

AMIP.. Atmospheric Model Intercomparison Project

COLA.. Center for Ocean, Land and Atmospheric Studies

DEMETER.....Development of a European Multimodel Ensemble system for seasonal to interannual prediction

DMI..Dipole Mode Index

ECHAM.. European Centre Hamburg Model

ECMWF...................................... European Centre for Medium Range Weather Forecasts

FAR ....False Alarm Ratio

GCM...Global Climate Model

GHA.. Greater Horn of Africa

HSS.. Heidke skill score

ICPAC... IGAD Climate Prediction and applications Centre

IRI.. International Research Institute for Climate and Society

ITCZ.. .Inter Tropical Convergence Zone

MAM.. March April May

NMC ....National Meteorological Centre

NWP...Numerical Weather Prediction

OND.. October November December

PoD... Probability of Detection

RMSE... Root Mean Square Error

SST... Sea Surface Temperature

CHAPTER ONE

INTRODUCTION

1.0 BACKGROUND

Droughts and floods have become common features in the African climate in recent years (Washington and Downing, 1999). Clearly, African resources are sensitive to climatic variability, as seen in assessments of agriculture, water resources, ecosystems, and health (e.g., Ominde and Juma, 1991; Watson *et al.*, 1998). Rainfall variability and long-term droughts make African geophysical time series some of the most striking on the planet. The ability to predict seasonal rainfall performance, including its temporal and spatial variability with reasonable lead time, could have major applications towards the planning and implementation of socio-economic activities towards sustainable development in the fragile economies of Africa.

Seasonal precipitation forecasts have come into regular use in Africa in recent years. Prior to each rainy season, climate outlook forums (COFs) are convened in the Greater Horn of Africa (GHACOF), West Africa; *Prévision Saisonnière en Afrique de l'Ouest* (PRESAO) and Southern Africa (SARCOF) regions. These seasonal forecasts are blended with local knowledge and expertise to develop a regional seasonal forecast for precipitation for 3-month periods of the coming season. These forecasts are presented using maps and are divided into different climatological zones, subsequent evolution of broader regions of similar forecasts, and associated tercile probability values, expressing the expected likelihood of the seasonal total rainfall being in each of three ranges: above normal, near normal and below normal.

Seasonal forecasts can be made in several ways, for example, using statistical or dynamical methods. Because the climate system is so complex, it is almost impossible to take all the factors that determine the future seasonal climate into account. Therefore, statistical climate forecasts are generally given in terms of the probability that rainfall will be either below normal, near normal, or above normal. Statistical models use a linear approach to predict complex interactions without any specific links to the underlying physical and dynamical processes. This means that they work best when large-scale developments are well and truly underway, but they have difficulty anticipating shifts.

The use of dynamical models in seasonal forecasting is becoming widespread globally (ECMWF, 2003). In principle, models that represent the dynamics of the atmosphere and ocean should be able to give better seasonal forecasts than purely statistical approaches because of their ability to consider simultaneously the wide range of linear and non-linear processes and interactions of the climate and its spatial-temporal evolution.

However, the dynamical climate models are also not perfect. The theoretical understanding of climate controls is still incomplete, and certain simplifying assumptions are unavoidable when building these models. This introduces biases into their simulations, which sometimes are surprisingly difficult to correct (AchutaRao and Sperber 2006; Bony and Dufresne 2005; Covey *et al*,. 2003; Mechoso *et al*., 1995; Oldenborgh *et al*., 2005).

Model imperfections have attracted criticism, with some authors arguing that model-based projections of climate are too unreliable to serve as a basis for public policy (Jones 2005; Lahsen 2005; Lindzen 2006; Singer 1999). In particular, early attempts at coupled modeling in the 1980s resulted in relatively crude representations of climate (Gates *et al*.1993). Since then, however, the theoretical understanding of climate, including process formulation and representation, has been refined, improving the physical basis for climate modeling. Against the background of these developments, one may wish to know how much climate models have improved and how much we can trust the latest coupled model generation.

There are many dynamical models available. However, ECHAM 4.5 is used in this study because it is the model used by ICPAC for seasonal forecasting over the Greater Horn of Africa. A collaborative study by IRI/ICPAC in 2002 showed it had the highest prediction skill over the region. Mutemi in 2003 also showed that the model has higher predictive skill for the OND season. However, ECHAM 4.5 has 24 members, where each member represents an ensemble run. The ensemble runs are based on similar initial physical conditions but different initial atmospheric conditions. The atmospheric initial conditions for the 24 members differ because they are generated by adding different small noise perturbations to the same atmospheric state several months before the starting dates.

. This study is devoted to assessing which members out of the 24 have the highest skill in simulating rainfall and hence can be used for ensemble modeling over the GHA region.

1.1 PROBLEM STATEMENT

Dynamical models offer a long term potential in providing seasonal predictions in an era of a possible changing climate. However. many problems still exist with dynamic models; most suffer significant climate drift and most don't adequately simulate some of the details of some fundamental modes of variability.

In practice, model errors are still a shortcoming in forecasting (Latif *et al*, 2001). Model agreement with observations of today's climate is the only way to assign model confidence. with the underlying assumption that a model that accurately describes present climate will make a better projection of the future. The achievement of demonstrable and significant skills in producing long-range weather forecasts is an important accomplishment. both from scientific and societal viewpoints.

1.2 OBJECTIVES

The main objective of this study was to assess the skill of ECHAM 4.5 in simulating seasonal rainfall over the GHA region.

To achieve this main objective, the following specific objectives were undertaken:

i. Contrast the spatial distribution of observed and model output rainfall over the GHA region.
ii. Determine the accuracy of ECHAM 4.5 in simulating rainfall over the GHA region.
iii. Assess the skill of ECHAM 4.5 using various skill scores.
iv. Determine the appropriate members for ensemble modeling over the region.

1.3 JUSTIFICATION

Risks posed by anomalous climate events such as droughts and floods are high in the GHA because of the lack of coping capacity among large sectors of the society. The population in this region is unable to absorb the shocks of climate related hazards due to lack of information and resources.

When a shock occurs because of a drought or flood hazard, the vulnerable economies of the GHA are affected in many ways. Some of these include negative effects on agricultural production, hydropower generation, water use, and water availability at household level. These impacts increase the need for food aid and food imports. Climate shocks like drought can have macro-economic implications in these regions, affecting the livelihood and food security of people throughout the region. Drought affects prices of agricultural products, export earnings and power generation. The contraction of the economy due to drought leads to unemployment. Drought depletes the assets of poor people and its impacts linger for many years.

Floods lead to displacement of people and animals, loss of life and property, environmental degradation, destruction of infrastructure, large losses to the economy, among many other socio-economic miseries.

The irregular recurrence of anomalous climate events such as droughts and floods demonstrate an urgent need for the enhancement of accurate seasonal prediction in the GHA region. Skillful forecasts would be useful for decision making in hydrology, agriculture, public health, and other sectors of the economy and governance.

1.4 STUDY AREA

The study area is the Greater Horn of Africa (GHA).It lies between Latitudes 21°N to 12°S and longitudes 23.5°E to 52°E and has ten countries as shown in Figure 1.

The region has complex topographical features, which include the Ethiopian highlands to the northeast and East African highlands to the southwest that include high mountains, Kenya (5199 m), Kilimanjaro (5895 m), Elgon (4321 m), Aberdare Ranges (3999 m) and the Mau escarpment (3098 m). Some of these mountains like Kenya and Kilimanjaro have permanent glaciers at their top throughout the year which makes them very special as potential indicators of regional and/or large-scale, together with long-term, climate fluctuations. The complex mountains are also the source of watersheds for some of the major rivers of the region. Figure 2 shows the elevation of the Greater Horn of Africa region.

The other unique physical characteristics of the region include the water masses, for example, Lake Victoria and the Indian Ocean and the Western and Eastern Highlands which decline to a plain towards the Indian Ocean. This configuration generates land/sea and land/lake breezes, as a result of the water and land temperature contrasts, due to differential solar heating and radiative cooling. 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.

In terms of seasonal rainfall distribution, the GHA region can be divided into three sectors, namely the northern, equatorial and southern sectors. The northern sector of the GHA sub-region has peak rainfall concentrated largely during the months of June to September. The southern parts of the sub region have peak rainfall concentrated mainly within the months of December to February.

The rainfall patterns over the equatorial parts of the GHA are quite complex. Close to the large water bodies, substantial rainfall is received throughout the year. Over much of the sector, however, the major rainfall periods are concentrated within two peak seasons of March-May and October-December. Parts of the western and coastal regions also receive significant rainfall during the months of July-August.

These rainfall patterns over the region are controlled by the seasonal migration of the Inter-Tropical Convergence Zone (ITCZ). The ITCZ forms a quasi-continuous belt of unsettled, often rainy weather around the tropics, sandwiched between generally fine weather to the north and south of the subtropical highs (Folland et al. 1991). It is associated with the convergence of air-streams from the subtropical highs. Where air-streams meet, strong upward motion occurs that causes rainfall if the air contains sufficient moisture. It is therefore a region of large-scale convergence of the interhemispheric tropical monsoonal wind systems that generally move meridionally with the overhead sun.

The other climatic factors known to influence precipitation over the region are complex including tropical storms, easterly waves, jet streams, the continental low level trough, extra-tropical weather systems (Ogallo 1989); interactions between mesoscale flows and the large-scale monsoonal flows (Mukabana and Pielke 1996), teleconnections with global-scale climatic anomalies like those associated with SST, the Quasi-biennial Oscillation in the equatorial lower stratospheric zonal wind (QBO), solar and lunar forcing (Ogallo 1988; Indeje and Semazzi 2000), and inter-seasonal 30-60 day Madden-Julian waves (Anyamba 1992). Figure 3shows the climatic zones of the Greater Horn of Africa region.

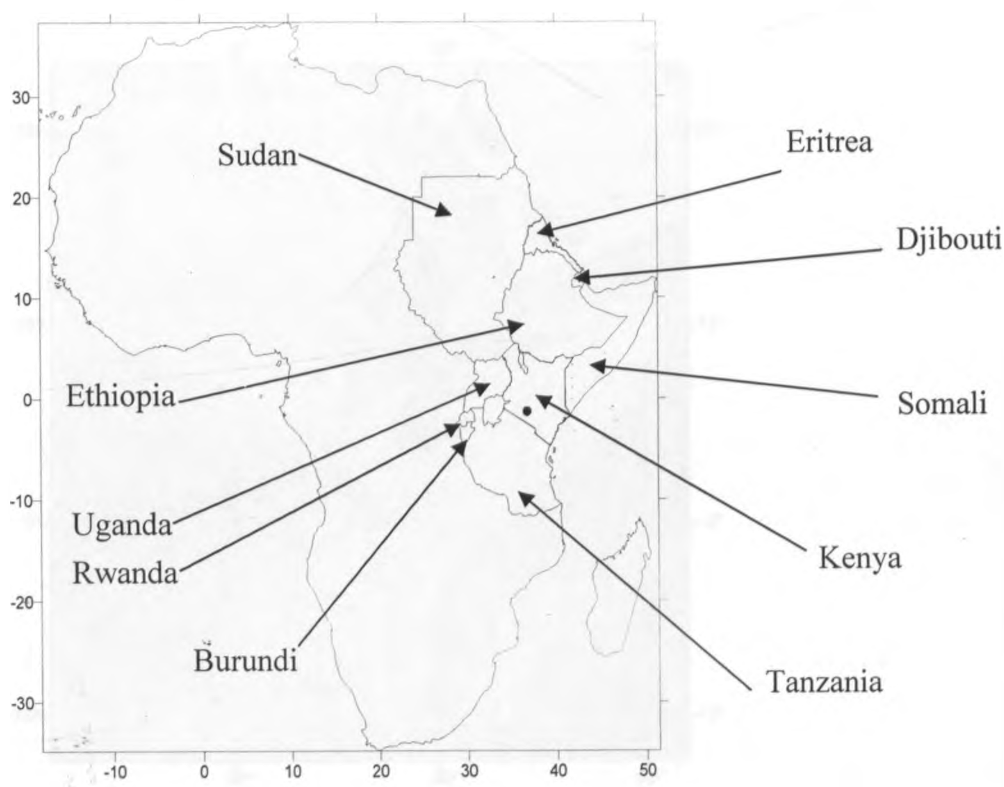

Figure 1: Countries in the Greater Horn of Africa region

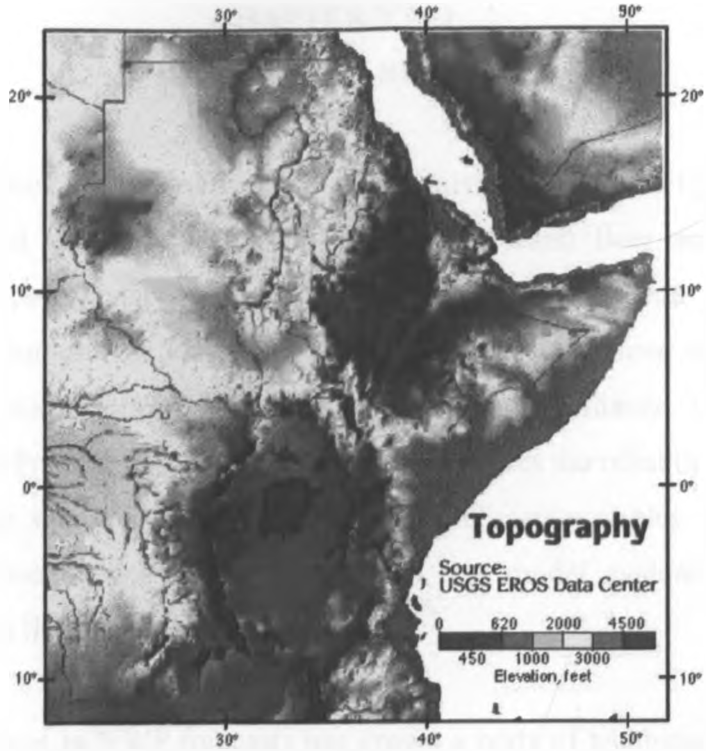

Figure 2: Elevation of the Greater Horn of Africa region

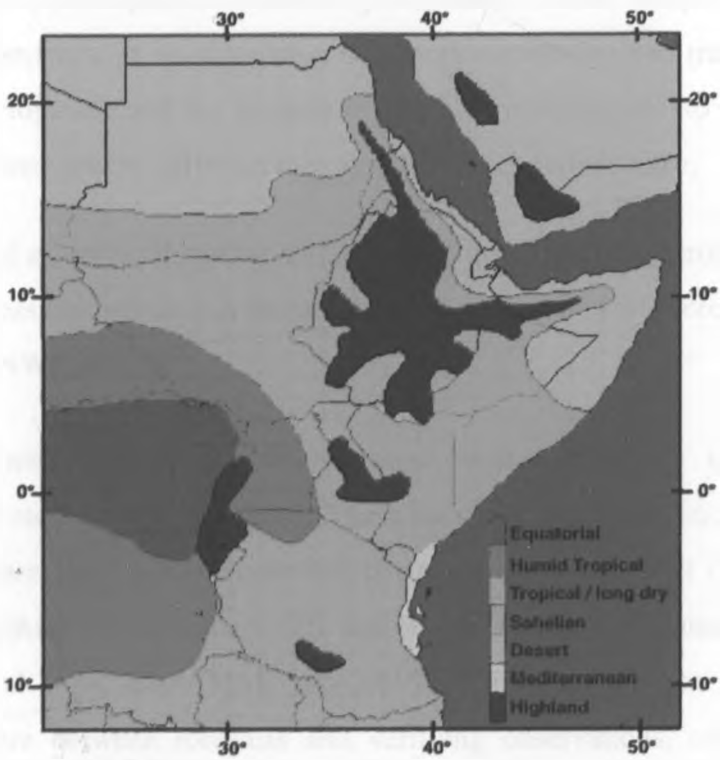

Figure 3: Climatic zones of the Greater Horn of Africa region

CHAPTER TWO
LITERATURE REVIEW

Previous model validation studies used conventional statistics to measure the variance between observed and modeled data. For example, Taylor (2001) and Boer and Lambert (2001) characterized model performance from correlation, root mean square (RMS) error, and variance ratio. Both studies found similar ways to combine these three statistics in a single diagram, resulting in nice graphical visualizations of model performance. Murphy et al (2004) introduced a "Climate Prediction Index" (CPI), which measures the reliability of a model based on the composite mean square errors of a broad range of climate variables. More recently, Min and Hense (2006) introduced a Bayesian approach into model evaluation, where skill is measured in terms of a likelihood ratio of a model.

Along with the advances in NWP forecasts has grown a body of techniques for monitoring the skill of those forecasts. In order to assess a model's performance we need measures of its simulation of the basic atmospheric variables (precipitation, wind, temperature, humidity) and the physical consistency of its simulation of energy conversion and transport processes such as cyclone development and the budgets of heat and momentum. No single "score" is adequate; hence we need several different measures of model performance.

Stanski *et al,* 1989 did a survey of common verification methods in meteorology. They found that the following measures which can be calculated at any set of grid were commonly used to assess the skill of NWP models.

Mean square error measures are one of the most basic and widely used methods of verification of NWP model output forecasts. These measures are Mean Square Error (MSE) and Root Mean Square Error (RMSE). RMSE is simply the square root of MSE, and is a measure of the amplitude of the error. MSE and RMSE can be calculated over any or all spatial directions and time. Both MSE and RMSE are equal to zero only for perfect agreement everywhere between forecasts and verifying observations, otherwise they are greater than zero. (Stanski *et al,* 1989)

Standard deviation is a basic statistical measure of the degree of variation of data about the mean. If one calculates the standard deviation of the errors in NWP forecasts, the trend of the standard deviation over a period of several years provides a measure of whether models have improved as new physics, numerical techniques, and better computers are implemented. The lower the standard deviation of the forecast error, the more reliable the forecast when compared over a period of several years. (Stanski *et al,* 1989)

The SI score was proposed by Teweles and Wobus (1954) as a means of verifying the USA's National Meteorological Centre (NMC) model forecasts. It has been used internally ever since, although it is rarely seen in published literature discussing NWP model skill in recent years. The S1 score is a function of the pressure difference (pressure gradient) between pairs of points selected within the main area of interest. The points can be either grid points or observing stations. The full range of the S1 score is from 0 to 200, with a low score being better than a high score. A perfect score of 0 occurs when the forecast and observed gradients are the same, even though the pressure values may be different. The worst possible score of 200 is attainable when the pressure gradients are exactly reversed.

A useful summary of the forecast and observed weather events can be presented in the form of a contingency. Such a table does not constitute a verification method itself, but provides the basis from which a number of useful scores can be obtained (Stanski *et al,* 1989). For probability forecasts a 3x 3 contingency table is recommended. An example is shown in table 1.

Table 1: A 3 by 3 Contingency Table

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

Percent correct (PC) is the summation of the diagonal elements divided by the total number of events. When probabilities are used in place of categorical forecasts, the percent correct is interpreted as the percentage time correct. The overall percentage correct is greatly influenced by the common (most frequent) categories, and can give misleading information.

Post agreement is the number correct divided by the number forecast for each category. False Alarm Ratio is sensitive only to false predictions of the severe event, not to missed events. The term False Alarm Ratio (FAR) is usually used when referring to a contingency table for severe weather forecasts. Probability of Detection (PoD), this is the number correct divided by the number observed in each category. It is a measure of the ability to correctly forecast a certain category, and is sometimes referred to as "hit rate", especially when applied to severe weather verification.

Bias is the number forecast divided by the number observed for each category. It measures the ability to forecast events at the same frequency as found in the sample without regard to forecast accuracy. Bias = 1 implies no Bias, Bias > 1 implies overforecasting the event and Bias < 1 implies underforecasting the even. The methods used in this study are discussed in detail in section 3.3.

Busuioc *et al.* (1999) verified Echam3 outputs using regional seasonal precipitation in Romania. The downscaling model used was a regression technique based on canonical correlation analysis between observed station precipitation and European-scale sea level pressure (SLP). The climate models considered were the T21 and T42 versions of the Hamburg ECHAM3 atmospheric GCM in time-slice mode. The downscaling model was skillful for all seasons except spring. The general features of the large-scale SLP variability were reproduced fairly well by both GCMs in all seasons. Thus, these models were considered skillful with respect to regional precipitation during winter, and partially during the other seasons.

Marengo *et al.* (2004) did a study on the annual and interannual variability of regional rainfall produced by the Center for Weather Forecasts and Climate Studies/Center for Ocean, Land and Atmospheric Studies (CPTEC/COLA) atmospheric global climate model. An evaluation was made of a 9-member ensemble of the model forced by observed global sea surface temperature (SST) anomalies for a 10-year period: 1982–1991. The Brier skill score and Relative Operating Characteristics (ROC) were used to assess the predictability of rainfall and to validate rainfall simulations in several regions, worldwide.

In general, the annual cycle of precipitation was well simulated by the model for several continental and oceanic regions in the tropics and mid latitudes (Marengo *et al.*, 2004). Interannual variability of rainfall during the peak rainy season was realistically simulated in Northeast Brazil, Amazonia, central Chile, and southern Argentina–Uruguay, Eastern Africa, and tropical Pacific regions, where the model showed good skill. Some regions, such as northwest Peru–Ecuador, and southern Brazil exhibited a realistic simulation of rainfall anomalies associated with extreme El Niño warming conditions, while in years with neutral or La Niña conditions, the agreement between observed and simulated rainfall anomalies is not always present.

In the monsoon regions of the world and in southern Africa, even though the model reproduced the annual cycle of rainfall, the skill of the model was low for the simulation of the interannual variability. The model captured the well-known signatures of rainfall anomalies of El Niño in 1982–83 and 1986–87, indicating its sensitivity to strong external forcing. In normal years, internal climate variability can affect the predictability of climate in some regions, especially in monsoon areas of the world (Marengo *et al.*, 2004).

Huth *et al.* (2000) studied ECHAM3 simulation of heat waves and dry spells over South Monrovia. The results showed several deficiencies of the ECHAM3 GCM in simulating heat waves in south Moravia (southeast Czech Republic): Heat waves in the model were too long, and their numbers were underestimated in the beginning of summer (June, July) but overestimated in August. For the dry spells duration and annual cycle of dry spells and dry days, the simulation was not good for both station and area-averaged values. The conclusion was that, whatever the treatment of the simulated precipitation, dry spells are too long in the model and the annual cycle of their occurrence is deformed.

Martin *et al.* (2000) studied the simulation of the Asian Summer Monsoon in ECHAM 4.5. The result showed that the errors in the monsoon circulation in ECHAM 4.5 were much smaller than those of EHAM4, where the monsoon circulation was weak in both lower and upper levels. This was attributed to the changes in convection and condensation schemes, which redistributed the convective precipitation.

Liebmann *et al.* (2007) studied ECHAM 4.5 simulation of onsets and end rainy season over South America. The observed rainfall from daily rainfall records were averaged onto grids that duplicated those of the model. The climatological annual rainfall from observations and the average over the 24 ensemble members did not agree for most of the areas in the region. However, the agreement between the climatological onset and end dates and the length of the rainy season between the observation and the ECHAM 4.5 were quite good.

Ininda (1998) used the UK Meteorological Office (UKMO) third annual cycle GCM to simulate rainfall variability over East Africa during the short rains season (October through December) and its linkages to global SST anomalies. Anomalous easterly flow over the eastern and central Indian Ocean, surface convergence over western Indian Ocean and westerly flow over the interior of the region were shown to be prominently present during anomalously wet short rains (OND) season. The study also investigated the month-to-month variability of East African rainfall during the long rains (March-May) and concluded that for this season, unlike the short rains, there were significant month-to-month variations in the response of regional climate to global SST anomalies. However, the simulations were performed for a very limited period of time (four years) that was not sufficient to comprehensively characterize the intra-seasonal and inter-annual variability of the regional climate.

Anyah *et al.* (2006) studied the multiyear simulation of East Africa rainfall during the October-December season, short rains. They used the International Center for Theoretical Physics (ICTP) regional climate model version 3 (ICTP-RegCM3). Observed rainfall variability over distinct homogeneous climate subregions was fairly reproduced by the model, except over central Kenya highlands and northeastern parts of Kenya. The spatial correlation between the simulated seasonal rainfall and some of the global teleconnections (DMI and Nino3.4 indices) showed that the regional model conserves some of the observed regional 'hot spots' where rainfall-ENSO/DMI associations are strong.

Sakwa (2006) studied the skill of high resolution regional model in the simulation of air flow and rainfall over East Africa. The study showed that the model performed well over the region. The study however recommended ensemble modeling over the region.

Gitutu (2006) studied the simulation of daily rainfall by Numerical Weather prediction models over Kenya. The models were United Kingdom Meteorological Office (UKMO) model, National Center for Environmental Prediction (NCEP) global model and the global spectral model member by the national center for medium range weather forecasting in India. Overall no model was better in terms of accuracy and skill.

Mutemi (2003) used ECHAM4.5 to study the variability of East Africa climate. The model reproduced the climatological mean pattern such as the bimodal seasonality of rainfall associated with the north–south migration of the ITCZ and monsoonal flow, except the correct amplitudes of the inter-annual variability linked to extreme El Nino episodes such as the 1982 and 1997 were not well reproduced.

The skill of ECHAM4.5 over the east African sub region has been addressed by IRI/ICPAC collaboration (2002). The results indicated that ECHAM4.5 was the best model especially between July-December months. The skill of the model was found to be higher during ENSO when large SST values are found over many parts of the equatorial tropics.

Ensemble modeling is now routinely applied on essentially all time scales, ranging from the scale of weather forecasts to the scale of climate-change scenarios, and its success has been demonstrated in many studies (e.g. *Palmer et al.* 2004). Simple ensemble-models can be constructed by pooling together the available single model predictions with equal weight. However, given that models may differ in their quality and skill, it has been suggested to further optimize the effect by weighting the participating models according to their prior performance (e.g. *Giorgi and Mearns 2002*).

The technique of ensemble modeling is used with great success at forecasting centers around the world (Tracton and Kalnay, 1993). Richardson in 2000 showed that probability forecasts derived from an ensemble prediction system are of greater benefit than a deterministic forecast produced by the same model.

In its simplest form, model ensemble forecast is produced by simply merging the individual forecasts with equal weights. Several approaches have attempted to combine model ensemble forecasts to a single reliable forecast that carries higher skills when compared to the individual member models. These include the simple ensemble mean (Peng et al. 2002; Pavan and Doblas-Reyes 2000; Palmer et al. 2004), regression-improved ensemble mean (Peng et al. 2002; Kharin and Zwiers 2002), bias-removed ensemble mean (Kharin and Zwiers 2002), and the multimodel superensemble (Krishnamurti et al. 1999). The multimodel super ensemble technique showed higher skill for short range and seasonal forecasting compared with member model forecasts (Krishnamurti et al. 2000a).

Webster *et al.*, 1998 discovered that the dynamical predictions suffer from a consistently large ensemble spread, which is compatible with the theory that chaotic weather systems in the Southern Hemisphere may trigger breaks in the Asian monsoon, providing short-term predictability, but limiting seasonal predictability

Zwiers et al. (2000) analyzed an ensemble of 47-year simulations done with the second generation Canadian General Circulation Model (GCM2) in which the SST and sea-ice conditions were specified from observations. They found that the fraction of the atmospheric variability in mean-seasonal conditions forced by the SST variability was large in the tropics, and smaller, but still statistically significant over the northeastern Pacific and North America.

Kalnay, 2003, noted that for dynamical models, the uncertainties in model initialization can be addressed by applying ensemble techniques, i.e. by repeatedly integrating the model forward in time from slightly-perturbed initial conditions, with the perturbations being designed so that they capture as much as possible of the underlying uncertainty.

Tapiador *et al.* (2006), studied member selection for GCM ensemble forecasting using ECMWF DEMETER project. They used entropy flux to determine the goodness of fit of the members. The entropy-based choices of the DEMETER members were then compared with ERA-40 datasets. This method was good for choosing members for forecasting rainfall.

In this study skill scores were used to determine which of the 24 members can be used for ensemble modeling in the GHA region.

CHAPTER THREE
MODEL APPLIED, DATA AND METHODOLOGY

3.0 INTRODUCTION

This chapter is devoted to the discussion of the model and data used in this study and the various methods used to achieve the objectives of the study.

3.1 ECHAM 4.5

The European Centre Hamburg Model (ECHAM) originated from the European Centre for Medium Range Weather Forecasts (ECMWF). The ECHAM4.5 is run at the International Research Institute for Climate and Society (IRI) at a spectral resolution of T42 and has 19 levels in the vertical (Roeckner et al., 1996). An AGCM ensemble of 24 members is produced, where the ensemble members are exposed to the same observed SST boundary conditions, but are initialised with differing atmospheric initial conditions. The atmospheric initial conditions differed because they are generated by adding different small noise perturbations to the same atmospheric state several months before the starting dates. The small noise perturbations are introduced in the lowest model level zonal wind field at the Gaussian grid point nearest near the equator and the date line. A Tropical point is chosen because it will most efficiently communicate the perturbation around the globe due to deep convection effect on the global angular momentum field. Table 2 shows the perturbations of the 24 members, Table 3 shows the models initial boundary fields and cloud parameters and Table 4 shows some model elements.

ECHAM4.5 solves prognostic equations for vorticity, divergence, surface pressure, temperature, water vapor, the sum of cloud water and ice water content, and a number of chemical constituents. The prognostic variables are represented by spherical harmonics with triangular truncation at wavenumber 42 (T42) except for the advection of water vapor, cloud water, and chemical species, which is treated with a flux-form semi-Lagrangian scheme (Rasch and Lawrence 1998). A hybrid sigma-pressure coordinate system is used with 19 irregularly spaced levels up to a pressure level of 10 hPa.

The radiation code was adopted from the ECMWF model (Morcrette 1991) with a few modifications. The water vapor continuum has been revised to include temperature-weighted band averages. The single-scattering properties of cloud droplets and ice crystals are derived from Mie theory with suitable adaptation to the broadband model. The effective radii of droplets and ice crystals are parameterized in terms of the liquid and ice water content, respectively.

A higher-order closure scheme is used to compute the turbulent transfer of momentum, heat, moisture, cloud water, and chemical species within and above the atmospheric boundary layer. The eddy diffusion coefficients are calculated as functions of the turbulent kinetic energy, which is obtained from the respective rate equations. Vertical fluxes in convective clouds are calculated using the mass flux scheme for penetrative, shallow, and midlevel convection developed by Tiedtke (1989). The cloud water content is calculated from the cloud water transport equation, including sources and sinks due to phase changes and precipitation formation by coalescence of cloud droplets and gravitational settling of ice crystals. Fractional cloud cover is parameterized as a function of relative humidity.

Table 2: The Perturbations of the 24 Members

MEMBER	PERTURBATION
1	0.001
2	0.002
3	0.003
4	0.004
5	0.005
6	0.006
7	0.007
8	0.008
9	0.009
10	0.010
11	0.011
12	0.012
13	0.013
14	0.014
15	0.015
16	0.016
17	0.017
18	0.018
19	0.019
20	0.020
21	0.021
22	0.022
23	0.023
24	0.024

Table 3: Initial Boundary Fields and Cloud Parameters

FIELDS	LAND	OCEAN
Sea Surface Temperature	Prognostic from AMIP spinup	Prescribed, Roeckner et al., (1996)
Soil Moisture	Prognostic from AMIP spinup	NA
Albedo	Prognostic from AMIP spinup	Prescribed, Roeckner et al., (1996)
Snow Cover	Prognostic from AMIP spinup	Prognostic from AMIP spinup
Soil Temperature	Prognostic from AMIP spinup	NA
Deep Soil Temperature	Prognostic from AMIP spinup	NA
Convective Cloud Cover	Prognostic from AMIP spinup	Prognostic from AMIP spinup
Convective Cloud Bottom	Prognostic from AMIP spinup	Prognostic from AMIP spinup
Convective Cloud Top	Prognostic from AMIP spinup	Prognostic from AMIP spinup
Sea Ice	NA	Sea ice cover is prescribed from SST distribution. Sea ice temperature and surface heat fluxes are prognostic.

Table 4: Model elements (Roeckner et al. 1996)

MODEL ELEMENTS	COMPONENT	SPECIFICATION
GRID	Prognostic variables	Vorticity, divergence, logarithm of surface pressure, temperature, specific humidity, mixing ratio of total cloud water and, optionally, a number of trace gases and aerosols
	Vertical	Hybrid sigma-pressure coordinate system
	Horizontal	Gaussian transform grid
PHYSICS	Vertical diffusion	Arakawa Scheme
	Longwave radiation	Fouquart and Morcrette schemes
	Shortwave radiation	Fouquart and Bonnel scheme
	Surface fluxes	Monin-Obukhov similarity theory
	Shortwave cloud optical properties	High-resolution Mie calculations
	Longwave cloud optical properties	Emissivity formulation
	Cumulus convection	Bulk mass flux concept of Tiedtke
	Stratiform clouds	Sundqvist approach.
	Surface albedo	Claussen Scheme

3.2 DATA

The data used in this study included observed rainfall and ECHAM 4.5 hindcast members. Details of these are provided in the next sections.

3.2.1 Observed rainfall

Monthly rainfall totals for the GHA region for the period January 1961- December 2008 were used in the study and the data was obtained from IGAD Climate Prediction and applications Centre (ICPAC), Nairobi. A total of 70, unevenly distributed, gauge stations were available. All available stations were used in the analyses. Table 5 shows the stations used in this study and Figure 4 shows their spatial distribution.

Table 5: List of Stations Used in the Study

	Station	Country	Longitude	Latitude
1	WAD HALFA	Sudan	31.48	21.82
2	ABU HAMAD	Sudan	33.32	19.53
3	PORT SUDAN	Sudan	37.22	19.58
4	NDONGOLA	Sudan	30.48	19.17
5	KARIMA	Sudan	31.85	18.55
6	ATBARA	Sudan	33.97	17.70
7	KHARTOUM	Sudan	32.55	15.60
8	KASSALA	Sudan	36.40	15.47
9	ED DUEIM	Sudan	32.33	14.00
10	WAD MEDANI	Sudan	33.48	14.40
11	EL GEDREF	Sudan	35.40	14.03
12	EL FASHER	Sudan	25.33	13.62
13	EL GENEINA	Sudan	22.45	13.48
14	EL OBEID	Sudan	30.23	13.17
15	KOSTI	Sudan	32.67	13.17
16	NYALA	Sudan	24.88	12.05
17	RASHAD	Sudan	31.05	11.87
18	KADUGLI	Sudan	29.72	11.00
19	MALAKAL	Sudan	31.65	9.55
20	WAU	Sudan	28.13	7.70
21	JUBA	Sudan	31.60	4.87
22	ASMARA	Eritrea	38.92	15.28
23	DJIBOUTI	Djibouti	43.15	11.55
24	MEKELE	Ethiopia	39.48	13.50
25	BAHAR DAR	Ethiopia	37.40	11.60
26	COMBOLCHA	Ethiopia	39.72	11.08
27	NEKEMTE	Ethiopia	36.60	9.05
28	JIMMA	Ethiopia	36.83	7.67
29	ADDIS ABABA	Ethiopia	38.80	8.98
30	DIRE DAWA	Ethiopia	41.87	9.60
31	ROBE	Ethiopia	40.00	7.10
32	GULU	Uganda	32.33	2.75
33	LIRA	Uganda	32.93	2.28
34	MASINDI	Uganda	31.72	1.68
35	SOROTI	Uganda	33.62	1.72
36	KASESE	Uganda	30.10	0.18
37	JINJA	Uganda	33.18	0.45
38	TORORO	Uganda	34.17	0.68
39	MBARARA	Uganda	30.65	-0.62
40	ENTEBBE	Uganda	32.45	0.05
41	KABALE	Uganda	29.98	-1.25
42	LODWAR	Kenya	35.62	3.12
43	MANDERA	Kenya	41.87	3.93
44	MARSABIT	Kenya	37.90	2.30
45	WAJIR	Kenya	40.07	1.75
46	KAKAMEGA	Kenya	34.78	0.28
47	KISUMU	Kenya	34.75	-0.10
48	KISII	Kenya	34.78	-0.67
49	KERICHO	Kenya	35.35	-0.37
50	NAKURU	Kenya	36.10	-0.27
51	NAROK	Kenya	35.83	-1.13
52	JKI.AIRP.	Kenya	36.92	-1.32
53	DAGORETTI	Kenya	36.75	-1.30
54	WILSON	Kenya	36.82	-1.32
55	MAKINDU	Kenya	37.83	-2.28
56	LAMU	Kenya	40.83	-2.27
57	VOI	Kenya	38.57	-3.40
58	MALINDI	Kenya	40.10	-3.23
59	MOMBASA	Kenya	39.62	-4.03
60	BUKOBA	Tanzania	31.82	-1.33
61	MUSOMA	Tanzania	33.80	-1.50
62	MWANZA	Tanzania	32.92	-2.47
63	KIGOMA	Tanzania	29.63	-4.88
64	DODOMA	Tanzania	35.77	-6.17
65	DAR.I.AIRP.	Tanzania	39.20	-6.87
66	MBEYA	Tanzania	33.47	-8.93
67	SONGEA	Tanzania	35.58	-10.68
68	MTWARA	Tanzania	40.18	-10.27
69	KIGALI	Rwanda	30.12	-1.97
70	BUJUMBURA	Burundi	29.32	-3.32

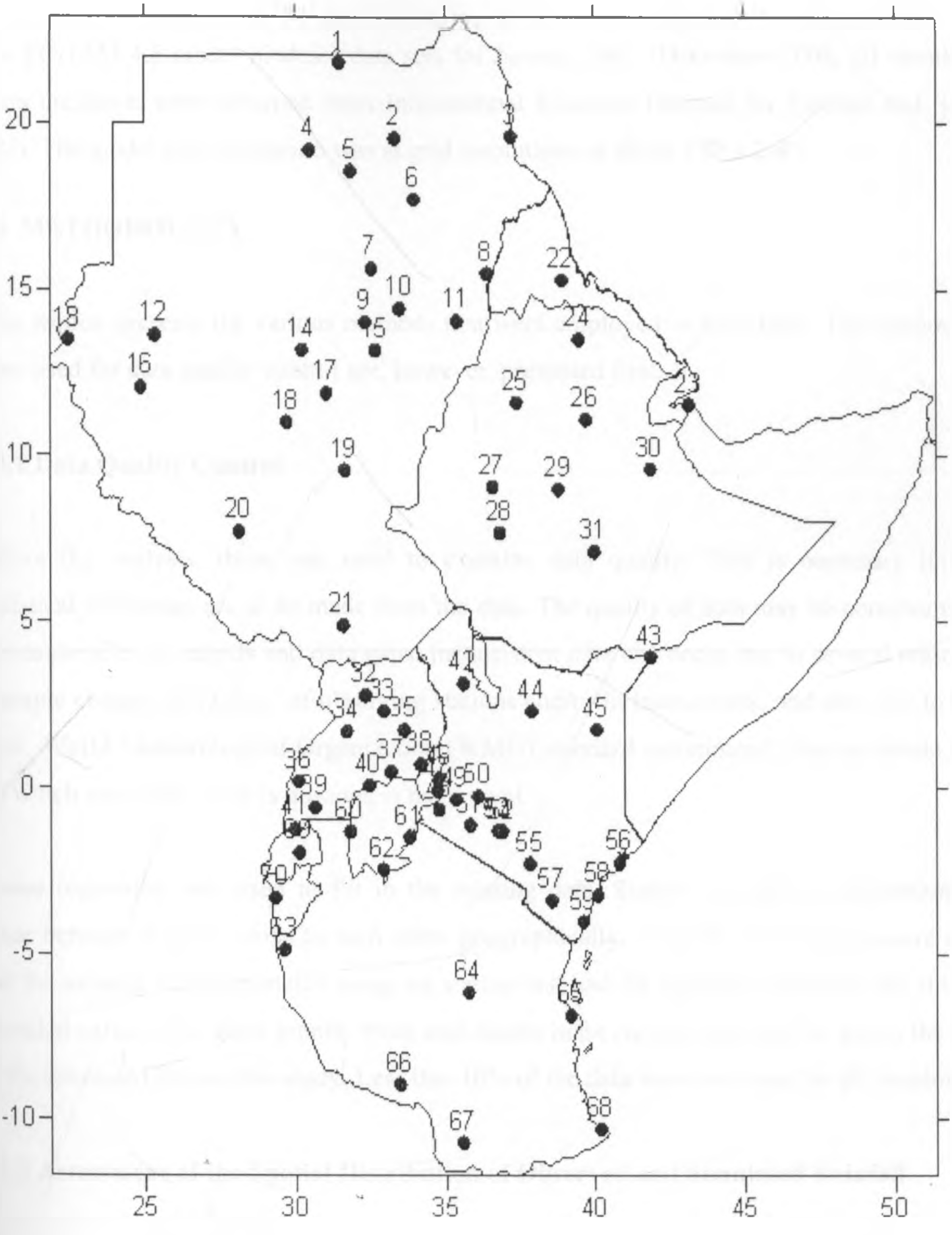

Figure 4: Spatial distribution of stations used in the study as given in Table 1

3.2.2 ECHAM 4.5 Archived Data

The ECHAM 4.5 model hindcast data sets for January 1961- December 2008, all months and years inclusive, were obtained from International Research Institute for Climate and Society (IRI). The model data resolution was at grid resolutions of about 2.8° x 2.8°.

3.3 METHODOLOGY

This section presents the various methods that were employed in this study. The methods that were used for data quality control are, however, presented first.

3.3.1 Data Quality Control

Before the analysis, there was need to examine data quality. This is necessary if correct statistical inferences are to be made from the data. The quality of data may be compromised by inconsistencies in records and data gaps. Inconsistent data can occur due to several reasons, for example change of location of observing stations and/or in instruments, and also due to human error. World Meteorological Organization (WMO) standard recommends that a climate dataset for which more than 10% is missing, is not a good.

Linear regression was used to fill in the missing data. Simple correlation calculations were made between stations close to each other geographically. Then the correlations were ranked, and the missing value estimated using the station that had the highest correlation and that had a recorded value in the same month. Mass and double mass curves were used to assess the quality of the estimated data in this study. Less that 10% of the data were estimated in all locations.

3.3.2 Assessment of the Spatial Distribution of Observed and Simulated Rainfall

By drawing the spatial maps of observed data and model output data, it is possible to study simple similarities and differences between ECHAM 4.5 hindcasts and corresponding observations of rainfall. This makes it possible to see how the model output data compares with the observed data.

3.3.3 ASSESSMENT OF MODEL SKILL AND MEASURES OF ACCURACY

Several methods were used to assess the skill and accuracy of ECHAM 4.5 in simulating rainfall on seasonal time scales over the GHA region. These included:

- Measures of Accuracy
  - Root mean square error
  - Correlation analysis
- Measures of Skill
  - Two-sample Kolmogorov-Smirnov test
  - Categorical statistics

Brief discussions of these methods are presented in the following sections.

3.3.3.1 Root Mean Square Error

Root mean square error is a frequently used measure for computing the differences between values predicted by a model and the actual observations. Equation 1 is the formula for computing the RMSE.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i - o_i)^2} \quad \text{...} (1)$$

In Equation 1, N is the total number of observation or forecasts, f is the forecasted value and o is the observed value.

3.3.3.2 Correlation Analysis

Correlation analysis provides the degree of linear association between a pair of variables. The simple correlation coefficient (r) between a model output variable (f_i) and the corresponding observation (O_i) is given by:

$$r = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(f_i - \bar{f}\right)\left(O_i - \bar{O}\right)}{\left[\frac{1}{N}\sum_{i=1}^{N}\left(f_i - \bar{f}\right)^2 \cdot \frac{1}{N}\sum_{i=1}^{N}\left(O_i - \bar{O}\right)^2\right]^{\frac{1}{2}}} \quad \text{.................................} (2)$$

In Equation 2, $\bar{O}$ and $\bar{f}$ are sample means of observed data and model outputs, respectively, and N is the total number of cases used in the analysis. The r value indicates the correlation of the forecast to the observation; a high (low) r value indicates higher (low) correlation between the two.

3.3.3.3 Two-Sample Kolmogorov-Smirnov Test

The two-sample Kolmogorov-Smirnov test does a non-parametric assessment to examine if the observed value and the forecast value have a similar distribution. This means that, if $F_o(x)$ is the observed distribution function of the rainfall and $F_e(x)$ is the forecast distribution function, then we test:

H_o: $F_o(x) = F_e(x)$ as the null hypothesis against
H_1: $F_o(x) \neq F_e(x)$ .... (3)

If the distributions are not different then we conclude that the observed and forecasted rainfall values are statistically the same, so the prediction model is appropriate. Or else, if we reject H_o then the observed and forecast distributions are different, meaning that the model may not be appropriate. Accordingly, we reject H_o at 5% level of significance if the P-Value is less than 5% (Degroot, 1975). The P values are used to indicate the distance between two distributions. The higher the P value the smaller the distance, hence a skillful forecast.

3.3.3.4 Categorical Statistics

Categorical statistics were used to analyse the relationship of model outputs and the observed rainfall values. The scores were evaluated using a 3 by 3 contingency table. Table 6 displays the basic structure and entries from the categorical analysis from which some skill scores were determined. Skill scores are measures of skill and those used in this study are briefly described below.

Table 6: A 3 by 3 Contingency Table

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

3.3.3.4.1 Bias Score

The bias score measures the ratio of the frequency of forecast rainfall events to the frequency of observed rainfall events. It indicates whether the forecast system has a tendency to underforecast (Bias<1) or overforecast (Bias>1) rainfall events. It ranges from 0 to ∞, the perfect score is 1 (100%).

Bias (Below Normal) = $\frac{J}{M}$ .... (4)

Bias (Normal) = $\frac{K}{N}$ .... (5)

Bias (Above Normal) = $\frac{L}{O}$ .... (6)

3.3.3.4.2 Probability of Detection (PoD)

PoD gives a simple measure of proportion of rainfall events successfully forecast by the model. It ranges from 0 to 1, the perfect score is 1 (100%).

PoD (Below Normal) = $\frac{A}{M}*100$.. (7)

PoD (Normal) = $\frac{E}{N}*100$.. (8)

$$\text{PoD (AboveNormal)} = \frac{I}{O} * 100 \quad \ldots\ldots (9)$$

3.3.3.4.3 False Alarm Ratio (FAR)

The FAR gives a simple proportional measure of the model's tendency to forecast rain where none was observed. The scores range from 0 to 1 (100%); the perfect score is 0.

$$\text{FAR (Below Normal)} = 100\text{-}(100 * \frac{A}{J}) \quad \ldots\ldots (10)$$

$$\text{FAR (Below Normal)} = 100\text{-}(100 * \frac{I}{L}) \quad \ldots\ldots (11)$$

3.3.3.4.4 Heidke Skill Score (HSS)

The score measures the fraction of correct forecasts after eliminating those forecasts which would be correct due purely to random chance. The numerator is the number of correct forecasts, and the reference forecast in this case is climatology. The score ranges from -∞ to 1, the perfect score is 1 (100%).

$$\text{HSS} = \frac{(A+E+I)-\{[(J*M)+(K*N)+(L*O)]/T\}}{T-\{[(J*M)+(K*N)+(L*O)]/T\}} \quad \ldots\ldots (12)$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 INTRODUCTION

In this chapter, the results of the analyses are presented and discussed, starting with the seasonal mean spatial distribution of the observed data, comparison of the spatial distribution of the observed anomalies versus the model output anomalies, correlation analysis, root mean square error analysis and two-sample Kolmogorov-Smirnov test.

4.1 SPATIAL DISTRIBUTION OF THE SEASONAL OBSERVED RAINFALL

The seasonal mean for the observed rainfall distribution for the two seasons is shown in Figure 5. The mean was calculated for the period 1961 to 2008.The equatorial sector (5°S to 5°N) and the southern sector (< 5°S) receive more rainfall in the two seasons than the northern sector (>5°N), with some regions in the northern sector receiving no rainfall the whole season.

The spatial distribution of rainfall in MAM is not the same as that of OND. In MAM high rainfall is received in areas near large water bodies (e.g. Lake Victoria) and over highlands, this is because MAM rainfall is mostly influenced by mesoscale features. While, OND rainfall is mostly influenced by large scale systems.

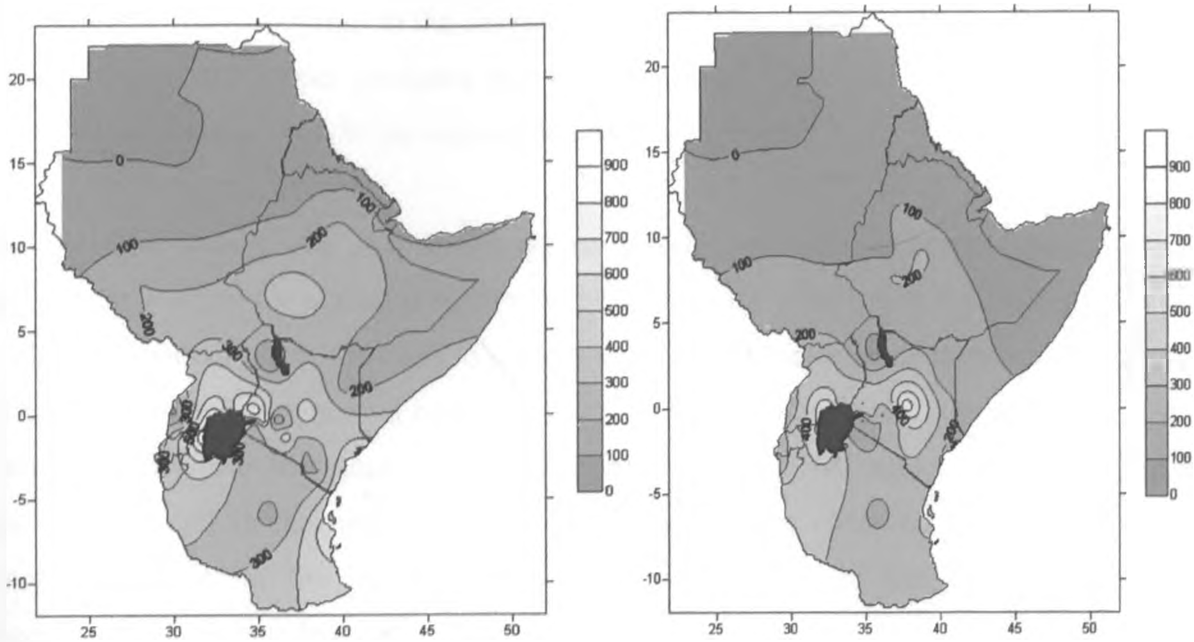

Figure 5: Spatial distribution of observed MAM (left panel) and OND rainfall (right panel) over the GHA region for 1961-2008 (in mm). Dark Green and light green shading represent, low and high rainfall, respectively.

4.2 Assessment of the Spatial Distribution of Observed and Simulated Rainfall

Spatial maps were drawn for the period 1961 to 2008 for the seasons March, April, May (MAM) and October, November, December (OND). The maps were used to compare the model output anomalies for each of the 24 members and the mean output of the 24 members to the observed anomalies. The distribution of the mean of 24 members and some examples of the members that had distributions almost similar to the observed are shown in Figure 6 below; more figures are shown in Appendix 1. The scale of the legend in the above figure was determined using terciles.

For MAM, the distribution of the mean of the 24 members doesn't compare well to the observed as expected Figure 6 (b). For example the area for below normal rainfall anomalies is greater than was actually observed. In Figure 6 (c) the area with normal rainfall anomalies is almost similar to the observation but the area for below normal rainfall extends to the coastal strip and the western part of Lake Victoria, contrary to what was observed. In Figure 6 (d) the area that has normal rainfall prediction is almost similar to the observation but the area for below normal rainfall extends to the coastal strip and the lake region, unlike in the observation. In Figure 6 (e) the model predicted below normal rainfall over the coastal strip while the observed rainfall was more in the near normal category.

For OND, the mean of the 24 members differs from the observation except in parts of Kenya and Tanzania where the normal prediction is the same as the observation Figure 6 (g). The area with below normal rainfall extends to most of the northern sector while there are only patches of rainfall in the below normal category observations. In Figure 6 (h), the area with normal rainfall prediction is the same as observed in most of the GHA region. In Figure 6 (j), the predicted rainfall in the normal category is similar to that observed for most areas. The predicted rainfall in the below normal category over part of the coastal strip differs significantly from that observed.

Some of the individual members presented have more similarities with the observation than the mean of all members. For both seasons the distribution of the mean of 24 members predicts a larger region for rainfall in the below normal category .This indicates that some members lower the mean, hence a higher forecast for below normal rainfall.

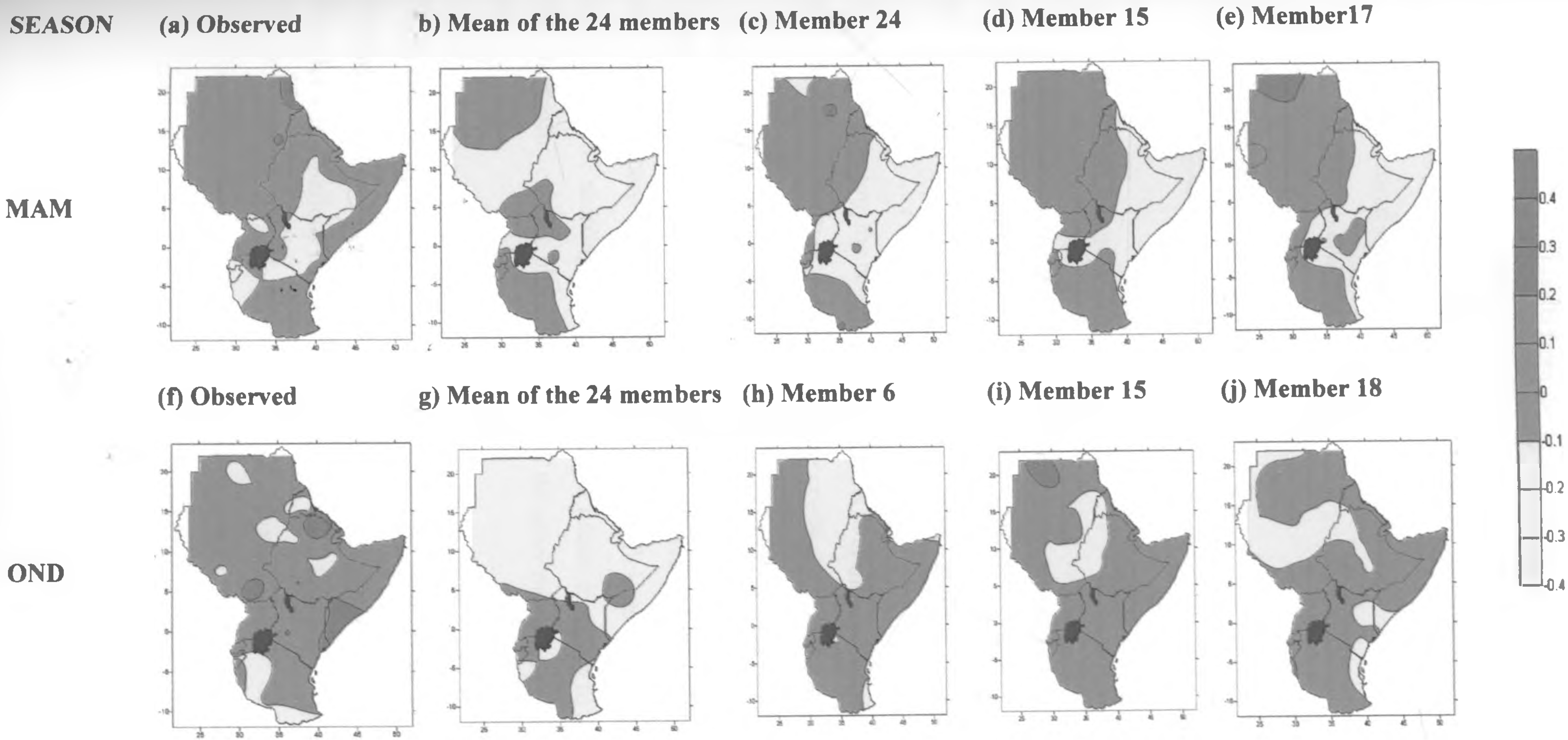

Figure 6: Observed and model rainfall anomalies for selected members for MAM and OND seasons over the GHA region for 1961to 2008. Green, blue and yellow shadings represent above normal, normal, and below normal rainfall respectively.

4.3 RESULTS FROM ASSESSMENT OF MODEL SKILL AND ACCURACY

This section presents the results from the various methods that were used to assess model skills and accuracy. These include results from the following methods:

- Measures of Accuracy
  - Root mean square error
  - Correlation analysis
- Measures of Skill
  - Two-sample Kolmogorov-Smirnov test
  - Categorical statistics

4.3.1 Correlation Analysis

Linear correlation coefficients were calculated between the observed rainfall and the model outputs, the coefficients of the mean of the 24 members and some examples of the members that had big coefficients are shown in Figure 7; more figures are shown in Appendix 2.

For the MAM season, the correlation coefficients over the equatorial sector exceed those in the northern sector of the region Figure 7 (a).The coefficients on the eastern part of Lake Victoria exceed those on the western part. The northern part of the northern sector has negative correlations, indicating an inverse relationship between the rainfall observation and the model output. In Figure 7 (b) the correlation coefficients over the equatorial sector are smaller than those in the northern sector. In Figure 7 (c) the coefficients for the stations along the Kenyan coast are negative showing that the model output relates inversely to the observation. In Figure 7 (d), the coefficients are bigger than those of the other members presented in parts (a), (b) and (c).

For the OND season, the coefficients are positive except for a few stations over the northern sector of the region Figure 7 (e). The southern and equatorial sectors have high coefficients except for a few stations to the west of Lake Victoria. In Figure 7 (f) the coefficients over the northern sector are smaller than those over the equatorial sector. In Figure 7 (g), the northern sector has some negative coefficients indicating a negative relationship between the observed rainfall and the model output. In Figure 7 (h), there are a few stations on the eastern part of the northern sector that have negative coefficients.

From Figure 7 we see that the OND season has higher coefficients than the MAM season for all the members. This can be attributed to the fact that OND rainfall is mostly influenced by large scale systems (Mutai et al., 2000). The regions near large water bodies (e.g. Lake Vicroria and Indian Ocean) and elevated terrain (e.g. Ethiopian highlands) have high coefficients too; the model seems to replicate the systems around these regions well. The equatorial sector also has high coefficients and these can be attributed to the presence of the intertropical convergence zone in this region in both seasons.

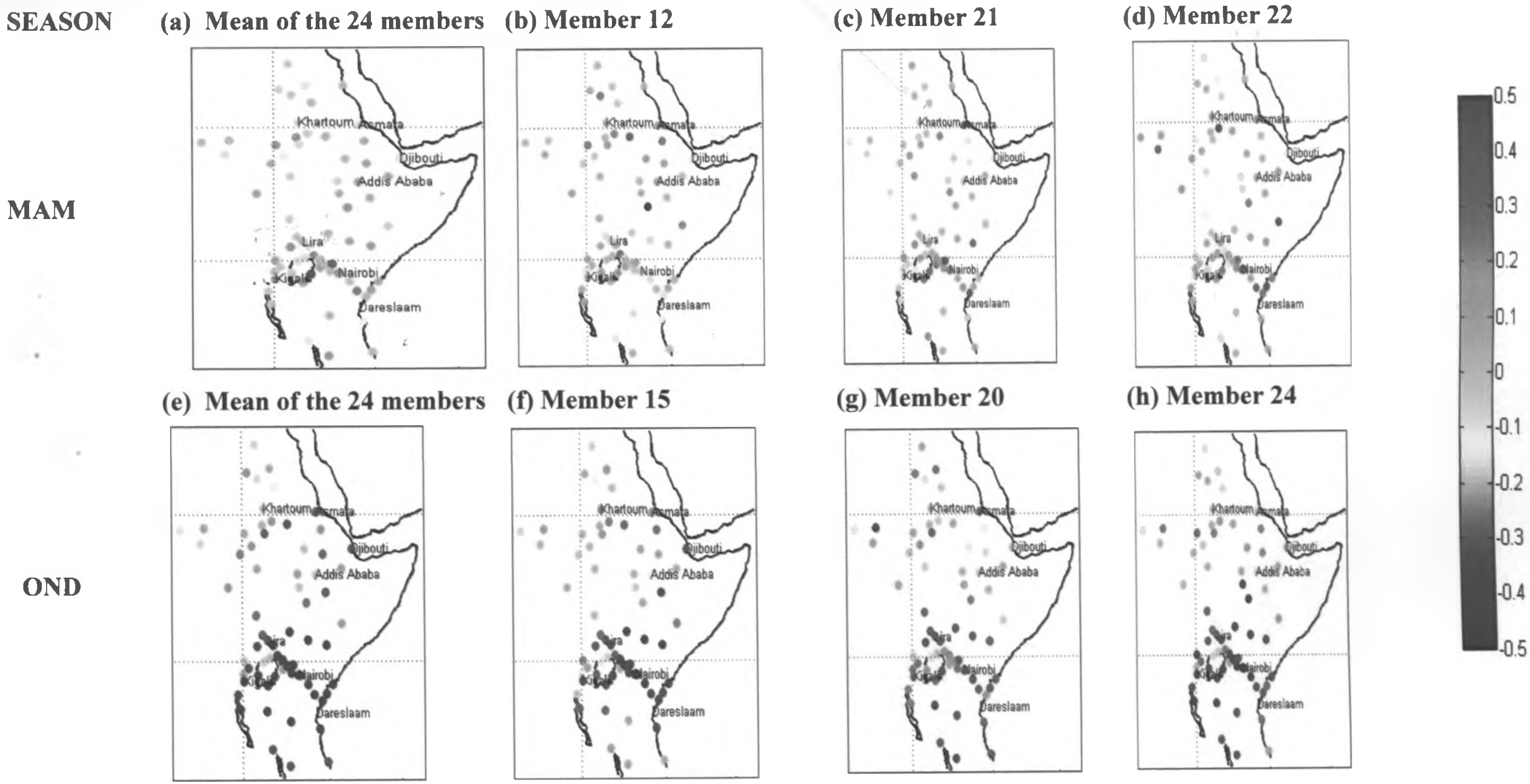

Figure 7: Spatial distribution of correlation coefficients for selected members over the GHA region for 1961 to 2008. Blue shading represents higher coefficients and red shading lower coefficients. The contour interval is 0.1

4.3.2 Root Mean Square Error Analysis

The Root Mean Square Error (RMSE) between the observed rainfall and model outputs was calculated for the period 1961 to 2008. Some examples of members with low errors are shown in Figure 8; more figures are shown in Appendix 3.

For the MAM season, the errors are bigger in the central part of the northern sector and the western part of the lake region Figure 8 (a). In Figure 8 (b), the bigger errors are observed over the central part of the northern sector. In Figure 8 (c), the errors over most of the region range from 1.2 to 1.4 except for a few stations in the northern and southern sectors which have bigger errors. Figure 8 (d) shows that the central part of the northern sector has bigger errors, as is the western part of the Lake Victoria.

For the OND season, the stations in the eastern part of the equatorial sector and the southern sector have smaller errors, while those in the northern sector and the western part of the equatorial sector have bigger errors Figure 8 (e). In Figure 8 (f), the whole GHA region has big errors except for some three stations to the north of Nairobi. In Figure 8 (g), the whole GHA region has errors ranging from 1.2 to 1.6. In Figure 8 (h), the errors are almost similar to those in (e).

In the RMSE analysis, the same observation as in the correlation analysis above was made, the OND season has lower RMSE values indicating the model captures the systems in this season better and more so in the equatorial sector. The area to the West of Lake Victoria has big errors for all the members presented. This could be attributed to a misrepresentation of the land – Lake Breeze in the model.

From Figure 7 and Figure 8 we see that the equatorial sector has big correlation coefficients and small RMSE values. This is an indication that the model correctly resolves the systems in these areas.

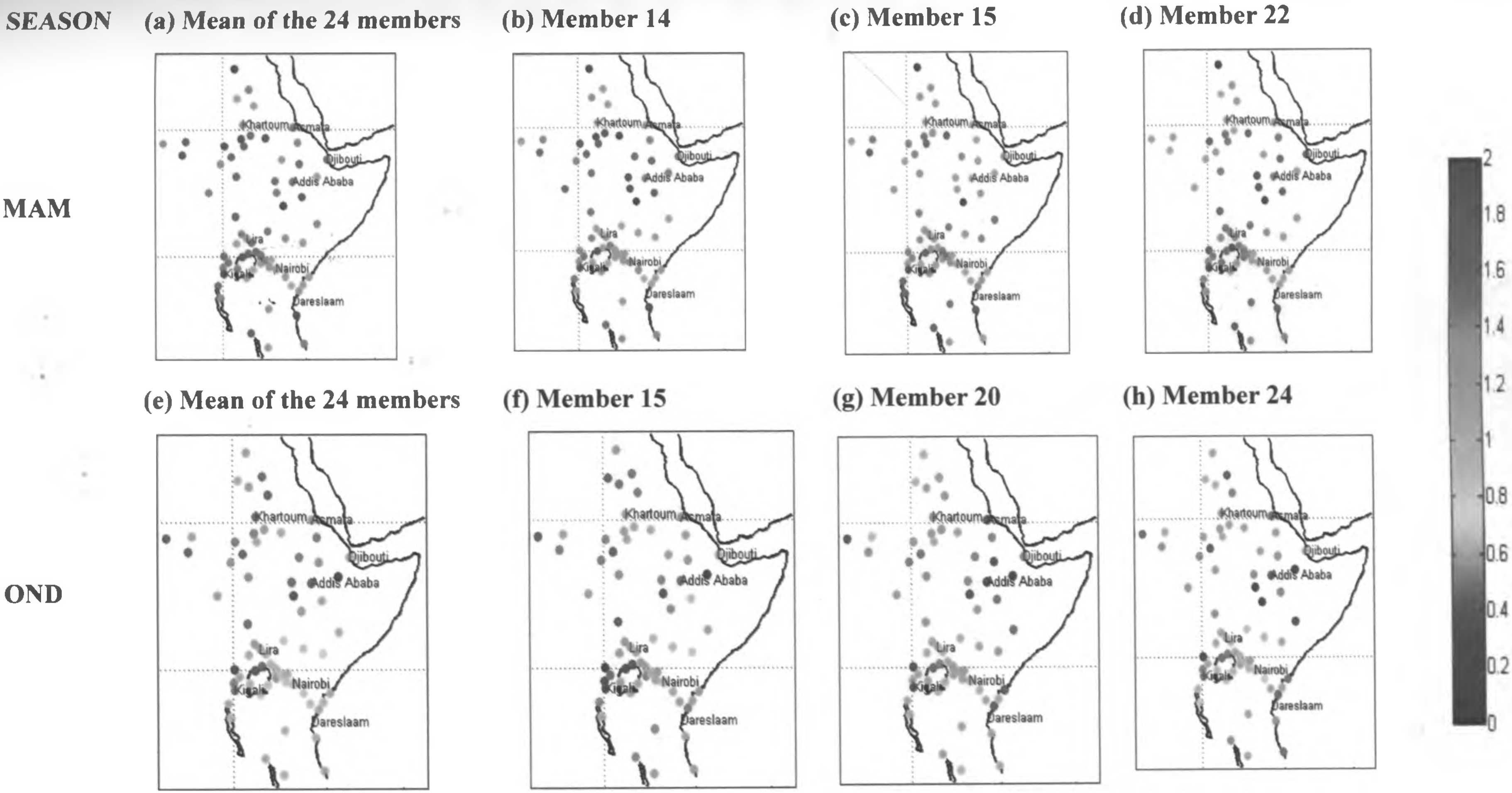

Figure 8: Spatial distribution of RMSE for selected members over the GHA region for 1961 to 2008. Blue shading represents higher errors and red shading lower errors. The contour interval is 0.1

4.3.3 Two-Sample Kolmogorov-Smirnov Test

The observed and model output values were used to perform a two-sample Kolmogorov-Smirnov test. In this test P values are used to indicate the distance between two distributions. The higher the P value the smaller the distance. The higher the P value the smaller the distance, hence a skillful forecast. The results for some of the members are shown in Figure 9; some more figures are given in Appendix 4.

For the MAM season. P values are small in the northern part of the north sector and the western part of the southern sector Figure 9 (a). P values are highest on the Eastern part of Lake Victoria which may be attributed to the land – Lake Breeze. In Figure 9 (b) the northern part of the northern sector has the lowest P values. Most of the equatorial sector has values ranging from 0.5 to 1. In Figure 9 (c) and (d) most of the region has values from 0.5 to 0.9 indicating the distance between the distributions is not big.

For the OND season, most stations to the north of Addis Ababa have low P values and those south have high values except for a few stations on the western side of the southern sector and some stations near Lira Figure 9 (e). In Figure 9 (f) most of the region has P values from 0.3 and above indicating a small difference in the distribution. The same is observed for Figure 9 (g). In Figure 9 (h) high values are seen in the equatorial and southern sector. This indicates the distance between the distributions is not big and hence the skill is high.

From Figure 9 we see that the north most part of the northern sector has low P values for all the members. This can be attributed to the fact that this is a desert. The areas around Lake Victoria and the coast have high P values for most members presented, indicating that the distribution for the forecast and observation are not far apart and, hence a good forecast. Some individual members have higher P values than the mean of all 24 members. For example members 21 and 24 in MAM and members 15, 18 and 24 in OND have higher P values than the 24-member mean.

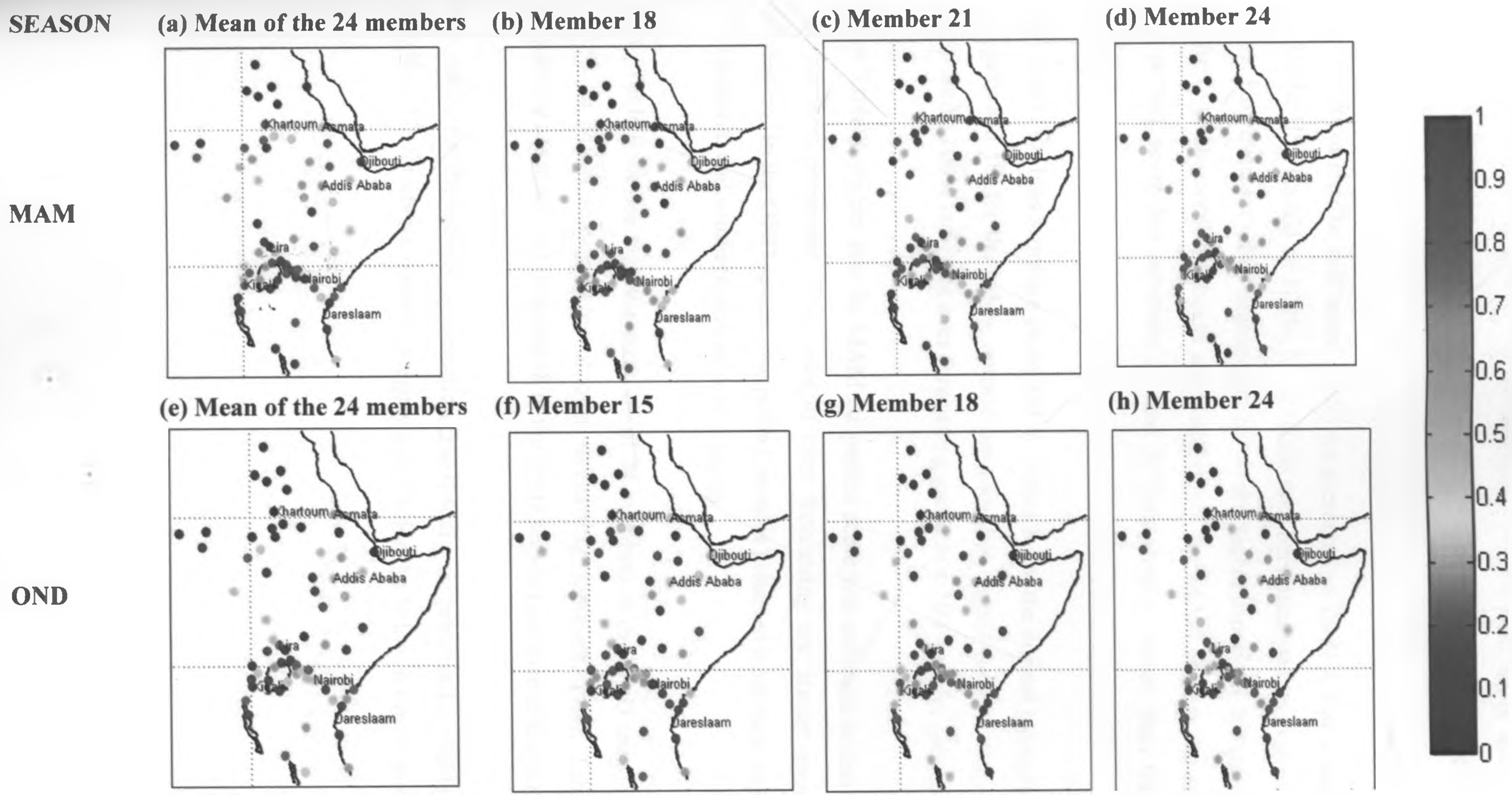

Figure 9: Spatial distribution of P values for selected members over the GHA region for 1961 to 2008. Blue shading represents higher P values and red shading lower P values. The contour interval is 0.1

4.3.4 Categorical Statistics

The results for bias, probability of detection, Heidke skill score and the false alarm ratio calculated from the 3 by 3 contingency table for some few ensemble members for some stations in the GHA region are shown in Tables 7 to 15 below.

The results of Heidke skill score (HSS) are presented in Table 7. For a forecast to be termed as good, the HSS should be 100%. None of the members presented has values close to this perfect score. However, for OND season, the scores are higher especially for stations in the equatorial sector (e.g. Dagoretti, Makindu and Kakamega). For MAM season, the scores are way below the perfect score but members 21 and 22 have higher scores than the average of all 24 members.

The results for bias score are presented in Tables 8, for the normal category, 9, for above normal category and 10, for the below normal category. For a good forecast, the bias score is 100%. A score above 100% indicates over forecasting and below 100% under forecasting.

From Table 8, we see that for MAM the perfect score was achieved in less than ten instances for the members presented. The cases of over forecasting are almost equal to those of under forecasting. In the OND season, the perfect score is achieved a lot more especially for stations in the equatorial and southern sectors of the region.

From Table 9 we see that, the mean of all 24 members in the OND season has the more perfect scores. In MAM season cases of over forecasting dominate. From Table 10, cases of over forecasting are many but member 18 in the OND season has close to ten perfect scores.

The results for Probability of Detection (PoD) score are presented in Tables 11, for the normal category, 12, for above normal category and 13, for the below normal category. PoD gives the proportion of rainfall events successfully forecast by the model. For a good forecast the PoD score is 100%.

From Table 11 we see that for the MAM season most of the stations had a score below 50%, indicating that the model successfully forecasts less than half of the rainfall events. Members 21 and 24 have scores that are close to those of the mean of all 24 members. For the OND season, ensemble member 22 has almost ten instances when the score is above 50% and its scores are better than those of the mean of all 24 members.

From Table 12 the OND has at least fifteen instances when the PoD score is 100% (the perfect score). The stations with the perfect scores, for example Mombasa and Bukoba, are those in the equatorial and southern sectors.

From Table 13 the scores for both seasons are low, implying the model's inability to detect below normal rainfall for the GHA region.

The results for False Alarm ratio (FAR) score are presented as a percentages in Tables 14, for above normal category and 15, for the below normal category. For a good forecast FAR score is 0%. From Table 14 we see the scores for both seasons are above 50% in most instances, indicating when the model forecasted above normal rainfall the observation was not in the below normal category. The same observation is made in Table 15.

Table 7: Heidke Skill Score (%) Results for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	3.00	12.95	-3.19	3.06	-3.13	-7.93	6.38	-11.82	-1.12	4.26
KASSALA	5.33	4.57	7.01	-2.67	5.56	8.84	6.07	9.20	2.94	15.79
WAD MEDANI	6.20	-13.13	3.49	5.37	-3.02	9.84	9.73	0.58	-2.72	3.38
KOSTI	4.38	-0.39	-0.39	-4.35	-7.09	10.93	0.00	1.16	-7.90	25.15
NYALA	-5.63	-16.54	-2.52	3.88	2.17	-2.06	-17.47	-12.15	-3.46	-6.31
RASHAD	2.17	-5.79	-4.90	3.87	-4.21	14.62	12.16	-0.52	13.72	4.89
KADUGLI	-10.02	21.05	-3.06	8.54	-9.88	4.43	-9.16	2.55	8.05	-1.54
MALAKAL	-4.14	-3.73	6.13	-7.65	-15.25	10.31	-5.36	25.05	0.52	-6.32
JUBA	13.18	-5.84	3.50	0.58	-9.59	8.30	-12.57	-7.65	0.33	10.34
ASMARA	-9.23	9.90	-16.23	15.35	-10.67	26.20	14.17	6.01	-3.73	1.46
DJIBOUTI	4.31	-8.81	7.51	7.63	-13.53	1.35	6.25	17.56	4.62	11.11
MEKELE	15.51	7.88	-10.45	2.62	0.52	3.03	24.67	2.36	13.85	-0.37
BAHAR DAR	-1.59	-23.48	-8.49	1.37	11.96	-4.69	-10.45	-7.72	-4.97	11.11
COMBOLCHA	6.43	15.79	0.39	-5.84	9.20	10.19	12.16	27.94	2.36	10.08
JIMMA	-13.46	17.39	5.05	-0.07	-13.54	0.32	5.39	-25.57	15.57	37.13
ADDIS ABABA	18.43	-2.72	-28.38	-6.25	8.84	-10.57	-11.93	-9.73	1.60	-18.72
DIRE DAWA	-2.99	-5.02	-10.38	1.09	-2.46	0.00	19.52	-9.92	-1.92	5.70
ROBE	21.47	7.57	-4.21	2.62	4.26	20.27	18.00	10.34	-4.76	10.82
LIRA	0.39	6.68	3.31	12.67	18.86	15.07	17.13	8.48	7.75	17.95
MASINDI	4.95	-20.24	33.77	-17.15	1.98	29.60	14.12	1.64	2.24	23.66
SOROTI	-8.11	13.01	2.75	-5.22	6.43	20.11	26.01	-6.02	7.45	27.37
KASESE	1.81	-7.61	6.67	-4.03	4.04	-1.99	-25.57	19.14	-19.17	10.37
JINJA	-21.28	-8.80	-8.51	-1.86	-5.32	12.39	-12.65	12.33	-15.63	3.13
TORORO	-18.71	-4.35	-6.94	1.79	-4.41	22.78	21.41	9.14	5.76	20.91
MBARARA	8.54	-12.79	14.85	5.26	12.61	17.57	17.57	10.52	5.01	8.06
ENTEBBE	17.79	-21.88	18.11	26.98	5.26	-16.31	-0.52	18.11	6.68	-12.13
KABALE	-3.53	-0.59	-0.39	11.98	15.63	9.14	-6.25	15.84	12.73	-6.67
MARSABIT	15.57	12.04	5.94	5.76	2.87	30.57	2.94	18.75	17.62	11.29
WAJIR	3.25	-9.52	3.00	-3.39	-6.39	8.33	25.00	6.60	19.33	19.28
KAKAMEGA	-21.56	3.44	6.43	-3.06	-12.35	26.72	2.75	19.38	14.18	26.44
KISUMU	2.36	-13.61	14.96	8.84	-10.24	20.59	9.02	20.84	0.00	17.13
KERICHO	2.94	-10.02	11.64	8.84	-16.54	20.63	7.48	14.40	7.20	20.63
NAROK	-0.07	2.43	2.49	11.17	-12.72	38.87	9.14	19.57	11.96	26.01
DAGORETTI	7.04	8.84	15.35	27.37	6.25	32.93	17.50	31.25	19.51	26.61
MAKINDU	10.88	7.16	1.09	15.68	16.17	46.34	15.38	31.25	47.62	34.52
LAMU	-12.13	-12.21	3.63	7.34	-2.72	22.22	18.52	29.49	8.33	17.24
MOMBASA	-2.13	-3.39	2.36	27.42	9.61	30.38	33.73	13.16	42.86	42.11
BUKOBA	-2.13	3.56	-11.77	-8.39	-30.49	17.24	-30.26	38.89	26.67	-5.48
MUSOMA	5.88	-18.98	7.34	12.50	-0.39	21.43	-4.76	3.75	21.43	32.93
MWANZA	2.36	1.20	5.64	11.81	-3.66	9.26	3.13	21.98	15.84	18.70
DODOMA	1.20	5.14	-8.80	-12.90	13.25	19.51	10.47	22.35	26.67	9.41
DAR I AIRP	2.49	-14.89	14.57	17.46	-15.32	4.94	17.50	2.53	6.10	-8.64
MBEYA	0.71	-2.59	-18.98	-12.28	3.88	18.75	2.75	11.11	12.50	12.50
MTWARA	-9.30	3.88	-12.13	-9.88	-9.73	22.54	-18.92	44.30	5.71	-1.32
KIGALI	-2.33	-7.94	0.26	-3.94	12.27	10.81	20.29	8.33	31.25	2.53
BUJUMBURA	4.95	-7.51	-2.19	3.29	14.96	17.50	17.50	18.52	2.53	3.75

Table 8: Bias Score (%) Results for the Normal Category for some Stations over the GHA region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	100.00	70.59	94.12	94.12	105.88	17.24	27.59	17.24	41.38	17.24
KASSALA	123.08	76.92	69.23	84.62	76.92	64.71	82.35	105.88	100.00	76.47
WAD MEDANI	76.92	61.54	69.23	46.15	84.62	58.82	105.88	83.33	70.59	76.47
KOSTI	55.56	27.78	38.89	50.00	50.00	46.67	100.00	66.67	80.00	80.00
NYALA	72.22	111.11	72.22	66.67	116.67	109.09	63.64	100.00	136.36	90.91
RASHAD	100.00	50.00	125.00	66.67	75.00	100.00	100.00	100.00	57.14	85.71
KADUGLI	80.00	40.00	106.67	60.00	73.33	131.25	106.25	93.75	87.50	100.00
MALAKAL	86.67	113.33	113.33	80.00	113.33	66.67	53.33	100.00	53.33	80.00
JUBA	106.67	100.00	93.33	126.67	73.33	92.31	115.38	130.77	61.54	107.69
ASMARA	100.00	83.33	111.11	94.44	77.78	53.33	53.33	120.00	113.33	100.00
DJIBOUTI	65.00	70.00	105.00	105.00	90.00	50.00	88.89	22.22	44.44	33.33
MEKELE	100.00	116.67	105.56	111.11	88.89	33.33	37.04	40.74	44.44	29.63
BAHAR DAR	100.00	133.33	50.00	50.00	75.00	110.53	100.00	110.53	115.79	115.79
COMBOLCHA	93.75	106.25	125.00	100.00	106.25	72.22	100.00	88.89	116.67	61.11
JIMMA	150.00	128.57	78.57	107.14	114.29	105.88	141.18	117.65	111.76	135.29
ADDIS ABABA	111.76	117.65	123.53	94.12	123.53	81.82	90.91	118.18	181.82	81.82
DIRE DAWA	47.06	52.94	70.59	47.06	64.71	84.21	126.32	52.63	41.18	89.47
ROBE	71.43	107.14	114.29	71.43	85.71	69.23	92.31	53.85	84.62	69.23
LIRA	87.50	106.25	81.25	68.75	75.00	100.00	112.50	118.75	106.25	131.25
MASINDI	88.24	129.41	100.00	94.12	105.88	90.91	86.36	109.09	104.55	86.36
SOROTI	87.50	118.75	75.00	81.25	81.25	42.86	28.57	50.00	50.00	78.57
KASESE	83.33	183.33	125.00	108.33	141.67	90.00	150.00	120.00	60.00	60.00
JINJA	57.14	57.14	57.14	57.14	57.14	93.33	106.67	106.67	100.00	93.33
TORORO	36.84	52.63	42.11	52.63	52.63	55.56	83.33	66.67	61.11	55.56
MBARARA	71.43	114.29	78.57	71.43	121.43	71.43	71.43	57.14	71.43	71.43
ENTEBBE	78.57	114.29	78.57	57.14	78.57	94.44	88.89	88.89	94.44	83.33
KABALE	66.67	120.00	80.00	73.33	126.67	114.29	128.57	135.71	114.29	100.00
MARSABIT	46.67	60.00	106.67	60.00	66.67	73.33	80.00	106.67	86.67	80.00
WAJIR	62.50	75.00	125.00	62.50	75.00	25.00	33.33	66.67	68.75	50.00
KAKAMEGA	100.00	106.25	106.25	118.75	100.00	47.37	78.95	63.16	52.63	57.89
KISUMU	111.76	123.53	111.76	111.76	117.65	75.00	85.71	64.29	50.00	57.14
KERICHO	94.12	100.00	117.65	111.76	105.88	64.29	125.00	64.29	42.86	64.29
NAROK	94.44	105.56	122.22	127.78	83.33	66.67	116.67	50.00	100.00	66.67
DAGORETTI	61.11	94.44	72.22	88.89	66.67	75.00	75.00	100.00	100.00	87.50
MAKINDU	57.89	78.95	68.42	78.95	68.42	66.67	100.00	133.33	133.33	133.33
LAMU	78.95	78.95	73.68	63.16	78.95	28.57	57.14	71.43	42.86	109.52
MOMBASA	63.16	66.67	86.67	73.33	80.00	40.00	40.00	100.00	40.00	60.00
BUKOBA	63.16	68.42	68.42	63.16	68.42	95.00	83.33	116.67	66.67	83.33
MUSOMA	112.50	143.75	100.00	112.50	87.50	40.00	40.00	80.00	40.00	60.00
MWANZA	105.56	133.33	105.56	105.56	94.44	100.00	100.00	88.24	70.59	94.12
DODOMA	91.67	108.33	83.33	66.67	75.00	166.67	166.67	200.00	133.33	200.00
DAR I AIRP	105.26	126.32	110.53	115.79	84.21	75.00	75.00	100.00	100.00	75.00
MBEYA	56.25	50.00	56.25	93.75	62.50	80.00	85.00	100.00	80.00	80.00
MTWARA	133.33	180.00	146.67	100.00	100.00	50.00	125.00	100.00	100.00	25.00
KIGALI	68.75	112.50	81.25	81.25	118.75	100.00	50.00	250.00	50.00	150.00
BUJUMBURA	53.85	92.31	69.23	53.85	69.23	100.00	100.00	50.00	100.00	75.00

Table 9: Bias Score (%) Results for the Above Normal Category for some Stations over the GHA region

	MAM					OND			
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22
KHARTOUM	100.00	133.33	100.00	100.00	120.00	105.26	105.26	110.53	94.74
KASSALA	95.00	95.00	105.00	110.00	130.00	92.86	107.14	107.14	107.14
WAD MEDANI	120.00	115.00	110.00	125.00	115.00	125.00	128.57	138.46	112.50
KOSTI	150.00	155.56	144.44	144.44	138.89	158.33	183.33	183.33	175.00
NYALA	133.33	126.67	153.33	146.67	120.00	94.44	127.78	100.00	105.56
RASHAD	104.55	109.09	86.36	113.64	100.00	68.75	106.25	100.00	93.75
KADUGLI	123.53	129.41	88.24	135.29	105.88	52.63	78.95	94.74	63.16
MALAKAL	95.00	85.00	80.00	100.00	75.00	73.68	78.95	84.21	84.21
JUBA	133.33	126.67	133.33	106.67	133.33	85.71	76.19	90.48	100.00
ASMARA	76.47	88.24	76.47	94.12	135.29	123.08	138.46	107.69	107.69
DJIBOUTI	138.46	115.38	100.00	107.69	107.69	126.67	133.33	160.00	126.67
MEKELE	123.08	84.62	100.00	115.38	138.46	85.71	100.00	109.52	95.24
BAHAR DAR	90.00	105.00	125.00	125.00	125.00	92.86	92.86	107.14	92.86
COMBOLCHA	130.77	123.08	115.38	130.77	115.38	93.75	93.75	112.50	75.00
JIMMA	68.42	94.74	89.47	68.42	73.68	43.75	87.50	93.75	68.75
ADDIS ABABA	100.00	128.57	107.14	114.29	92.86	112.50	131.25	131.25	81.25
DIRE DAWA	122.22	100.00	122.22	105.56	100.00	84.21	68.42	94.74	161.11
ROBE	166.67	158.33	158.33	166.67	133.33	117.65	129.41	141.18	100.00
LIRA	133.33	126.67	126.67	133.33	126.67	80.95	85.71	76.19	61.90
MASINDI	116.67	83.33	100.00	111.11	100.00	115.38	107.69	107.69	69.23
SOROTI	153.85	123.08	130.77	153.85	138.46	127.78	144.44	155.56	127.78
KASESE	118.75	62.50	93.75	100.00	93.75	109.52	76.19	104.76	95.24
JINJA	120.00	113.33	120.00	126.67	120.00	94.12	105.88	111.76	88.24
TORORO	150.00	142.86	135.71	142.86	135.71	100.00	94.74	105.26	78.95
MBARARA	131.25	87.50	118.75	125.00	93.75	116.67	116.67	138.89	111.11
ENTEBBE	111.11	88.89	94.44	111.11	105.56	100.00	105.88	111.76	76.47
KABALE	133.33	73.33	120.00	120.00	86.67	100.00	100.00	94.44	77.78
MARSABIT	164.29	142.86	107.14	142.86	142.86	106.67	126.67	106.67	80.00
WAJIR	133.33	113.33	86.67	113.33	113.33	75.00	114.29	128.57	76.47
KAKAMEGA	120.00	120.00	113.33	100.00	113.33	112.50	125.00	125.00	112.50
KISUMU	85.71	78.57	85.71	92.86	85.71	100.00	131.25	125.00	83.33
KERICHO	107.14	92.86	78.57	92.86	85.71	112.50	116.67	118.75	112.50
NAROK	123.08	107.69	115.38	92.31	115.38	131.25	118.75	156.25	100.00
DAGORETTI	138.46	107.69	107.69	92.31	115.38	75.00	125.00	100.00	50.00
MAKINDU	172.73	163.64	163.64	145.45	154.55	60.00	100.00	80.00	40.00
LAMU	106.67	113.33	120.00	120.00	100.00	50.00	75.00	50.00	25.00
MOMBASA	107.14	94.74	100.00	105.26	84.21	100.00	200.00	100.00	50.00
BUKOBA	107.14	78.57	100.00	100.00	92.86	100.00	300.00	300.00	200.00
MUSOMA	107.69	92.31	146.15	115.38	123.08	100.00	166.67	133.33	100.00
MWANZA	92.86	64.29	100.00	92.86	92.86	100.00	113.33	113.33	106.67
DODOMA	122.22	127.78	111.11	111.11	100.00	150.00	200.00	150.00	100.00
DAR I AIRP	40.00	53.33	66.67	66.67	80.00	100.00	125.00	125.00	50.00
MBEYA	166.67	160.00	120.00	120.00	166.67	78.57	100.00	78.57	64.29
MTWARA	56.25	37.50	56.25	68.75	81.25	50.00	50.00	150.00	0.00
KIGALI	166.67	100.00	150.00	133.33	116.67	200.00	200.00	150.00	150.00
BUJUMBURA	200.00	163.64	209.09	181.82	190.91	100.00	100.00	133.33	66.67

Table 10: Bias Score (%) Results for the Below Normal Category for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	100.00	100.00	106.25	106.25	75.00	0.00	0.00	0.00	0.00	0.00
KASSALA	86.67	126.67	120.00	100.00	80.00	141.18	111.76	88.24	94.12	105.88
WAD MEDANI	93.33	113.33	113.33	113.33	93.33	120.00	70.59	88.24	120.00	113.33
KOSTI	91.67	125.00	125.00	108.33	116.67	104.76	52.38	76.19	71.43	80.95
NYALA	100.00	60.00	80.00	93.33	60.00	100.00	94.74	100.00	73.68	105.26
RASHAD	92.86	128.57	100.00	107.14	121.43	127.78	94.44	100.00	138.89	127.78
KADUGLI	93.75	125.00	106.25	100.00	118.75	130.77	123.08	115.38	169.23	153.85
MALAKAL	123.08	107.69	115.38	123.08	123.08	171.43	178.57	121.43	171.43	135.71
JUBA	66.67	77.78	77.78	72.22	94.44	128.57	121.43	85.71	135.71	92.86
ASMARA	130.77	138.46	115.38	115.38	84.62	120.00	110.00	80.00	85.00	100.00
DJIBOUTI	113.33	126.67	93.33	86.67	106.67	133.33	80.00	133.33	140.00	126.67
MEKELE	82.35	94.12	94.12	76.47	82.35	0.00	0.00	0.00	0.00	0.00
BAHAR DAR	112.50	68.75	106.25	106.25	87.50	93.33	106.67	80.00	86.67	66.67
COMBOLCHA	84.21	78.95	68.42	78.95	84.21	142.86	107.14	100.00	107.14	121.43
JIMMA	92.31	76.92	138.46	138.46	123.08	153.33	66.67	86.67	120.00	93.33
ADDIS ABABA	88.24	58.82	70.59	94.12	82.35	100.00	80.95	66.67	71.43	80.95
DIRE DAWA	138.46	161.54	107.69	161.54	146.15	160.00	110.00	200.00	92.31	150.00
ROBE	81.82	63.64	59.09	81.82	90.91	105.56	77.78	94.44	111.11	94.44
LIRA	82.35	70.59	94.12	100.00	100.00	136.36	109.09	118.18	163.64	109.09
MASINDI	92.31	84.62	100.00	92.31	92.31	100.00	115.38	76.92	123.08	115.38
SOROTI	73.68	68.42	100.00	78.95	89.47	118.75	112.50	81.25	112.50	112.50
KASESE	94.12	76.47	88.24	94.12	76.47	94.12	100.00	82.35	129.41	123.53
JINJA	115.79	121.05	115.79	110.53	115.79	112.50	87.50	81.25	112.50	125.00
TORORO	133.33	120.00	140.00	120.00	126.67	172.73	136.36	145.45	200.00	200.00
MBARARA	94.44	100.00	100.00	100.00	88.89	106.25	106.25	93.75	112.50	106.25
ENTEBBE	106.25	100.00	125.00	125.00	112.50	107.69	107.69	100.00	138.46	130.77
KABALE	100.00	105.56	100.00	105.56	88.89	87.50	75.00	75.00	112.50	106.25
MARSABIT	94.74	100.00	89.47	100.00	94.74	116.67	94.44	88.89	127.78	127.78
WAJIR	105.88	111.76	88.24	123.53	111.76	233.33	160.00	100.00	160.00	166.67
KAKAMEGA	82.35	76.47	82.35	82.35	88.24	161.54	100.00	123.08	153.85	161.54
KISUMU	100.00	94.12	100.00	94.12	94.12	112.50	83.33	105.56	137.50	127.78
KERICHO	100.00	105.88	100.00	94.12	105.88	116.67	75.00	111.11	133.33	116.67
NAROK	88.24	88.24	64.71	76.47	105.88	95.00	75.00	85.00	100.00	95.00
DAGORETTI	111.76	100.00	123.53	117.65	123.53	166.67	100.00	100.00	166.67	106.67
MAKINDU	100.00	83.33	94.44	94.44	100.00	200.00	100.00	100.00	166.67	166.67
LAMU	121.43	114.29	114.29	128.57	128.57	0.00	0.00	0.00	0.00	160.00
MOMBASA	140.00	142.86	114.29	121.43	142.86	175.00	125.00	100.00	200.00	175.00
BUKOBA	140.00	160.00	140.00	146.67	146.67	106.25	75.00	25.00	125.00	100.00
MUSOMA	84.21	68.42	68.42	78.95	94.74	200.00	133.33	100.00	200.00	200.00
MWANZA	100.00	93.75	93.75	100.00	112.50	100.00	87.50	100.00	125.00	106.25
DODOMA	83.33	66.67	100.00	111.11	116.67	50.00	33.33	33.33	83.33	33.33
DAR.I.AIRP	157.14	114.29	121.43	114.29	142.86	133.33	100.00	66.67	166.67	133.33
MBEYA	82.35	94.12	123.53	88.24	76.47	150.00	121.43	121.43	164.29	150.00
MTWARA	111.76	88.24	100.00	129.41	117.65	160.00	100.00	80.00	140.00	140.00
KIGALI	85.00	90.00	85.00	95.00	75.00	71.43	85.71	42.86	100.00	57.14
BUJUMBURA	79.17	75.00	66.67	87.50	75.00	100.00	100.00	125.00	125.00	125.00

Table 11: Probability of Detection (PoD) Score (%) Results for the Normal Category for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	47.06	29.41	29.41	35.29	47.06	6.90	20.69	10.34	27.59	17.24
KASSALA	38.46	23.08	15.38	15.38	30.77	23.53	11.76	47.06	47.06	41.18
WAD MEDANI	30.77	0.00	15.38	15.38	23.08	23.53	41.18	27.78	29.41	35.29
KOSTI	22.22	22.22	22.22	16.67	22.22	13.33	13.33	6.67	13.33	40.00
NYALA	22.22	38.89	27.78	33.33	44.44	27.27	0.00	27.27	27.27	9.09
RASHAD	25.00	16.67	25.00	25.00	25.00	21.43	35.71	21.43	21.43	28.57
KADUGLI	6.67	26.67	33.33	13.33	6.67	50.00	31.25	18.75	37.50	31.25
MALAKAL	33.33	40.00	46.67	26.67	13.33	20.00	20.00	53.33	13.33	20.00
JUBA	46.67	26.67	26.67	40.00	20.00	23.08	7.69	23.08	7.69	38.46
ASMARA	38.89	33.33	27.78	44.44	22.22	26.67	26.67	46.67	33.33	26.67
DJIBOUTI	35.00	20.00	55.00	55.00	25.00	16.67	33.33	11.11	22.22	22.22
MEKELE	50.00	44.44	33.33	38.89	33.33	22.22	33.33	22.22	29.63	22.22
BAHAR DAR	25.00	8.33	8.33	8.33	16.67	42.11	31.58	36.84	47.37	47.37
COMBOLCHA	43.75	43.75	56.25	25.00	43.75	27.78	44.44	55.56	38.89	22.22
JIMMA	21.43	35.71	21.43	35.71	21.43	41.18	52.94	29.41	58.82	70.59
ADDIS ABABA	52.94	29.41	17.65	35.29	52.94	9.09	18.18	18.18	54.55	9.09
DIRE DAWA	11.76	11.76	23.53	11.76	17.65	31.58	63.16	15.79	5.88	26.32
ROBE	42.86	28.57	35.71	28.57	21.43	38.46	23.08	15.38	15.38	15.38
LIRA	31.25	43.75	25.00	37.50	37.50	37.50	43.75	37.50	37.50	50.00
MASINDI	29.41	35.29	58.82	5.88	35.29	54.55	40.91	50.00	40.91	50.00
SOROTI	25.00	50.00	18.75	12.50	37.50	7.14	7.14	14.29	7.14	28.57
KASESE	16.67	41.67	25.00	25.00	25.00	20.00	10.00	30.00	20.00	20.00
JINJA	7.14	14.29	14.29	35.71	21.43	33.33	20.00	33.33	20.00	20.00
TORORO	10.53	21.05	5.26	21.05	26.32	27.78	44.44	22.22	22.22	22.22
MBARARA	35.71	21.43	28.57	35.71	42.86	21.43	35.71	21.43	7.14	7.14
ENTEBBE	35.71	14.29	28.57	21.43	35.71	22.22	33.33	38.89	44.44	22.22
KABALE	13.33	33.33	20.00	26.67	60.00	35.71	35.71	42.86	57.14	21.43
MARSABIT	26.67	20.00	33.33	33.33	13.33	26.67	20.00	33.33	26.67	20.00
WAJIR	18.75	18.75	43.75	12.50	12.50	0.00	0.00	16.67	18.75	12.50
KAKAMEGA	12.50	43.75	37.50	31.25	25.00	21.05	21.05	26.32	21.05	26.32
KISUMU	52.94	41.18	58.82	47.06	41.18	25.00	21.43	21.43	0.00	7.14
KERICHO	52.94	41.18	58.82	47.06	29.41	21.43	25.00	14.29	0.00	14.29
NAROK	38.89	44.44	38.89	55.56	22.22	33.33	33.33	8.33	0.00	8.33
DAGORETTI	33.33	44.44	27.78	50.00	22.22	50.00	50.00	50.00	50.00	37.50
MAKINDU	31.58	36.84	21.05	42.11	36.84	33.33	33.33	33.33	66.67	66.67
LAMU	15.79	21.05	31.58	31.58	31.58	28.57	42.86	57.14	28.57	57.14
MOMBASA	31.58	13.33	33.33	40.00	33.33	20.00	20.00	40.00	40.00	40.00
BUKOBA	31.58	36.84	21.05	21.05	15.79	35.00	16.67	83.33	50.00	33.33
MUSOMA	25.00	25.00	25.00	43.75	25.00	20.00	0.00	20.00	20.00	40.00
MWANZA	44.44	55.56	33.33	44.44	27.78	23.53	23.53	41.18	23.53	29.41
DODOMA	25.00	41.67	8.33	8.33	8.33	33.33	33.33	66.67	33.33	33.33
DAR [AIRP	47.37	36.84	63.16	47.37	26.32	25.00	50.00	25.00	25.00	25.00
MBEYA	25.00	12.50	12.50	18.75	25.00	30.00	35.00	35.00	35.00	35.00
MTWARA	40.00	66.67	26.67	20.00	20.00	25.00	25.00	50.00	25.00	0.00
KIGALI	25.00	37.50	25.00	18.75	56.25	0.00	0.00	0.00	50.00	0.00
BUJUMBURA	23.08	30.77	15.38	15.38	30.77	50.00	50.00	0.00	25.00	25.00

Table 12: Probability of Detection (PoD) Score (%) Results for the Above Normal Category for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	26.67	53.33	33.33	40.00	26.67	31.58	47.37	21.05	31.58	31.58
KASSALA	40.00	40.00	60.00	50.00	60.00	28.57	50.00	28.57	28.57	50.00
WAD MEDANI	50.00	40.00	60.00	60.00	40.00	50.00	50.00	30.77	25.00	43.75
KOSTI	61.11	55.56	55.56	50.00	38.89	41.67	66.67	50.00	41.67	66.67
NYALA	46.67	20.00	46.67	40.00	46.67	22.22	38.89	27.78	44.44	33.33
RASHAD	50.00	45.45	40.91	54.55	36.36	43.75	50.00	37.50	43.75	37.50
KADUGLI	41.18	58.82	23.53	58.82	35.29	26.32	26.32	47.37	15.79	21.05
MALAKAL	25.00	30.00	40.00	30.00	25.00	36.84	15.79	42.11	42.11	36.84
JUBA	46.67	33.33	53.33	40.00	26.67	47.62	33.33	42.86	42.86	47.62
ASMARA	17.65	41.18	17.65	47.06	41.18	53.85	46.15	23.08	38.46	23.08
DJIBOUTI	38.46	38.46	38.46	30.77	15.38	46.67	40.00	66.67	53.33	46.67
MEKELE	38.46	38.46	15.38	38.46	38.46	38.10	66.67	52.38	57.14	38.10
BAHAR DAR	35.00	25.00	55.00	50.00	70.00	35.71	21.43	28.57	28.57	57.14
COMBOLCHA	38.46	61.54	30.77	38.46	23.08	37.50	43.75	56.25	25.00	43.75
JIMMA	31.58	68.42	47.37	26.32	21.05	12.50	31.25	12.50	18.75	43.75
ADDIS ABABA	50.00	42.86	21.43	28.57	35.71	25.00	31.25	31.25	18.75	37.50
DIRE DAWA	50.00	44.44	44.44	50.00	33.33	42.11	36.84	36.84	55.56	42.11
ROBE	58.33	58.33	41.67	41.67	33.33	52.94	52.94	64.71	35.29	58.82
LIRA	33.33	46.67	33.33	46.67	46.67	47.62	47.62	33.33	28.57	42.86
MASINDI	38.89	5.56	55.56	44.44	44.44	61.54	46.15	38.46	38.46	53.85
SOROTI	38.46	38.46	46.15	38.46	38.46	66.67	77.78	55.56	55.56	66.67
KASESE	37.50	25.00	43.75	37.50	37.50	42.86	19.05	61.90	19.05	52.38
JINJA	13.33	26.67	26.67	26.67	26.67	35.29	23.53	47.06	29.41	41.18
TORORO	21.43	35.71	42.86	35.71	35.71	57.89	52.63	57.89	47.37	57.89
MBARARA	37.50	18.75	56.25	43.75	43.75	55.56	44.44	66.67	55.56	55.56
ENTEBBE	55.56	16.67	55.56	61.11	27.78	23.53	35.29	52.94	41.18	29.41
KABALE	33.33	20.00	40.00	40.00	26.67	38.89	33.33	44.44	33.33	33.33
MARSABIT	50.00	42.86	35.71	28.57	57.14	66.67	53.33	53.33	40.00	46.67
WAJIR	53.33	26.67	40.00	46.67	33.33	50.00	71.43	57.14	47.06	52.94
KAKAMEGA	26.67	33.33	46.67	33.33	26.67	62.50	50.00	62.50	50.00	62.50
KISUMU	21.43	21.43	21.43	35.71	14.29	66.67	56.25	68.75	33.33	75.00
KERICHO	21.43	21.43	14.29	35.71	14.29	62.50	50.00	62.50	62.50	75.00
NAROK	30.77	30.77	38.46	38.46	23.08	75.00	50.00	68.75	50.00	75.00
DAGORETTI	30.77	38.46	46.15	38.46	46.15	50.00	50.00	50.00	25.00	68.75
MAKINDU	45.45	63.64	54.55	45.45	54.55	60.00	60.00	40.00	40.00	40.00
LAMU	33.33	20.00	46.67	46.67	33.33	50.00	50.00	50.00	25.00	35.29
MOMBASA	21.43	36.84	42.11	63.16	36.84	100.00	100.00	50.00	50.00	50.00
BUKOBA	21.43	14.29	14.29	21.43	7.14	50.00	100.00	100.00	100.00	100.00
MUSOMA	30.77	23.08	53.85	30.77	15.38	33.33	33.33	66.67	33.33	33.33
MWANZA	14.29	21.43	28.57	42.86	28.57	53.33	46.67	60.00	60.00	60.00
DODOMA	50.00	44.44	38.89	33.33	61.11	100.00	100.00	50.00	50.00	100.00
DAR I AIRP	6.67	13.33	26.67	33.33	6.67	50.00	50.00	75.00	50.00	25.00
MBEYA	60.00	53.33	26.67	46.67	66.67	50.00	35.71	35.71	42.86	35.71
MTWARA	18.75	6.25	25.00	25.00	25.00	50.00	0.00	100.00	0.00	50.00
KIGALI	33.33	16.67	25.00	33.33	25.00	50.00	50.00	100.00	50.00	50.00
BUJUMBURA	45.45	27.27	45.45	45.45	63.64	33.33	33.33	66.67	33.33	33.33

Table 13: Probability of Detection (PoD) Score (%) Results for the Below Normal Category for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	Member_15	Member_21	Member_22	Member_24	Mean_24	Member_15	Member_18	Member_22	Member_24
KHARTOUM	31.25	43.75	31.25	31.25	18.75	0.00	0.00	0.00	0.00	0.00
KASSALA	33.33	46.67	33.33	26.67	20.00	64.71	52.94	41.18	29.41	41.18
WAD MEDANI	33.33	33.33	26.67	33.33	33.33	46.67	29.41	41.18	40.00	26.67
KOSTI	25.00	16.67	16.67	25.00	25.00	61.90	23.81	42.86	28.57	47.62
NYALA	20.00	6.67	20.00	33.33	13.33	47.37	26.32	26.32	21.05	42.11
RASHAD	28.57	28.57	21.43	28.57	35.71	61.11	38.89	38.89	61.11	44.44
KADUGLI	31.25	56.25	37.50	43.75	37.50	30.77	23.08	38.46	69.23	46.15
MALAKAL	38.46	23.08	23.08	30.77	30.77	64.29	57.14	57.14	42.86	28.57
JUBA	33.33	27.78	27.78	22.22	33.33	42.86	28.57	14.29	50.00	35.71
ASMARA	23.08	46.15	23.08	38.46	15.38	70.00	55.00	40.00	25.00	50.00
DJIBOUTI	33.33	26.67	20.00	26.67	33.33	40.00	40.00	60.00	33.33	53.33
MEKELE	41.18	35.29	29.41	29.41	29.41	0.00	0.00	0.00	0.00	0.00
BAHAR DAR	37.50	18.75	18.75	43.75	31.25	13.33	26.67	20.00	13.33	20.00
COMBOLCHA	31.58	31.58	15.79	26.32	47.37	57.14	35.71	42.86	42.86	57.14
JIMMA	15.38	23.08	38.46	38.46	30.77	46.67	26.67	6.67	53.33	60.00
ADDIS ABABA	35.29	23.53	5.88	23.53	29.41	42.86	28.57	28.57	33.33	19.05
DIRE DAWA	30.77	30.77	7.69	38.46	46.15	20.00	40.00	20.00	38.46	50.00
ROBE	45.45	31.82	18.18	36.36	50.00	50.00	55.56	38.89	38.89	44.44
LIRA	35.29	23.53	47.06	41.18	52.94	45.45	45.45	54.55	54.55	45.45
MASINDI	46.15	23.08	53.85	15.38	23.08	46.15	46.15	15.38	30.77	46.15
SOROTI	21.05	36.84	42.11	36.84	36.84	62.50	62.50	18.75	50.00	56.25
KASESE	47.06	17.65	41.18	29.41	41.18	35.29	17.65	41.18	35.29	47.06
JINJA	36.84	42.11	42.11	36.84	42.11	56.25	31.25	43.75	18.75	43.75
TORORO	26.67	33.33	40.00	46.67	26.67	63.64	45.45	36.36	36.36	63.64
MBARARA	44.44	33.33	44.44	33.33	38.89	56.25	56.25	31.25	43.75	50.00
ENTEBBE	43.75	25.00	50.00	68.75	50.00	23.08	30.77	46.15	23.08	23.08
KABALE	44.44	44.44	38.89	55.56	44.44	43.75	18.75	43.75	37.50	31.25
MARSABIT	52.63	57.89	42.11	47.37	36.84	66.67	33.33	50.00	66.67	55.56
WAJIR	35.29	35.29	23.53	35.29	41.18	66.67	80.00	40.00	73.33	73.33
KAKAMEGA	17.65	29.41	29.41	29.41	23.53	76.92	38.46	53.85	61.54	69.23
KISUMU	29.41	11.76	47.06	35.29	23.53	50.00	38.89	50.00	62.50	50.00
KERICHO	29.41	17.65	47.06	35.29	23.53	55.56	37.50	50.00	50.00	50.00
NAROK	29.41	29.41	29.41	29.41	29.41	65.00	35.00	55.00	60.00	60.00
DAGORETTI	47.06	35.29	58.82	64.71	47.06	66.67	33.33	66.67	66.67	46.67
MAKINDU	44.44	22.22	33.33	44.44	44.44	100.00	33.33	100.00	100.00	66.67
LAMU	28.57	35.71	28.57	35.71	28.57	0.00	0.00	0.00	0.00	40.00
MOMBASA	40.00	42.86	28.57	50.00	50.00	75.00	75.00	50.00	100.00	100.00
BUKOBA	40.00	53.33	40.00	40.00	13.33	56.25	0.00	25.00	50.00	25.00
MUSOMA	52.63	15.79	36.84	47.37	52.63	100.00	66.67	33.33	100.00	100.00
MWANZA	43.75	25.00	50.00	37.50	37.50	43.75	37.50	43.75	50.00	50.00
DODOMA	27.78	27.78	33.33	33.33	50.00	33.33	16.67	33.33	66.67	16.67
DAR.I.AIRP	50.00	21.43	35.71	57.14	35.71	33.33	33.33	0.00	33.33	33.33
MBEYA	17.65	29.41	23.53	11.76	17.65	64.29	35.71	57.14	50.00	57.14
MTWARA	23.53	35.29	23.53	35.29	35.29	80.00	40.00	60.00	80.00	60.00
KIGALI	35.00	30.00	45.00	40.00	40.00	57.14	71.43	28.57	71.43	42.86
BUJUMBURA	41.67	29.17	33.33	45.83	41.67	50.00	50.00	75.00	50.00	50.00

Table 14: False Alarm Ratio (FAR) Score (%) Results for the Above Normal Category for some Stations over the GHA Region

MAM					OND				
Mean_24	Member_15	Member_21	Member_22	Member_	Mean_24	Member_15	Member_18	Member_22	Member_24
68.75	56.25	70.59	70.59	75.00	100.00	100.00	100.00	100.00	100.00
61.54	63.16	72.22	73.33	75.00	54.17	52.63	53.33	68.75	61.11
64.29	70.59	76.47	70.59	64.29	61.11	58.33	53.33	66.67	76.47
72.73	86.67	86.67	76.92	78.57	40.91	54.55	43.75	60.00	41.18
80.00	88.89	75.00	64.29	77.78	52.63	72.22	73.68	71.43	60.00
69.23	77.78	78.57	73.33	70.59	52.17	58.82	61.11	56.00	65.22
66.67	55.00	64.71	56.25	68.42	76.47	81.25	66.67	59.09	70.00
68.75	78.57	80.00	75.00	75.00	62.50	68.00	52.94	75.00	78.95
50.00	64.29	64.29	69.23	64.71	66.67	76.47	83.33	63.16	61.54
82.35	66.67	80.00	66.67	81.82	41.67	50.00	50.00	70.59	50.00
70.59	78.95	78.57	69.23	68.75	70.00	50.00	55.00	76.19	57.89
50.00	62.50	68.75	61.54	64.29	100.00	100.00	100.00	100.00	100.00
66.67	72.73	82.35	58.82	64.29	85.71	75.00	75.00	84.62	70.00
62.50	60.00	76.92	66.67	43.75	60.00	66.67	57.14	60.00	52.94
83.33	70.00	72.22	72.22	75.00	69.57	60.00	92.31	55.56	35.71
60.00	60.00	91.67	75.00	64.29	57.14	64.71	57.14	53.33	76.47
77.78	80.95	92.86	76.19	68.42	87.50	63.64	90.00	58.33	66.67
44.44	50.00	69.23	55.56	45.00	52.63	28.57	58.82	65.00	52.94
57.14	66.67	50.00	58.82	47.06	66.67	58.33	53.85	66.67	58.33
50.00	72.73	46.15	83.33	75.00	53.85	60.00	80.00	75.00	60.00
71.43	46.15	57.89	53.33	58.82	47.37	44.44	76.92	55.56	50.00
50.00	76.92	53.33	68.75	46.15	62.50	82.35	50.00	72.73	61.90
68.18	65.22	63.64	66.67	63.64	50.00	64.29	46.15	83.33	65.00
80.00	72.22	71.43	61.11	78.95	63.16	66.67	75.00	81.82	68.18
52.94	66.67	55.56	66.67	56.25	47.06	47.06	66.67	61.11	52.94
58.82	75.00	60.00	45.00	55.56	78.57	71.43	53.85	83.33	82.35
55.56	57.89	61.11	47.37	50.00	50.00	75.00	41.67	66.67	70.59
44.44	42.11	52.94	52.63	61.11	42.86	64.71	43.75	47.83	56.52
66.67	68.42	73.33	71.43	63.16	71.43	50.00	60.00	54.17	56.00
78.57	61.54	64.29	64.29	73.33	52.38	61.54	56.25	60.00	57.14
70.59	87.50	52.94	62.50	75.00	55.56	53.33	52.63	54.55	60.87
70.59	83.33	52.94	62.50	77.78	52.38	50.00	55.00	62.50	57.14
66.67	66.67	54.55	61.54	72.22	31.58	53.33	35.29	40.00	36.84
57.89	64.71	52.38	45.00	61.90	60.00	66.67	33.33	60.00	56.25
55.56	73.33	64.71	52.94	55.56	50.00	66.67	0.00	40.00	60.00
76.47	68.75	75.00	72.22	77.78	100.00	100.00	100.00	100.00	75.00
71.43	70.00	75.00	58.82	65.00	57.14	40.00	50.00	50.00	42.86
71.43	66.67	71.43	72.73	90.91	47.06	100.00	0.00	60.00	75.00
37.50	76.92	46.15	40.00	44.44	50.00	50.00	66.67	50.00	50.00
56.25	73.33	46.67	62.50	66.67	56.25	57.14	56.25	60.00	52.94
66.67	58.33	66.67	70.00	57.14	33.33	50.00	0.00	20.00	50.00
68.18	81.25	70.59	50.00	75.00	75.00	66.67	100.00	80.00	75.00
78.57	68.75	80.95	86.67	76.92	57.14	70.59	52.94	69.57	61.90
78.95	60.00	76.47	72.73	70.00	50.00	60.00	25.00	42.86	57.14
58.82	66.67	47.06	57.89	46.67	20.00	16.67	33.33	28.57	25.00
47.37	61.11	50.00	47.62	44.44	50.00	50.00	40.00	60.00	60.00

Table 15: False Alarm Ratio (FAR) Score (%) Results for the Below Normal Category for some Stations over the GHA Region

	MAM					OND				
Station	Mean_24	member_15	member_21	member_22	member_24	Mean_24	member_15	member_18	member_22	member_24
KHARTOUM	73.33	60.00	66.67	60.00	77.78	70.00	55.00	80.95	66.67	62.50
KASSALA	57.89	57.89	42.86	54.55	53.85	69.23	53.33	73.33	73.33	58.82
WAD MEDANI	58.33	65.22	45.45	52.00	65.22	60.00	61.11	77.78	77.78	61.11
KOSTI	59.26	64.29	61.54	65.38	72.00	73.68	63.64	72.73	76.19	57.89
NYALA	65.00	84.21	69.57	72.73	61.11	76.47	69.57	72.22	57.89	66.67
RASHAD	52.17	58.33	52.63	52.00	63.64	36.36	52.94	62.50	53.33	53.85
KADUGLI	66.67	54.55	73.33	56.52	66.67	50.00	66.67	50.00	75.00	66.67
MALAKAL	73.68	64.71	50.00	70.00	66.67	50.00	80.00	50.00	50.00	58.82
JUBA	65.00	73.68	60.00	62.50	80.00	44.44	56.25	52.63	57.14	52.38
ASMARA	76.92	53.33	76.92	50.00	69.57	56.25	66.67	78.57	64.29	76.92
DJIBOUTI	72.22	66.67	61.54	71.43	85.71	63.16	70.00	58.33	57.89	69.57
MEKELE	68.75	54.55	84.62	66.67	72.22	55.56	33.33	52.17	40.00	63.64
BAHAR DAR	61.11	76.19	56.00	60.00	44.00	61.54	76.92	73.33	69.23	50.00
COMBOLCHA	70.59	50.00	73.33	70.59	80.00	60.00	53.33	50.00	66.67	65.00
JIMMA	53.85	27.78	47.06	61.54	71.43	71.43	64.29	86.67	72.73	36.36
ADDIS ABABA	50.00	66.67	80.00	75.00	61.54	77.78	76.19	76.19	76.92	72.73
DIRE DAWA	59.09	55.56	63.64	52.63	66.67	50.00	46.15	61.11	65.52	50.00
ROBE	65.00	63.16	73.68	75.00	75.00	55.00	59.09	54.17	64.71	54.55
LIRA	75.00	63.16	73.68	65.00	63.16	41.18	44.44	56.25	53.85	40.00
MASINDI	66.67	93.33	44.44	60.00	55.56	46.67	57.14	64.29	44.44	50.00
SOROTI	75.00	68.75	64.71	75.00	72.22	47.83	46.15	64.29	56.52	36.84
KASESE	68.42	60.00	53.33	62.50	60.00	60.87	75.00	40.91	80.00	47.62
JINJA	88.89	76.47	77.78	78.95	77.78	62.50	77.78	57.89	66.67	50.00
TORORO	85.71	75.00	68.42	75.00	73.68	42.11	44.44	45.00	40.00	31.25
MBARARA	71.43	78.57	52.63	65.00	53.33	52.38	61.90	52.00	50.00	52.38
ENTEBBE	50.00	81.25	41.18	45.00	73.68	76.47	66.67	52.63	46.15	68.75
KABALE	75.00	72.73	66.67	66.67	69.23	61.11	66.67	52.94	57.14	64.71
MARSABIT	69.57	70.00	66.67	80.00	60.00	37.50	57.89	50.00	50.00	46.15
WAJIR	60.00	76.47	53.85	58.82	70.59	33.33	37.50	55.56	38.46	40.00
KAKAMEGA	77.78	72.22	58.82	66.67	76.47	44.44	60.00	50.00	55.56	37.50
KISUMU	75.00	72.73	75.00	61.54	83.33	33.33	57.14	45.00	60.00	29.41
KERICHO	80.00	76.92	81.82	61.54	83.33	44.44	57.14	47.37	44.44	33.33
NAROK	75.00	71.43	66.67	58.33	80.00	42.86	57.89	56.00	50.00	42.86
DAGORETTI	77.78	64.29	57.14	58.33	60.00	33.33	60.00	50.00	50.00	35.29
MAKINDU	73.68	61.11	66.67	68.75	64.71	0.00	40.00	50.00	0.00	0.00
LAMU	68.75	82.35	61.11	61.11	66.67	0.00	33.33	0.00	0.00	33.33
MOMBASA	80.00	61.11	57.89	40.00	56.25	0.00	50.00	50.00	0.00	0.00
BUKOBA	80.00	81.82	85.71	78.57	92.31	50.00	66.67	66.67	50.00	50.00
MUSOMA	71.43	75.00	63.16	73.33	87.50	66.67	80.00	50.00	66.67	50.00
MWANZA	84.62	66.67	71.43	53.85	69.23	46.67	58.82	47.06	43.75	40.00
DODOMA	59.09	65.22	65.00	70.00	38.89	33.33	50.00	66.67	50.00	33.33
DAR.I.AIRP.	83.33	75.00	60.00	50.00	91.67	50.00	60.00	40.00	0.00	75.00
MBEYA	64.00	66.67	77.78	61.11	60.00	36.36	64.29	54.55	33.33	54.55
MTWARA	66.67	83.33	55.56	63.64	69.23	0.00	100.00	33.33	0.00	66.67
KIGALI	80.00	83.33	83.33	75.00	78.57	75.00	75.00	33.33	66.67	75.00
BUJUMBURA	77.27	83.33	78.26	75.00	66.67	66.67	66.67	50.00	50.00	66.67

4.4 COMPARISION OF THE SKILL OF THE MEAN OF 5 MEMBERS AND THE MEAN OF 24 MEMBERS

The analyses in the previous sections show that some of the individual members in most instances simulated the observed rainfall better than the mean of all the 24 members.

For example in the Section 4.2., the spatial distribution of members 15 and 24 was better than that of the mean of all 24 members in the MAM season and members 15 and 18 were better than the mean of all 24 members in the OND season. In Section 4.3.1 the linear correlation coefficients were bigger than those of the mean of all 24 members, for members 21 and 22 in the MAM season and member 24 in the OND season. In Section 4.3.2 the errors were smaller than those of the mean of all 24 members, for member 24 in the OND season. In Section 4.3.3 the P values for the two-sample Kolmogorov-Smirnov test were higher than those of the mean of all 24 members, for members 21 and 24 in the MAM season and for members 18 and 24 in the OND season.

The individual members that performed better than the mean of all 24 members in most instances were 15, 18, 21, 22 and 24. . It is common for forecast to be made using the mean of all members in a model. The next section compares the skill of the mean of 5 and 24 members. The results from the comparison of the means of 5 and 24 members could provide new forecasting options over the region. Similar methodology used in the previous section will also be used in this section.

4.4.1 Assessment of the Spatial Distribution Means of 5 and 24 Members

Spatial distribution maps were drawn for the period 1961 to 2008 using the anomalies of the mean of the five members; these were compared with the mean of 24 members.

For MAM season, the forecast of the mean of 5 members is better than that of the mean of the 24 members, although it still predicts below normal rainfall for the coastal strip of the region which differs with the observation. For the OND season, the forecast using the mean of the 5 members is better than that of the 24 members. In the northern sector the region forecasted to have below normal rainfall is still too big compared to the actual observation.

SEASON (a) Observed (b) Mean of the 24 members (c) Mean of 5 members

MAM

(d) Observed (e) Mean of the 24 members (f) Mean of 5 members

OND

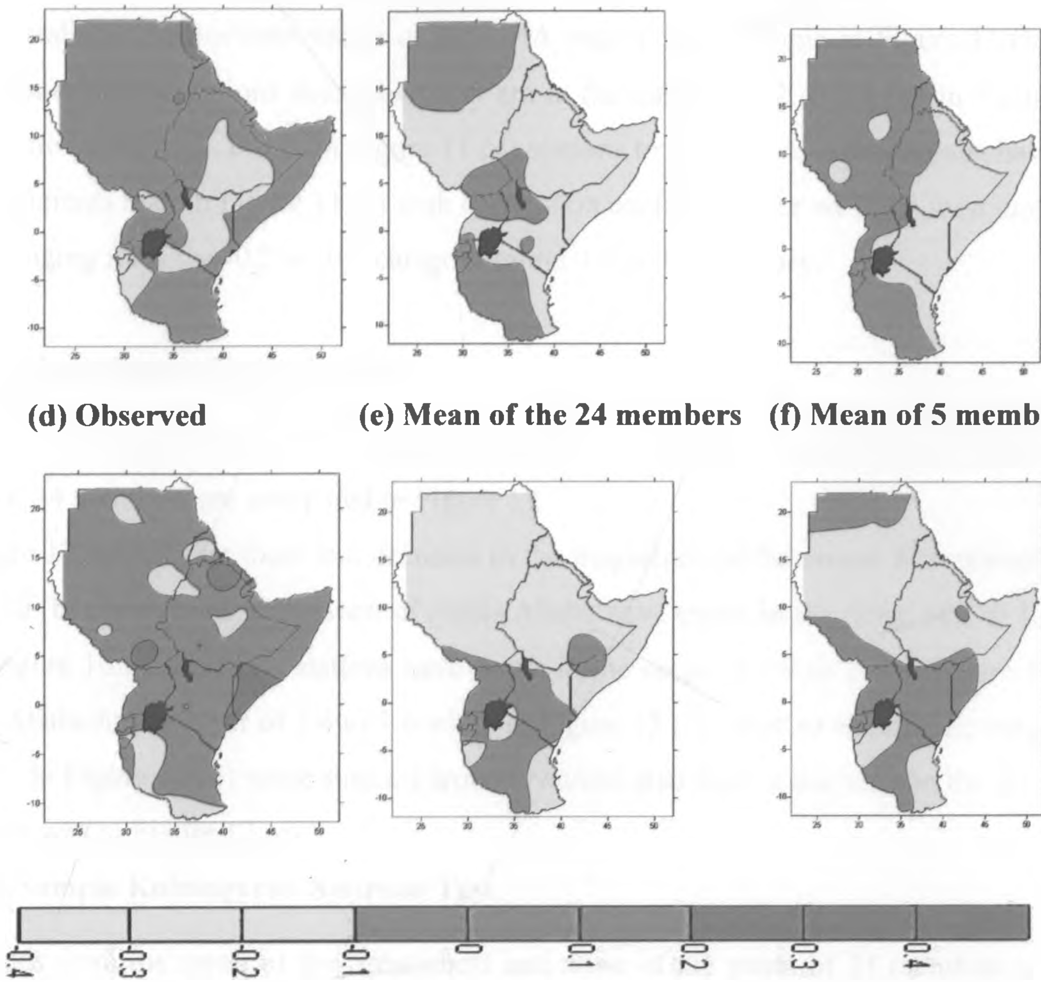

Figure 10: Spatial distribution of observed (left panel), mean of 24 members (middle panel) and mean of 5 members MAM rainfall anomalies (right panel) over the GHA region for 1961 to 2008. Green, blue and yellow shading represent above normal, normal and below normal rainfall, respectively

4.4.2 Correlation Analysis

The correlation coefficients from the mean of the 5 members and those of the mean of 24 members are compared in Figure 11.

From Figure 11 we see that for both seasons there is an improvement in the coefficient values especially in the northern sector of the GHA region. For example in Figure 11 (b), the coefficients for the stations near Khartoum are in the range of 0.2 to 0.3 but in Figure 11 (a) they are between -0.3 to 0. In Figure 11 (d) stations to the west of Addis Ababa have higher coefficients than in Figure 11 (c) with correlation coefficients for west the west most stations changing from the -0.2 to -0.1 category to the 0.2 to 0.3 category.

4.4.3 Root Mean Square Error Analysis

The Root Mean Square Error (RMSE) values from the mean of the 5 members and those of the mean of 24 members are compared in Figure 12.

From Figure 12 we see that there is a decrease in the magnitude of the errors. For example in Figure 10 (b) the stations to the west of Addis Ababa have errors in the range of 1 to 1.4 while in Figure 10 (a) the same stations have errors in the range of 1.4 to 2. For Figure 12 (d) Addis Ababa has an error of 1.4 to 1.6 while in Figure 12 (c) it has an error in the range on 1.8 to 2. In Figure 12 (d) some stations around Nairobi also show a decrease in the error from what it was in Figure 12 (c).

4.4.4 Two-Sample Kolmogorov-Smirnov Test

The P values from the mean of the 5 members and those of the mean of 24 members are compared in Figure 13.

Changes in the P values are observed over the equatorial sector and northern sector for the MAM season, some examples include the stations to the north of Nairobi where P values increase from the 0.3 to 0.4 range to the 0.8 to 0.9 range. For the OND season notable increase in the P values is around Addis Ababa where values change from 0.4 to 0.6 to 0.7 to 0.9 range.

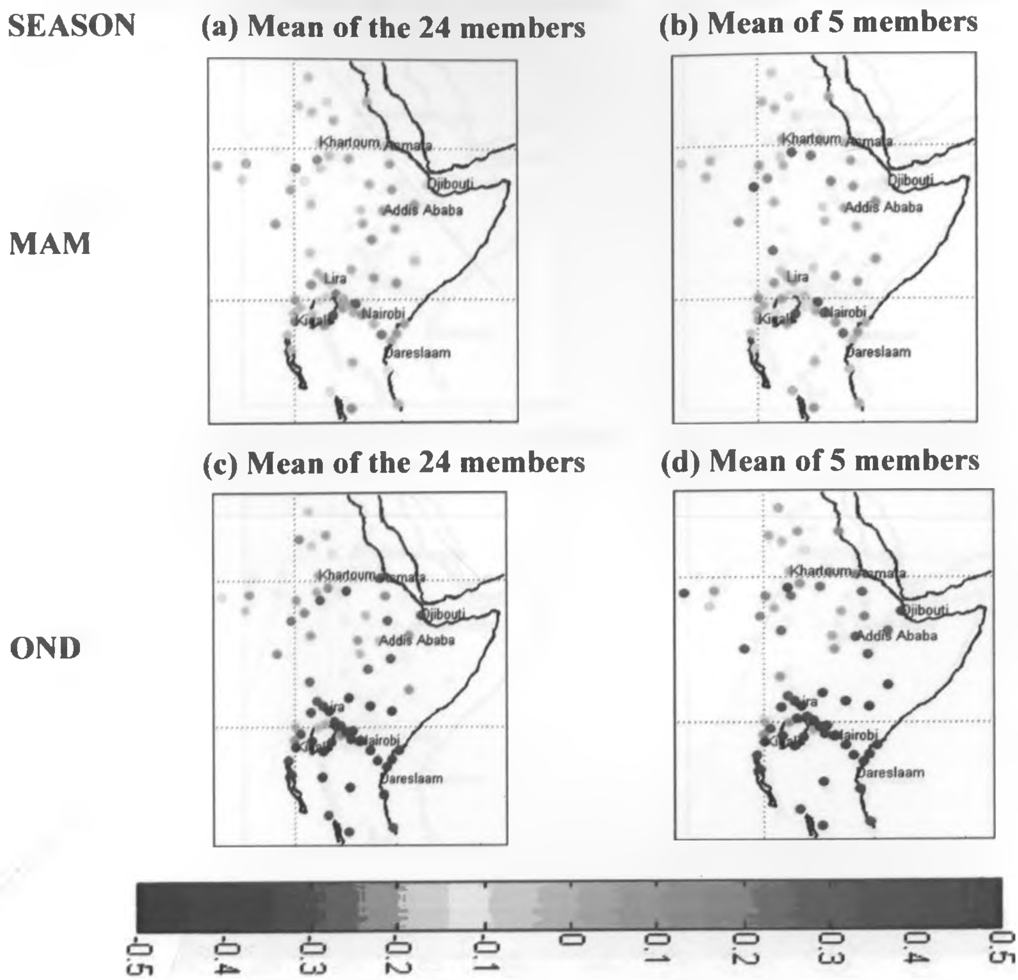

Figure 11: Spatial distribution of correlation coefficient values for the mean of 24 members (left panel) and the mean of 5 members (right panel) over the GHA region for 1961 to 2008. Blue shading represents higher coefficients and red shading lower coefficients. The legend interval is 0.1

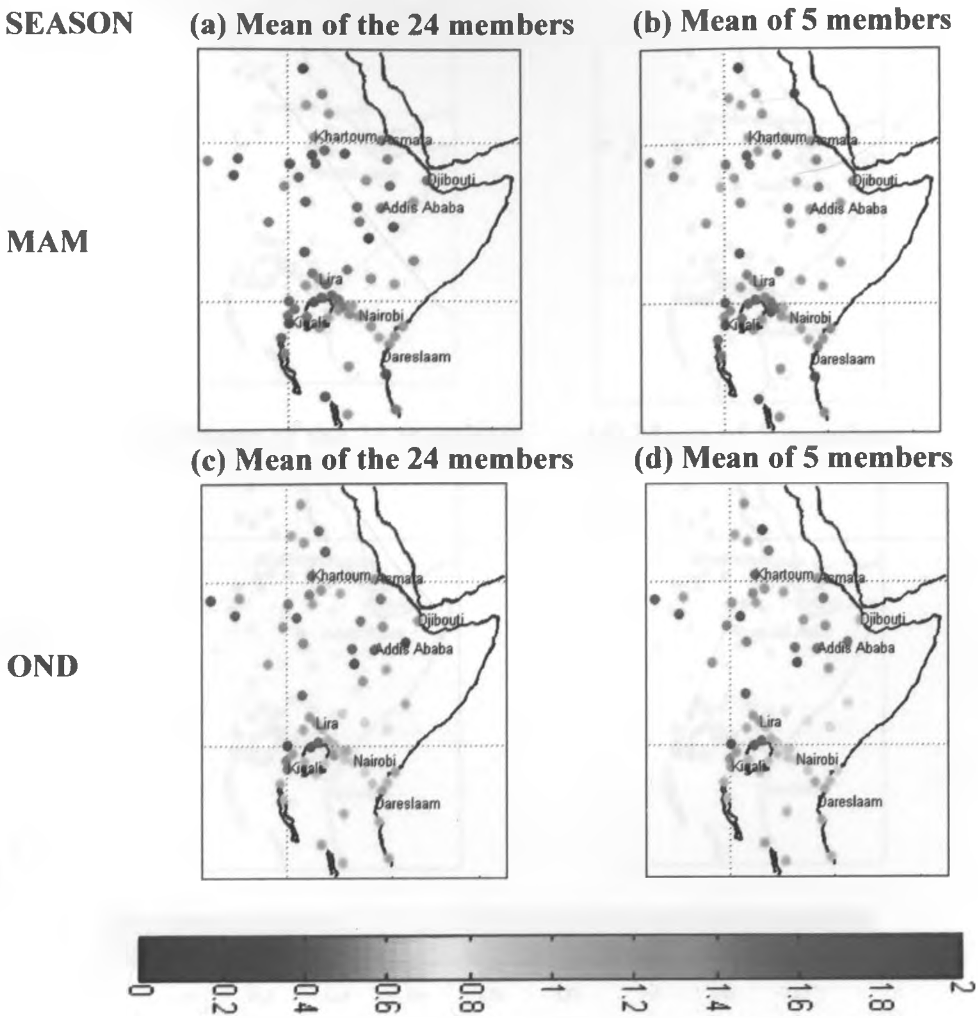

Figure 12: Spatial distribution of RMSE values for the mean of 24 members (left panel) and the mean of 5 members (right panel) over the GHA region for 1961 to 2008. Blue shading represents higher errors and red shading lower errors. The legend interval is 0.1

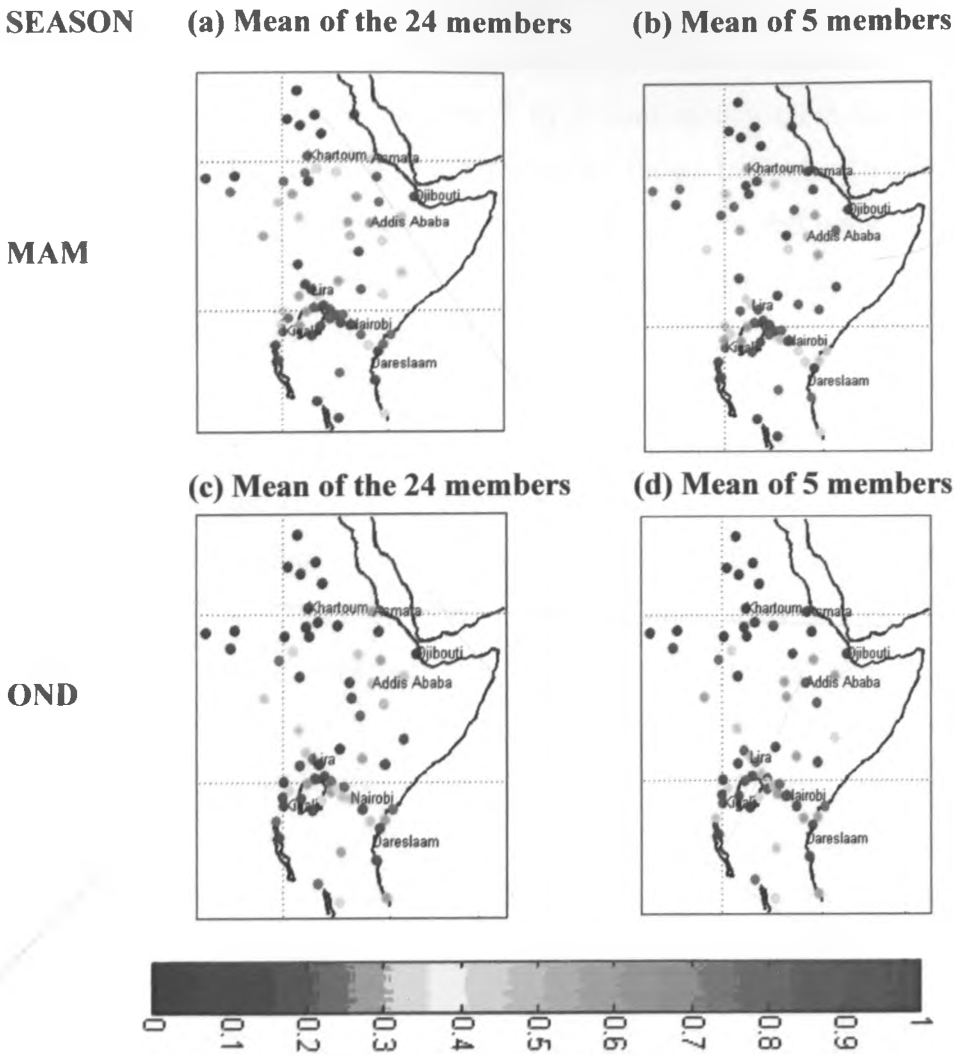

Figure 13: Spatial distribution of P values for the mean of 24 members (left panel) and mean of 5 members (right panel) over the GHA region for 1961 to 2008. Blue shading represents higher p values and red shading lower p values. The legend interval is 0.1

4.3.5 Categorical Statistics

The results for bias, probability of detection (PoD), Heidke skill score (HSS) and the false alarm ratio (FAR) calculated from the 3 by 3 contingency table for the mean of the 5 members for some stations in the GHA region are shown in Tables 16 and 17. In the tables b represents below normal category, n the normal category and a above normal category. The skill score results are compared with those of the mean of all 24 members which are presented in Tables 18 and 19.

Comparing the skill scores of the mean of all 24 members and those of the mean of 5 members in MAM, the HSS scores over the equatorial sector are higher. For example, the HSS for Kisumu, Kericho, Narok and Dagoretti increase from below 10% to above 10%. For the bias score, in the below normal category there are still many instances of over forecasting (bias>100%). The same applies to the above normal category. For the normal category there are many cases of under forecasting (bias<100%). For the PoD, there are more instances when the score is above 50% in all the categories compared to the results from the mean of all 24 members. For most of the stations there is a decrease in the FAR score for both categories. For example, Bahar Dar changes from 67.67 and 61.11 to 63.16 and 54.55 for below normal and above normal categories, respectively.

For the OND season, the HSS for the mean of 5 members indicates an increase in values for some stations over the region. For example the HSS for Djibouti increases from 1% to 7%, Combolcha from 10% to 25% and Bujumbura from 18% to 31.25%. The perfect bias score (100%) is attained in almost twenty instance; Masindi and Kigali have 100% in the three categories. The over forecasting cases also reduce. FAR also reduces in most stations over the region. For example, the FAR for Bujumbura reduces from 50% and 66.67% to 43.75% and 50% in the below normal and above normal categories, respectively

Table 16: Skill Scores (%) for MAM for some Stations Over the GHA Region for the Mean of 5 Members

Station	HSS	Bias_b	Bias_n	Bias_a	POD-b	POD-n	POD-a	FAR_b	FAR_a
KHARTOUM	-9.80	94.44	106.25	100.00	33.33	31.25	14.29	64.71	85.71
KASSALA	1.59	120.00	40.00	133.33	26.67	13.33	61.11	77.78	54.17
WAD MEDANI	6.13	78.95	71.43	153.33	31.58	21.43	60.00	60.00	60.87
KOSTI	-3.13	114.29	58.82	129.41	21.43	23.53	47.06	81.25	63.64
NYALA	-6.95	111.76	60.00	125.00	35.29	20.00	31.25	68.42	75.00
RASHAD	2.52	114.29	63.64	108.70	42.86	9.09	52.17	62.50	52.00
KADUGLI	-1.52	93.33	92.86	110.53	33.33	7.14	52.63	64.29	52.38
MALAKAL	-4.55	106.67	100.00	95.00	26.67	30.77	35.00	75.00	63.16
JUBA	7.28	63.16	121.43	126.67	21.05	57.14	40.00	66.67	68.42
ASMARA	-10.89	127.78	80.00	86.67	44.44	13.33	20.00	65.22	76.92
DJIBOUTI	-2.72	120.00	70.59	112.50	40.00	17.65	37.50	66.67	66.67
MEKELE	-9.52	111.76	75.00	113.33	41.18	12.50	26.67	63.16	76.47
BAHAR DAR	7.57	118.75	50.00	122.22	43.75	14.29	55.56	63.16	54.55
COMBOLCHA	2.62	100.00	60.00	142.86	47.37	20.00	35.71	52.63	75.00
JIMMA	-12.50	93.33	120.00	88.89	33.33	13.33	27.78	64.29	68.75
ADDIS ABABA	-3.73	110.53	56.25	138.46	42.11	12.50	38.46	61.90	72.22
DIRE DAWA	-1.67	153.85	55.56	105.88	38.46	16.67	41.18	75.00	61.11
ROBE	4.89	86.36	85.71	141.67	40.91	35.71	33.33	52.63	76.47
LIRA	-12.57	117.65	56.25	126.67	41.18	6.25	26.67	65.00	78.95
MASINDI	2.23	106.25	85.71	105.56	43.75	21.43	38.89	58.82	63.16
SOROTI	9.90	117.65	61.11	130.77	47.06	33.33	38.46	60.00	70.59
KASESE	8.20	122.22	33.33	122.22	50.00	16.67	50.00	59.09	59.09
JINJA	-23.32	141.18	40.00	112.50	35.29	6.67	12.50	75.00	88.89
TORORO	-5.22	146.67	41.18	118.75	40.00	17.65	31.25	72.73	73.68
MBARARA	-7.51	133.33	40.00	122.22	40.00	6.67	38.89	70.00	68.18
ENTEBBE	-0.56	133.33	36.36	109.09	53.33	0.00	45.45	60.00	58.33
KABALE	7.46	137.50	44.44	128.57	56.25	16.67	42.86	59.09	66.67
MARSABIT	12.67	123.53	58.82	121.43	58.82	17.65	50.00	52.38	58.82
WAJIR	12.50	131.25	62.50	106.25	56.25	25.00	43.75	57.14	58.82
KAKAMEGA	-0.39	112.50	80.00	105.88	31.25	20.00	47.06	72.22	55.56
KISUMU	10.24	137.50	71.43	88.89	31.25	21.43	27.78	77.27	68.75
KERICHO	10.09	143.75	71.43	83.33	37.50	21.43	22.22	73.91	73.33
NAROK	12.39	106.25	88.89	107.14	37.50	44.44	42.86	64.71	60.00
DAGORETTI	10.25	105.00	61.11	106.67	60.00	22.22	40.00	57.14	62.50
LAMU	-9.30	110.00	26.32	110.00	43.75	5.26	30.77	69.57	80.00
MOMBASA	3.88	120.00	58.82	105.88	50.00	17.65	41.18	65.00	61.11
BUKOBA	-15.85	123.53	70.59	107.14	29.41	17.65	21.43	76.19	80.00
MUSOMA	2.36	100.00	85.71	112.50	38.89	14.29	50.00	61.11	55.56
MWANZA	-8.81	120.00	58.82	125.00	40.00	11.76	31.25	66.67	75.00
DODOMA	-0.42	88.24	45.45	140.00	29.41	18.18	55.00	66.67	60.71
DAR.I.AIRP.	5.57	143.75	105.88	46.67	50.00	47.06	13.33	65.22	71.43
MBEYA	-21.88	87.50	50.00	162.50	6.25	0.00	50.00	92.86	69.23
MTWARA	-15.18	100.00	150.00	56.25	27.78	21.43	18.75	72.22	66.67
KIGALI	-6.88	105.56	53.33	140.00	38.89	6.67	40.00	63.16	71.43
BUJUMBURA	-9.31	91.30	30.77	191.67	34.78	7.69	41.67	61.90	78.26

Table 17: Skill Scores (%) for OND for Some Stations Over the GHA Region for the Mean of 5 Members

Station	HSS	Bias_b	Bias_n	Bias_a	POD-b	POD-n	POD-a	FAR_b	FAR_a
KHARTOUM	-7.01	185.71	50.00	81.25	57.14	11.11	18.75	69.23	76.92
KASSALA	-5.00	112.50	87.50	100.00	31.25	25.00	43.75	72.22	56.25
WAD MEDANI	-9.38	137.50	50.00	112.50	37.50	6.25	37.50	72.73	66.67
KOSTI	21.16	73.91	100.00	166.67	52.17	43.75	44.44	29.41	73.33
NYALA	-3.94	111.11	93.33	93.33	33.33	33.33	26.67	70.00	71.43
RASHAD	-4.77	140.00	60.00	84.62	55.00	6.67	30.77	60.71	63.64
KADUGLI	4.62	157.14	100.00	55.56	50.00	31.25	27.78	68.18	50.00
MALAKAL	-1.02	178.57	50.00	87.50	57.14	11.11	31.25	68.00	64.29
JUBA	8.30	128.57	92.31	85.71	57.14	15.38	42.86	55.56	50.00
ASMARA	8.06	100.00	86.67	115.38	55.00	26.67	30.77	45.00	73.33
DJIBOUTI	7.51	126.67	50.00	133.33	53.33	11.11	53.33	57.89	60.00
MEKELE	4.00	100.00	14.81	123.81	53.33	11.11	57.14	100.00	53.85
BAHAR DAR	-9.80	82.35	117.65	100.00	23.53	35.29	21.43	71.43	78.57
COMBOLCHA	25.00	107.14	83.33	112.50	57.14	50.00	43.75	46.67	61.11
JIMMA	-2.99	120.00	94.12	87.50	26.67	41.18	25.00	77.78	71.43
ADDIS ABABA	-10.20	90.48	72.73	131.25	42.86	9.09	25.00	52.63	80.95
DIRE DAWA	-0.85	108.33	117.65	78.95	25.00	35.29	36.84	76.92	53.33
ROBE	12.27	90.00	73.33	146.15	35.00	40.00	53.85	61.11	63.16
LIRA	24.76	127.27	118.75	71.43	54.55	50.00	47.62	57.14	33.33
MASINDI	31.98	100.00	100.00	100.00	53.85	59.09	53.85	46.15	46.15
SOROTI	17.35	118.75	57.14	116.67	56.25	7.14	66.67	52.63	42.86
KASESE	-1.40	121.43	80.00	95.24	35.71	20.00	42.86	70.59	55.00
JINJA	-9.38	112.50	100.00	88.24	31.25	20.00	29.41	72.22	66.67
TORORO	16.39	163.64	77.78	84.21	36.36	33.33	57.89	77.78	31.25
MBARARA	17.02	125.00	42.86	122.22	62.50	14.29	55.56	50.00	54.55
ENTEBBE	6.61	130.77	77.78	100.00	30.77	38.89	41.18	76.47	58.82
KABALE	9.26	106.25	107.14	88.89	37.50	50.00	33.33	64.71	62.50
MARSABIT	33.73	116.67	93.33	86.67	72.22	33.33	60.00	38.10	30.77
WAJIR	31.74	166.67	56.25	82.35	86.67	12.50	64.71	48.00	21.43
KAKAMEGA	19.69	138.46	63.16	112.50	53.85	26.32	62.50	61.11	44.44
KISUMU	23.91	111.11	64.29	118.75	50.00	21.43	75.00	55.00	36.84
KERICHO	14.17	116.67	57.14	118.75	50.00	7.14	68.75	57.14	42.11
NAROK	20.00	90.00	75.00	131.25	55.00	16.67	62.50	38.89	52.38
DAGORETTI	28.22	113.33	88.24	100.00	73.33	35.29	50.00	35.29	50.00
MAKINDU	37.38	100.00	93.33	106.25	64.71	40.00	68.75	35.29	35.29
LAMU	25.35	130.00	119.05	58.82	40.00	61.90	47.06	69.23	20.00
MOMBASA	21.26	112.50	89.47	100.00	50.00	36.84	61.54	55.56	38.46
BUKOBA	17.02	112.50	95.00	91.67	56.25	35.00	50.00	50.00	45.45
MUSOMA	19.38	140.00	66.67	100.00	66.67	16.67	60.00	52.38	40.00
MWANZA	15.40	112.50	100.00	86.67	56.25	29.41	46.67	50.00	46.15
DODOMA	6.01	114.29	87.50	100.00	50.00	12.50	50.00	56.25	50.00
DAR I AIRP	24.11	150.00	95.00	57.14	78.57	40.00	35.71	47.62	37.50
MBEYA	6.07	76.47	105.56	123.08	35.29	33.33	46.15	53.85	62.50
MTWARA	18.27	105.56	140.00	53.33	50.00	46.67	40.00	52.63	25.00
KIGALI	20.53	100.00	100.00	100.00	65.00	23.08	46.67	35.00	53.33
BUJUMBURA	31.25	100.00	84.21	123.08	56.25	47.37	61.54	43.75	50.00

Table 18: Skill Scores (%) for MAM for Some Stations Over the GHA Region for the Mean of 24 Members

Station	HSS	Bias_b	Bias_n	Bias_a	POD-b	POD-n	POD-a	FAR_a	FAR_b
KHARTOUM	3.00	100.00	100.00	100.00	31.25	47.06	26.67	68.75	73.33
KASSALA	5.33	86.67	123.08	95.00	33.33	38.46	40.00	61.54	57.89
WAD MEDANI	6.20	93.33	76.92	120.00	33.33	30.77	50.00	64.29	58.33
KOSTI	4.38	91.67	55.56	150.00	25.00	22.22	61.11	72.73	59.26
NYALA	-5.63	100.00	72.22	133.33	20.00	22.22	46.67	80.00	65.00
RASHAD	2.17	92.86	100.00	104.55	28.57	25.00	50.00	69.23	52.17
KADUGLI	-10.02	93.75	80.00	123.53	31.25	6.67	41.18	66.67	66.67
MALAKAL	-4.14	123.08	86.67	95.00	38.46	33.33	25.00	68.75	73.68
JUBA	13.18	66.67	106.67	133.33	33.33	46.67	46.67	50.00	65.00
ASMARA	-9.23	130.77	100.00	76.47	23.08	38.89	17.65	82.35	76.92
DJIBOUTI	4.31	113.33	65.00	138.46	33.33	35.00	38.46	70.59	72.22
MEKELE	15.51	82.35	100.00	123.08	41.18	50.00	38.46	50.00	68.75
BAHAR DAR	-1.59	112.50	100.00	90.00	37.50	25.00	35.00	66.67	61.11
COMBOLCHA	6.43	84.21	93.75	130.77	31.58	43.75	38.46	62.50	70.59
JIMMA	-13.46	92.31	150.00	68.42	15.38	21.43	31.58	83.33	53.85
ADDIS ABABA	18.43	88.24	111.76	100.00	35.29	52.94	50.00	60.00	50.00
DIRE DAWA	-2.99	138.46	47.06	122.22	30.77	11.76	50.00	77.78	59.09
ROBE	21.47	81.82	71.43	166.67	45.45	42.86	58.33	44.44	65.00
LIRA	0.39	82.35	87.50	133.33	35.29	31.25	33.33	57.14	75.00
MASINDI	4.95	92.31	88.24	116.67	46.15	29.41	38.89	50.00	66.67
SOROTI	-8.11	73.68	87.50	153.85	21.05	25.00	38.46	71.43	75.00
KASESE	1.81	94.12	83.33	118.75	47.06	16.67	37.50	50.00	68.42
JINJA	-21.28	115.79	57.14	120.00	36.84	7.14	13.33	68.18	88.89
TORORO	-18.71	133.33	36.84	150.00	26.67	10.53	21.43	80.00	85.71
MBARARA	8.54	94.44	71.43	131.25	44.44	35.71	37.50	52.94	71.43
ENTEBBE	17.79	106.25	78.57	111.11	43.75	35.71	55.56	58.82	50.00
KABALE	-3.53	100.00	66.67	133.33	44.44	13.33	33.33	55.56	75.00
MARSABIT	15.57	94.74	46.67	164.29	52.63	26.67	50.00	44.44	69.57
WAJIR	3.25	105.88	62.50	133.33	35.29	18.75	53.33	66.67	60.00
KAKAMEGA	-21.56	82.35	100.00	120.00	17.65	12.50	26.67	78.57	77.78
KISUMU	2.36	100.00	111.76	85.71	29.41	52.94	21.43	70.59	75.00
KERICHO	2.94	100.00	94.12	107.14	29.41	52.94	21.43	70.59	80.00
NAROK	-0.07	88.24	94.44	123.08	29.41	38.89	30.77	66.67	75.00
DAGORETTI	7.04	111.76	61.11	138.46	47.06	33.33	30.77	57.89	77.78
MAKINDU	10.88	100.00	57.89	172.73	44.44	31.58	45.45	55.56	73.68
LAMU	-12.13	121.43	78.95	106.67	28.57	15.79	33.33	76.47	68.75
MOMBASA	-2.13	140.00	63.16	107.14	40.00	31.58	21.43	71.43	80.00
BUKOBA	-2.13	140.00	63.16	107.14	40.00	31.58	21.43	71.43	80.00
MUSOMA	5.88	84.21	112.50	107.69	52.63	25.00	30.77	37.50	71.43
MWANZA	2.36	100.00	105.56	92.86	43.75	44.44	14.29	56.25	84.62
DODOMA	1.20	83.33	91.67	122.22	27.78	25.00	50.00	66.67	59.09
DAR.I.AIRP.	2.49	157.14	105.26	40.00	50.00	47.37	6.67	68.18	83.33
MBEYA	0.71	82.35	56.25	166.67	17.65	25.00	60.00	78.57	64.00
MTWARA	-9.30	111.76	133.33	56.25	23.53	40.00	18.75	78.95	66.67
KIGALI	-2.33	85.00	68.75	166.67	35.00	25.00	33.33	58.82	80.00
BUJUMBURA	4.95	79.17	53.85	200.00	41.67	23.08	45.45	47.37	77.27

Table 19: Skill Scores (%) for OND for Some Stations Over the GHA Region for the Mean of 24 Members

Station	HSS	Bias_b	Bias_n	Bias_a	POD-b	POD-n	POD-a	FAR_a	FAR_b
KHARTOUM	-7.93	0.00	17.24	105.26	0.00	6.90	31.58	100.00	70.00
KASSALA	8.84	141.18	64.71	92.86	64.71	23.53	28.57	54.17	69.23
WAD MEDANI	9.84	120.00	58.82	125.00	46.67	23.53	50.00	61.11	60.00
KOSTI	10.93	104.76	46.67	158.33	61.90	13.33	41.67	40.91	73.68
NYALA	-2.06	100.00	109.09	94.44	47.37	27.27	22.22	52.63	76.47
RASHAD	14.62	127.78	100.00	68.75	61.11	21.43	43.75	52.17	36.36
KADUGLI	4.43	130.77	131.25	52.63	30.77	50.00	26.32	76.47	50.00
MALAKAL	10.31	171.43	66.67	73.68	64.29	20.00	36.84	62.50	50.00
JUBA	8.30	128.57	92.31	85.71	42.86	23.08	47.62	66.67	44.44
ASMARA	26.20	120.00	53.33	123.08	70.00	26.67	53.85	41.67	56.25
DJIBOUTI	1.35	133.33	50.00	126.67	40.00	16.67	46.67	70.00	63.16
MEKELE	3.03	0.00	33.33	85.71	0.00	22.22	38.10	100.00	55.56
BAHAR DAR	-4.69	93.33	110.53	92.86	13.33	42.11	35.71	85.71	61.54
COMBOLCHA	10.19	142.86	72.22	93.75	57.14	27.78	37.50	60.00	60.00
JIMMA	0.32	153.33	105.88	43.75	46.67	41.18	12.50	69.57	71.43
ADDIS ABABA	-10.57	100.00	81.82	112.50	42.86	9.09	25.00	57.14	77.78
DIRE DAWA	0.00	160.00	84.21	84.21	20.00	31.58	42.11	87.50	50.00
ROBE	20.27	105.56	69.23	117.65	50.00	38.46	52.94	52.63	55.00
LIRA	15.07	136.36	100.00	80.95	45.45	37.50	47.62	66.67	41.18
MASINDI	29.60	100.00	90.91	115.38	46.15	54.55	61.54	53.85	46.67
SOROTI	20.11	118.75	42.86	127.78	62.50	7.14	66.67	47.37	47.83
KASESE	-1.99	94.12	90.00	109.52	35.29	20.00	42.86	62.50	60.87
JINJA	12.39	112.50	93.33	94.12	56.25	33.33	35.29	50.00	62.50
TORORO	22.78	172.73	55.56	100.00	63.64	27.78	57.89	63.16	42.11
MBARARA	17.57	106.25	71.43	116.67	56.25	21.43	55.56	47.06	52.38
ENTEBBE	-16.31	107.69	94.44	100.00	23.08	22.22	23.53	78.57	76.47
KABALE	9.14	87.50	114.29	100.00	43.75	35.71	38.89	50.00	61.11
MARSABIT	30.57	116.67	73.33	106.67	66.67	26.67	66.67	42.86	37.50
WAJIR	8.33	233.33	25.00	75.00	66.67	0.00	50.00	71.43	33.33
KAKAMEGA	26.72	161.54	47.37	112.50	76.92	21.05	62.50	52.38	44.44
KISUMU	20.59	112.50	75.00	100.00	50.00	25.00	66.67	55.56	33.33
KERICHO	20.63	116.67	64.29	112.50	55.56	21.43	62.50	52.38	44.44
NAROK	38.87	95.00	66.67	131.25	65.00	33.33	75.00	31.58	42.86
DAGORETTI	32.93	166.67	75.00	75.00	66.67	50.00	50.00	60.00	33.33
MAKINDU	46.34	200.00	66.67	60.00	100.00	33.33	60.00	50.00	0.00
LAMU	22.22	0.00	28.57	50.00	0.00	28.57	50.00	100.00	0.00
MOMBASA	30.38	175.00	40.00	100.00	75.00	20.00	100.00	57.14	0.00
BUKOBA	17.24	106.25	95.00	100.00	56.25	35.00	50.00	47.06	50.00
MUSOMA	21.43	200.00	40.00	100.00	100.00	20.00	33.33	50.00	66.67
MWANZA	9.26	100.00	100.00	100.00	43.75	23.53	53.33	56.25	46.67
DODOMA	19.51	50.00	166.67	150.00	33.33	33.33	100.00	33.33	33.33
DAR.I.AIRP.	4.94	133.33	75.00	100.00	33.33	25.00	50.00	75.00	50.00
MBEYA	18.75	150.00	80.00	78.57	64.29	30.00	50.00	57.14	36.36
MTWARA	22.54	160.00	50.00	50.00	80.00	25.00	50.00	50.00	0.00
KIGALI	10.81	71.43	100.00	200.00	57.14	0.00	50.00	20.00	75.00
BUJUMBURA	17.50	100.00	100.00	100.00	50.00	50.00	33.33	50.00	66.67

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 SUMMARY

Verification statistics have been presented for seasonal rainfall forecasts over the GHA region for ECHAM 4.5 members. Grid box rainfall was averaged and assigned to an observing station. The observed rainfall at the observing stations was then verified against the model outputs.

The spatial distribution patterns of the observed rainfall did not wholly match with patterns from any of the 24 members or with the pattern of the mean of all 24 members. However, for some individual members the patterns had some differences with the observations, mostly in the northern sector of the GHA region.

Correlation analyses yielded bigger coefficients for the equatorial sector (5°N to 5°S) in both seasons. Root mean square error values were small in the equatorial sector; this is an indication that the model resolves correctly the different features that enhance convection over this sector. The northern sector of the region had small coefficients and big RMSE values in both seasons.

Correlation analyses yielded higher coefficients for the OND season. RMSE values were also low for the OND; this can be attributed to the fact that OND rainfall is mostly influenced by large scale systems like perturbation in global Sea Surface Temperatures (SSTs) (Mutai et al., 2000). Two-Sample Kolmogorov-Smirnov test results had higher P values for most of the region in the OND season, including areas with features that enhance convection.

Categorical statistics were also computed. These included: Bias which indicates if the model is over forecasting (bias>100%) or under forecasting (bias<100%), False Alarm Ratio which gives a simple proportional measure of the model's tendency to forecast rain where none was observed, and Probability of Detection which gives a simple measure of proportion of rainfall events successfully forecast by the model. These statistics showed more skill for the OND season.

5.1 CONCLUSIONS

For all the analyses made the mean of all 24 members did not show much skill in predicting rainfall, indicating that not all members are appropriate for forecasting in the GHA region. Some individual members namely: 15, 18, 21, 22 and 24 performed better than the mean of all 24 members in most instances, and hence, more analyses were done using the mean of these 5 members.

Comparing the skill of the mean of the 5 members and that of the mean of the 24 members, the mean of 5 members had more skill.Much improvement in the forecasting skill was noted in the northern sector (>5°N) of the region. This provides an important input to all future modeling activities over the region.

When considering individual members and the mean of all 24 members, spatial representation comparison showed more differences in the northern sector of the region. The measures of accuracy showed higher model accuracy in the equatorial sector and the OND season. Similarly, measures of skill showed higher skill in the equatorial sector and the OND season. This shows that the model simulates rainfall better for the OND season and the equatorial sector. The mean of all 24 members did not show much skill. Thus it is not advisable to use it over the GHA region. Although a few individual members showed higher skill it is not advisable to make a forecast with just one member. The use of many members takes care of the sensitivity of the prediction to uncertainties in the initial conditions; hence the mean of five members was used. When five members that showed higher skill and accuracy were used there was considerable improvement of model accuracy and skill in the northern sector and the MAM season.

The five members show higher skill and accuracy than when all 24 members are used. For this reason, it is inferred that these 5 members have the right parameterization for the GHA region. The use of the 5 members will improve seasonal rainfall prediction over the GHA region and hence improve early warning. Improvement of early warning will reduce negative effects on, agricultural production, hydropower generation, water use, and water availability at household level caused by floods and droughts. The results of this research can be used as a guide by forecasters in the GHA region to identify which ECHAM 4.5 members simulate rainfall in the region skillfully.

5.2 RECOMMENDATIONS

The mean of the 5 members could be used for seasonal forecasting in the GHA region. Better results were obtained for OND compared to MAM. Such observations have been observed in some previous studies for example IRI/ICPAC collaboration, 2002. Further studies of the systems that influence MAM rainfall are however still required to improve the skill of MAM season and also the model's skills at higher levels that are required for addressing regional and local climate applications.

A similar study should be done for other weather parameters such as moisture, wind speed and direction and temperature in order to get the overall performance of the model members.

The network of stations over the GHA region is very sparse. For this reason, policy makers should work towards increasing the number of stations. Observations of weather parameters need to be put on grids for easier comparison with the model outputs.

There are different ways to combine model members. In this study simple average was used where each member was weighted equally. Further studies can be done using weighted averages of the five members, where weights are determined by using the historical relationship between forecasts and observations.

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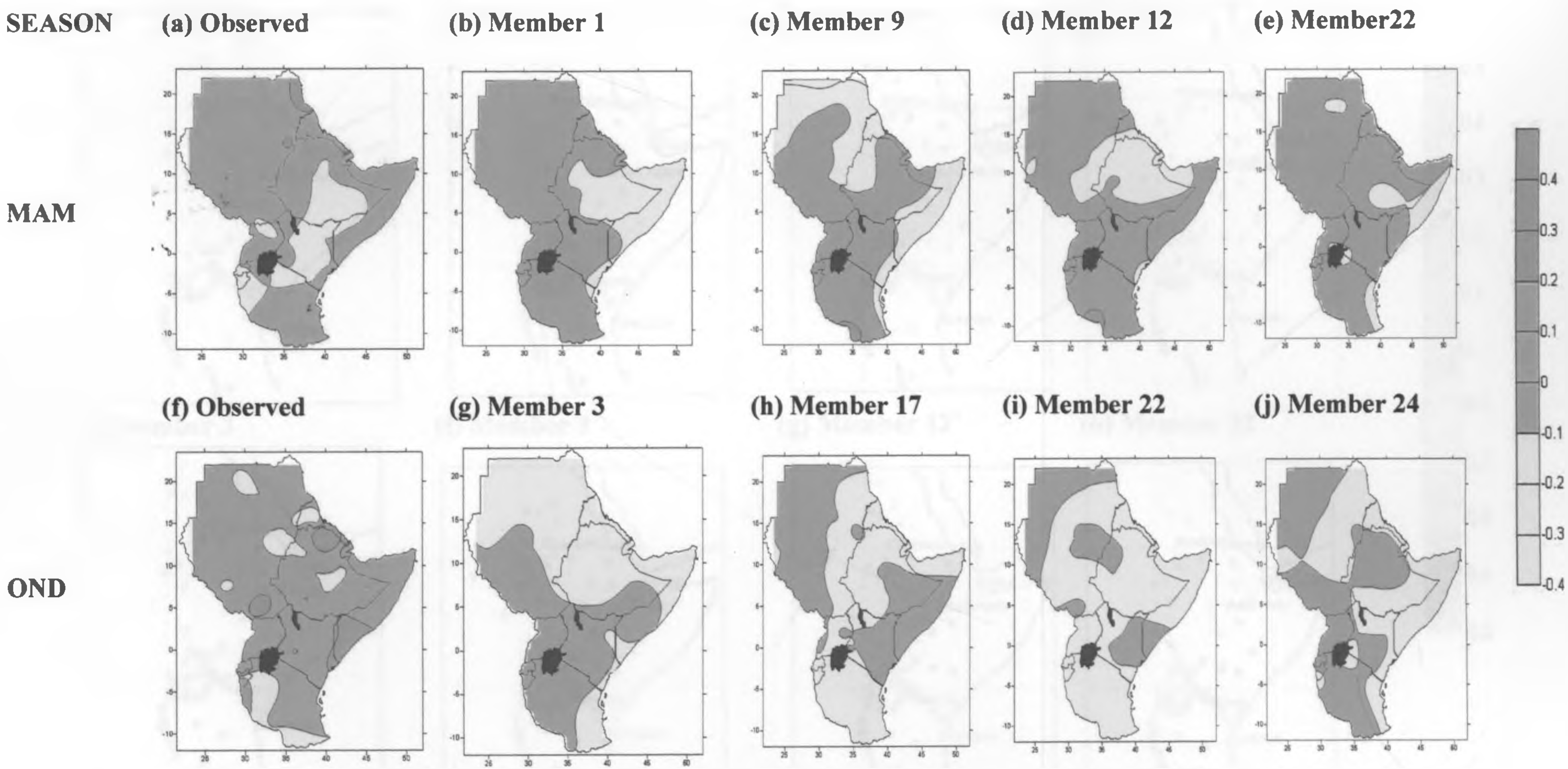
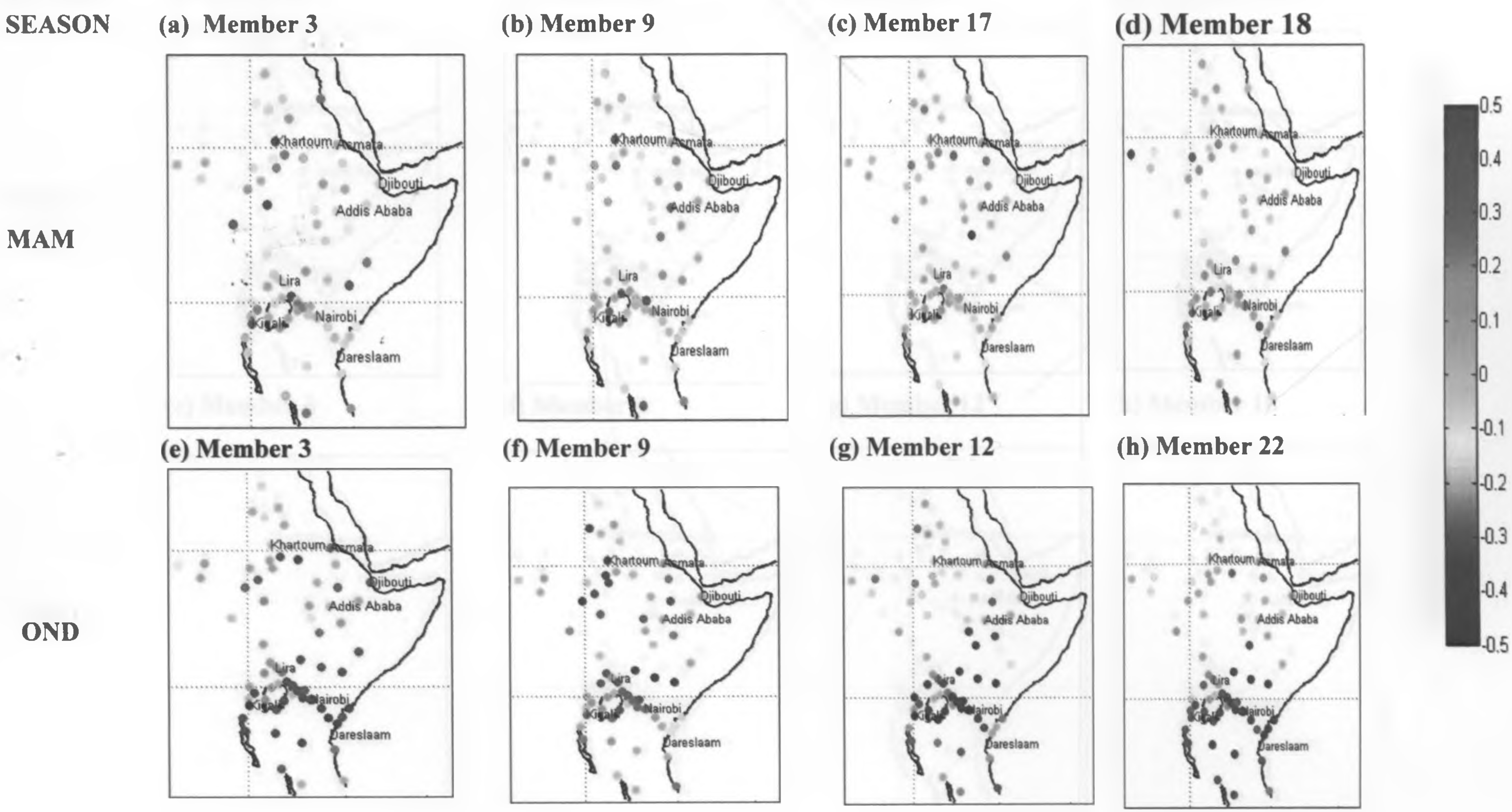
APPENDIX 1: OBSERVED AND MODEL RAINFALL ANOMALIES FOR SELECTED MEMBERS



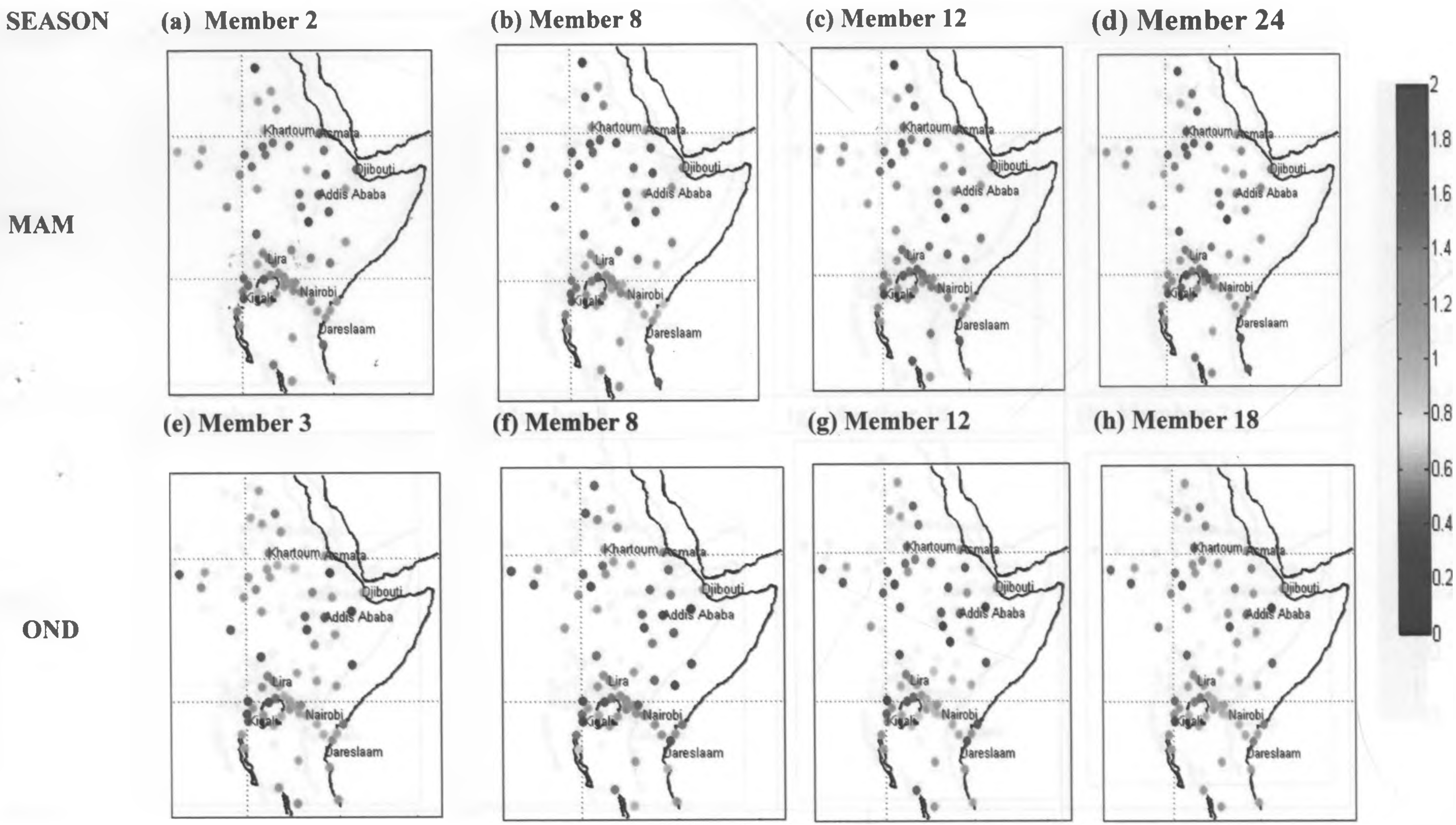
This section shows the observed and model rainfall anomalies for selected members for MAM and OND seasons over the GHA region for 1961t0 2008. Green, blue and yellow shadings represent above normal, normal, and below normal rainfall respectively.

APPENDIX 2: CORRELATION COEFFICIENTS FOR SELECTED MEMBERS



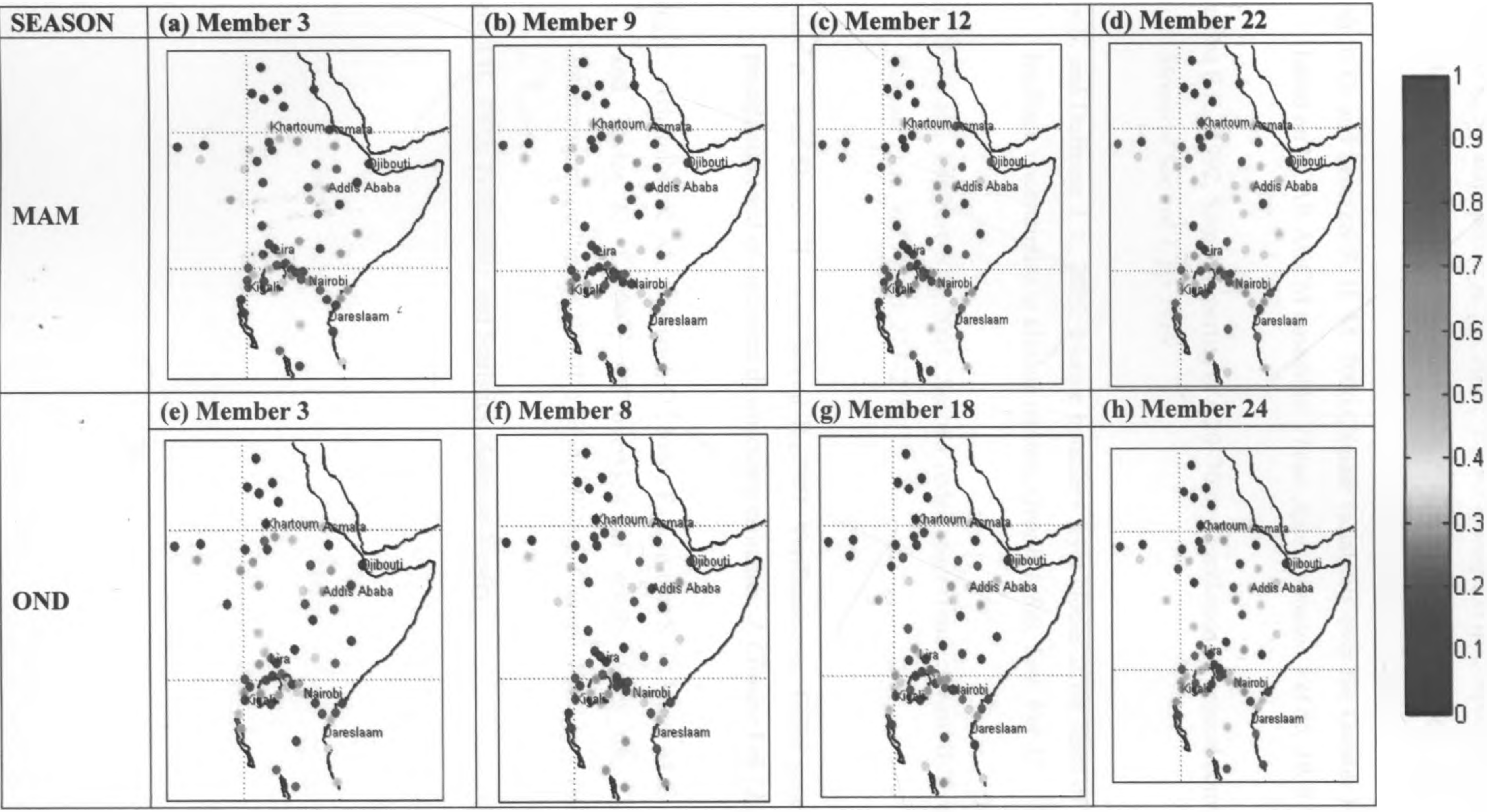
This section shows the spatial distribution of correlation coefficients for selected members over the GHA region for 1961 to 2008. Blue shading represents higher coefficients and red shading lower coefficients. The contour interval is 0.1

APPENDIX 3: ROOT MEAN SRUARE ERRORS FOR SELECTED MEMBERS



This section shows the spatial distribution of RMSE for selected members over the GHA region for 1961 to 2008. Blue shading represents higher errors and red shading lower errors. The contour interval is 0.1

APPENDIX 4: P VALUES FOR SELECTED MEMBERS



This section shows the spatial distribution of P values for selected members over the GHA region for 1961 to 2008. Blue shading represents higher P values and red shading lower P values. The contour interval is 0.1

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