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Skill and Usefulness of Regional Seasonal Forecasts For Adoption to Climate Change For Agricultural Production in Tanzania

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Abstract

The world climate is changing and sub-Saharan Africa experiences it through climate variability. Since the majority of people in the region depend on agriculture for their livelihood, the predictability of rainfall is very critical in reducing their vulnerability and seizing opportunities. This study aimed at verifying skill and usefulness of the forecasts from two drought monitoring centres—GHACOF and SARCOF—by looking at accuracy, bias and skill in 16 synoptic stations in Tanzania. The results have indicated that seasonal forecasts by the two centres have similar patterns of accuracy. Both have better accuracy in the northern parts of Tanzania compared to the southern parts during October-November-December (OND) period. During January-February-March for SARCOF and March-April-May for GHACOF forecasts show better accuracy indices in the southern parts compared to the northern parts of the country. The usefulness of both forecasts is still very low because the accuracy levels are below 0.8. The forecasts are not showing much bias, i.e., they are not over- or under-forecast rainfall amounts. However, the forecasting skill for both centres is very low (majority of stations with HSS < 0.2). This study recommends the two centres, together with national meteorological services, to improve accuracy and skill of seasonal rainfall forecasts. The seasonal forecasts should be disseminated widely to users, including farmers. However, a caution should be provided to farmers as the accuracies of the seasonal forecasts are seasonal, location and forecast dependent.

Key words: *rainfall forecast, climate change, agriculture, adaptation.*

Introduction

The climates of Africa are varied and very variable: varied because they range from humid equatorial regimes to sub-tropical Mediterranean-type climates, and very variable because all these climates exhibit differing degrees of temporal variability, particularly with regard to rainfall (Hume et al., 2001). Understanding and predicting these seasonal and annual variations in climate has become the major challenge facing climate scientists in recent years. Seasonal and annual climate forecasting has taken great strides forward, both in its development and application

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(Folland et al., 1991; Stockdale et al., 1998; Washington and Downing, 1999; SARCOF, 2000). But the ultimate causes of high rainfall variability that modulates or influences some African climate regimes remain uncertain (Rowell et al., 1995; Sud & Lau, 1996; Xue & Shukla, 1998).

Accurate prediction of the state of the weather is difficult after 6 days, and even more difficult after 10–14 days (Folland & Woodcock, 1986; Murphy & Palmer, 1986; Pierce et al., 1997; Washington & Downing, 1999). This is due to non-linearity within the climate system, and the growth of numerical forecasting model errors over time. However, recent advancements in seasonal forecasting provide a basis for early warning of climate hazards (Murphy et al., 2001).

Agricultural production in Tanzania—and much of sub-Saharan Africa—is mainly dependent on rainfall. Rainfall, a major source of water in the tropics, shows high temporal and spatial variability. Such fluctuations represent a significant portion of the total uncertainty in agricultural production. The risk associated with such variable rainfall acts as a major deterrent for farmers to invest in agriculture (Rao & Okwach, 2004). Hence, the ability to make a successful forecast of an impending climatic condition has a significant bearing on food security of many people in the region.

The Greater Horn of Africa (GHA) and the Southern African Region (SAR) together have a population of about 360 million people. Countries included under the GHA are Burundi, Djibouti, Ethiopia, Eritrea, Kenya, Rwanda, Somalia, Sudan, Tanzania and Uganda; while SAR comprises of Angola, Botswana, Comoros, Lesotho, Malagasy, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe. Tanzania appears in both lists because it exhibits climatic patterns that are experienced in both regions. These sub-regions are facing food insecurity as a result of extreme climatic events in the form of droughts and floods that are becoming rather frequent (Ogallo, 2000). Advance warnings of extreme climate anomalies at time scales of months to years would, therefore, be extremely important in agricultural planning and operations.

The ability to forecast rainfall on a seasonal or even longer time scale is important in reducing a significant portion of total uncertainty in rain-fed agriculture. Advances in climate science have recognized that climate variability over East Africa, including Tanzania, is associated with a number of remote oceanic and atmospheric thermodynamic and circulation patterns. Some of these patterns are the El Nino/La Nina over the central equatorial Pacific ocean, SO (Southern Oscillation) and the Indian Ocean dipole. There are other forcing mechanisms influencing rainfall patterns in particular, such as the now more widely recognized and less well understood oceanic-atmospheric interactions in both the Indian Ocean south of Madagascar and the Southern Atlantic (World Bank, 2003). These have led to the development of climate forecast tools and techniques to assist in decision-making and improve the ability of users to cope with climate variability.

ENSO based forecasting tools are being used by two drought monitoring centres (DMCs) in sub-Saharan Africa: one in Nairobi for the GHA, and another in Botswana for the SAR. These centres have been generating useful climate and weather products since 1998 for use within the regions. Some of the reasons or problems in the use of these products, especially in the agricultural sector, have been attributed to a number of factors such as the lack of access to the products, low confidence in the products, difficulties in interpreting probabilistic forecasts into actual rainfall amounts that could be used for agricultural planning processes, inadequacies in the forecasts information on other aspects such as rainfall distribution, and onset, cessation and occurrences of dry spells (DMCN, 2003). These have rendered the use of seasonal forecasts ineffective in determining suitable agronomic practices or enterprises, thereby affecting their impact in the agriculture and food security sector.

Several attempts have been made to try to address the challenges associated with failure in the use of climate forecasts. Some of the developed methods have shown potential to adequately transform climate forecast information into useful products. For example a 3-phase SST system can be used to predict crop yields using crop simulation models. Everinham et al. (2003) and Phillips et al. (1998) used ENSO indices to predict seasonal rainfall patterns and utilize predicted patterns to simulate maize yield variability in Zimbabwe.

All the methods that transform forecast information into products have to be tested, evaluated and calibrated to have a significant impact in reducing food insecurity. The products used in this study were those generated by the Greater Horn of Africa Climate Outlook Forum (GHACOF) and the Southern Africa Region Climate Outlook Forum (SARCOF) issued by the DMCs in Nairobi and Harare (now in Botswana), respectively.

Forecast verification is the process of assessing the quality of a forecast. A forecast is compared or verified against a corresponding observation of what actually occurred, or some good estimate of the true outcome. There are many types of forecasts, each of which calls for slightly different methods of verification (WWRP/WGNE, 2007). Forecasts issued by GHACOF and SARCOF are probabilistic categorical forecasts (PCFs). Methods for verifying multi-category forecasts start with a contingency table showing the frequency of forecasts and observations in the various bins. However, any multi-category forecast verification can be converted into dichotomous, a series of yes/no-type verifications (WWRP/WGNE, 2007). This method is normally used to verify probabilistic binary forecasts (PBFs).

According to Murphy (1993), three elements describe the goodness of forecast: consistency, quality and value. However, the quality of forecast, which measures the degree to which the forecast corresponds to what actually happened, is more important in forecast verification. The quality element has nine attributes: bias, association, accuracy, skill, reliability, resolution, sharpness, discrimination and uncertainty.

To compute attributes of quality of forecasts or categorical statistics, a contingency table (Murphy & Winkler, 1987) for dichotomous forecast verification is constructed. The categorical statistics or attributes of quality that can be computed using contingency table, among others, include: accuracy, bias, probability of detection (POD), false-alarm rate (FAR), probability of false detection (POFD), critical success index (CSI), Equitable threat score (ETS), and Heidke Skill Score (HSS).

Traditionally, verification has emphasized on accuracy and skill of forecasts. In this study, traditional attributes (accuracy and skill) were used together with bias to evaluate the forecasts issued by GHACOF and SARCOF for selected stations in Tanzania. On the other hand, verification methods that measure overall performance such as Brier Score (Brier, 1950) do not meet the needs of users for information regarding the quality of probability forecasts (Klopper & Landman, 2003).

Moreover, WWRP/WGNE (2007) describes three important reasons for forecast verification, which are to monitor, improve and compare quality of different forecast systems. It is precisely for these reasons that this study was conducted. In particular, it was aimed at informing the general public on the reliability of the various forecast products in specific locations, and also to provide feedback to the producers of forecast products on the degree of skill and bias of their products.

Materials and Methods

Study Area

The study evaluated forecasts using seasonal rainfall data from 16 stations in various agro-climatic zones (Fig. 1). Historical rainfall data from these stations, together with some other stations, are used in coming up with seasonal rainfall forecasts.

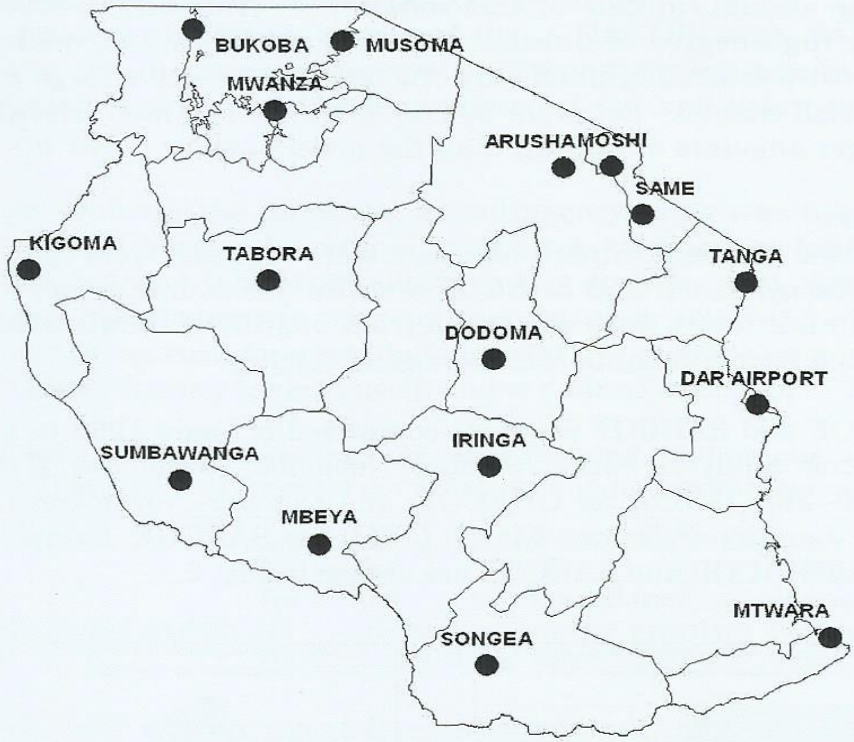


Figure 1: ***Map of Tanzania showing Agro-climatic zones*** *(*Mhita et al., 2003*)*

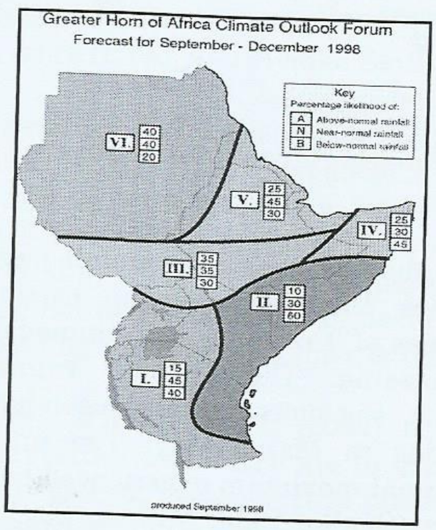
The climate of Tanzania exhibits two distinct seasonal rainfall patterns: bimodal and unimodal rainfall regimes. Bimodal behaviour exists over northern and north-eastern coastal areas of Tanzania, and unimodal over western, central and southern Tanzania. The bimodal rainfall is characterized by two annual maxima, i.e., the short rainfall season between October–December, and the long rains in March–May. The unimodal rainfall is characterised by a single annual maximum experienced between December and March. Further studies (Ogallo, 1986; Mutoni, 2001) have split the bimodal and unimodal regimes into several homogeneous zones. The homogeneous zones over the bimodal areas include northern coastal areas, northern areas, north eastern highlands and Lake Victoria basin. The unimodal zones are western, central, south-western highlands and southern areas (Mhita et al, 2003).

Annual rainfall in bimodal region may differ from one location to another within the same zone. The range of difference depends on location, altitude and topography. The annual rainfall usually ranges from 800 to 1800mm. For the unimodal areas, the central zone receives the lowest amount of rainfall. The annual rainfall for this zone ranges from 500 to 800mm, with a relatively high degree of unreliability. The southern and western areas and the south-western highlands are the ones that receive large amount of annual rainfall ranges – i.e., from 800 to 2000mm. The more elevated areas receive larger amounts of rainfall than the lower ones.

Data Source

Products of the seasonal rainfall forecasts were obtained from the GHACOF website (*www.icpac.net*) and SARCOF website (*www.dmc.co.zw*). Observed seasonal rainfall totals were computed from monthly rainfall totals, which were obtained from Tanzania Meteorological Agency.

The GHACOF and SARCOF products comprised of years 1998 to 2007. The rainy seasons analysed were October–November–December (OND) and March–April–May (MAM) for GHACOF; and October–November–December (OND) and January–February–March (JFM) for SARCOF. Sample forecast products for GHACOF and SARCOF are shown in Fig. 2.



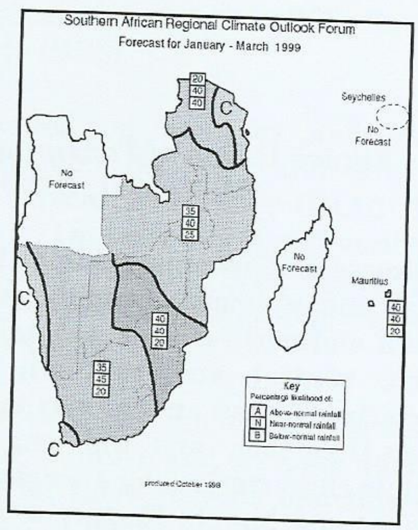


Figure 2: ***Sample GHACOF and SARCOF forecast products***

The rainfall data for the month of September were not considered in the GHACOF forecasts even though the month is included in producing forecasts. This is because the amount of rainfall for September is always insignificant compared to the combined amounts for the months of October, November and December. The monthly rainfall data comprised a minimum of 37 years (1970–2007). The records were used to compute rainfall long term averages for each station.

Evaluation of SARCOF and GHACOF Products

Climate forecast products produced by GHACOF and SARCOF are probabilistic multi-category forecasts (three-category tercile forecasts) representing above normal (AN), near normal (N) and below normal (BN) rainfall (Fig. 2).

In order to evaluate the forecasts, a contingency table was used to match forecasts against observed seasonal rainfall. A contingency table is a two-dimensional 'square' table that displays the discrete joint distribution of forecasts and observations in terms of frequencies or relative frequencies. In dichotomous categorical forecasts having only two possible outcomes (Yes or No), a 2 × 2 contingency table is used, and is defined as shown in Table 1.

Table 1: General contingency table showing total numbers of observed and forecast occurrences and non-occurrences.

		Observed events		
		Yes	***No***	***Total***
Forecasted events	Yes	hits	false alarms	forecast yes
	No	misses	correct negatives	forecast no
	Total	observed yes	observed no	total

In Table 1, 'hits' refer to event forecasted to occur, and did occur; 'misses' refer to events forecasted not to occur, but did occur; 'false alarms' refer to events forecasted to occur, but did not occur; and 'correct negatives' refers to events forecasted not to occur, and did not occur.

This verification technique was used in the probabilistic multi-category forecasts by converting them into Yes/No scenario by defining 'Yes' to be 'in category *i*' and 'No' to be 'not in category *i*' (WWRP/WGNE, 2007). For example, in the forecast for a certain location with 35/45/20 rating for above normal/near normal/below normal, the probability with the highest score is considered as the most likely to occur, and in this case is near normal (45% probability). Therefore, if the observed rainfall is either above normal or below normal then it will be considered to be a miss.

Observed monthly rainfalls were aggregated to obtain seasonal rainfalls for each year for OND, JFM and MAM. The long-term means were computed and a 75% of this mean was used to determine between near normal and below normal seasons; and 125% of the mean was used to delineate between near normal and above normal seasons. This method was adapted from Buizer (2000). Taking the example for the long-term mean for Arusha of 421.1mm (1961–2007), the upper and lower limits for near normal would be 526.3mm and 315.8mm, respectively.

Marching of forecast against observed seasonal rainfall was performed in order to compute variables in the contingency table (hits, misses, false alarms and correct negatives). The contingency table was then used to compute Accuracy, Bias and Heidke skill score (HSS) (Cohen's K) using the following equations (Wilks, 1995):

$$\text{Accuracy} = \frac{H + CN}{N} \quad (1)$$

$$\text{Bias} = \frac{H + FA}{H + M} \quad (2)$$

$$HSS = \frac{H + CN + EC}{N - EC} \quad (3)$$

Where expected correct is given as:

$$EC = \frac{1}{N}[(H + M)(H + FA) + (CN + M)(CN + FA)] \quad (4)$$

Where: H = hits, M = misses, FA = false alarms, CN = correct negatives, N = total forecasts, EC = randomly expected correct.

The resulting accuracy, bias and *HSS* indices were then used to evaluate the accuracy and skill of the forecasts. The range of values for accuracy is from 0 to 1; with 1 representing 100% of correct forecast. If bias is equal to 1, it means there was no bias in the forecast; otherwise if bias is less than 1 it means under-forecast, or it is over-forecast if the value is greater than 1.

In a tercile forecast system, a large number of random forecasts will have an expected hit rate of 33.3%. *HSS* is the percentage of correct forecasts obtained after subtracting the number of forecasts that would have been correct by chance. Therefore, with an *HSS* of +1, this will indicate a set of perfect hits; and a score of -1 will indicate a set with no hits (Heidke, 1926).

Results and Discussions

Accuracy of Seasonal Rainfall Forecasts

GHACOF Products

GHACOF seasonal rainfall forecasts for OND show some good accuracy in the western and northern parts of the country (i.e., Bukoba and Kigoma), and medium accuracy for Mwanza, Arusha and Moshi stations (Fig. 3 (a)). Also, there is good accuracy for Dodoma and Dar es Salaam stations. However, there is poor forecast accuracy for Tabora, Musoma and most of the stations in the southern parts of the country.

In contrast to the OND accuracy, the MAM accuracy indices are better in the southern parts of the country, including some regions along the central corridor. Bukoba and Mwanza still show good accuracy indices as in the OND region. On the contrary, Same and Arusha stations have very poor accuracy indices. Overall, Bukoba, Dodoma, Dar es Salaam and Tanga have the same level of accuracy in both OND and MAM. In general, a good number of stations in MAM appear to have better accuracy indices compared to OND.

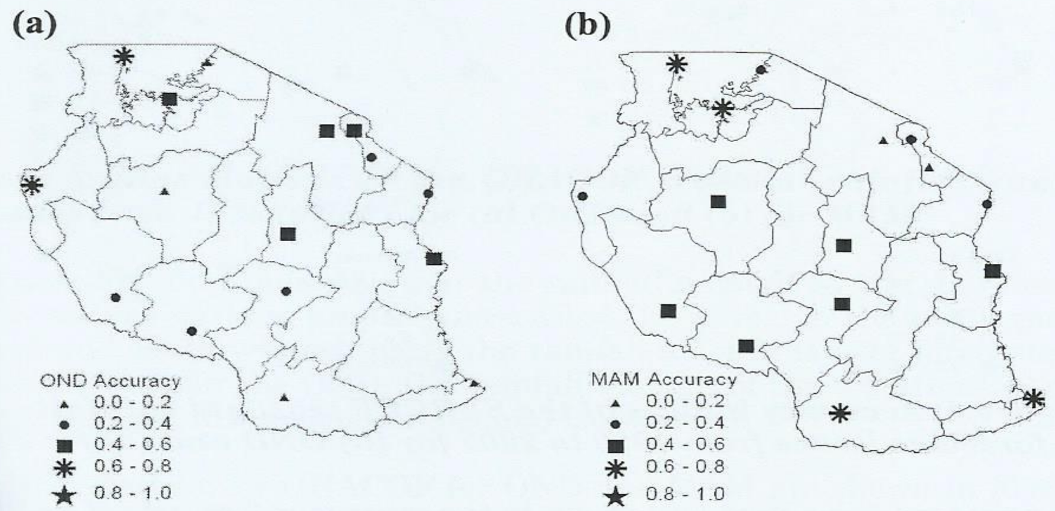


Figure 3: ***Accuracy indices of the GHACOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for MAM.***

Therefore, these forecasts are useful and more applicable at Bukoba station, followed by Mwanza station. However, they are not useful for Same, Tanga and Musoma stations because of poor accuracy in those areas. In the remaining stations (Tabora, Mbeya, Sumbawanga and Iringa), the forecasts have poor accuracy during OND, but have medium accuracy during MAM. Forecasts have medium accuracy in Dodoma and Dar es Salaam. Therefore, usefulness of forecasts for some stations is either during OND or during MAM.

SARCOF Products

Figure 4 shows the accuracy of forecasts for SARCOF products over 16 stations in Tanzania. In general, OND forecasts seem to be poor because all the accuracy indices are between medium and poor (< 0.6). Four stations (Same, Musoma, Tabora and Songea) have very poor accuracy indices, while the other four stations have medium accuracy (Bukoba, Kigoma, Arusha and Moshi).

During MAM, accuracy indices for stations in the central and southern parts of Tanzania are better compared to stations in the north. The accuracy seems to have improved from OND to JFM. One might conclude that the SARCOF JFM forecast products are more useful for stations having uni-modal rainfall characteristics.

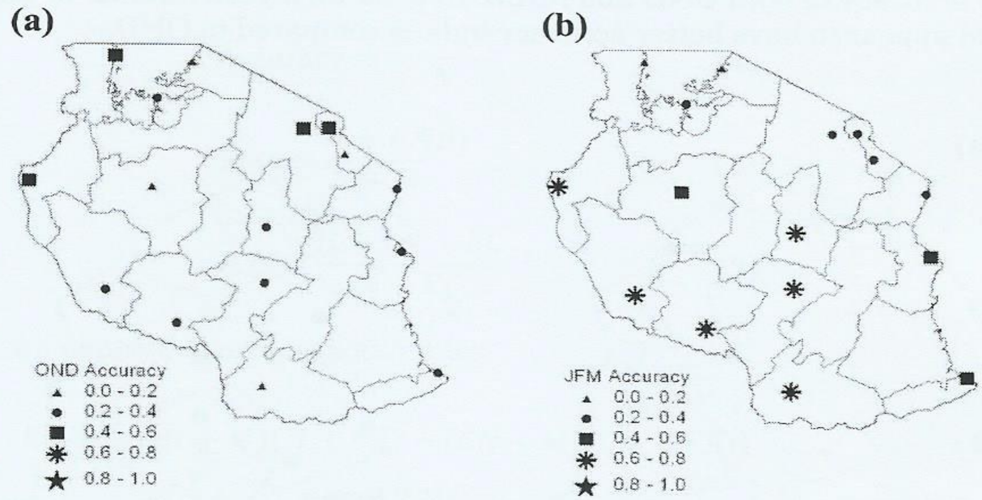


Figure 4: ***Accuracy indices of the SARCOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for JFM.***

There appears to be a good agreement in the consensus forecasts of SARCOF and GHACOF in terms of spatial similarities in accuracy indices. For example, during OND, both forecasts show better accuracy indices in the northern parts of Tanzania compared to the southern parts. During JFM and MAM, both forecasts show the southern parts having better accuracy indices compared to the northern parts. At station level, and in the OND period, the accuracy indices of the two products are similar for Songea, Mbeya, Iringa, Sumbawanga, Tabora, Tanga, Arusha and Moshi, which is 50% of the stations analyzed. Even for the remaining stations the differences are not quite significant. The same trend appears to hold for JFM and MAM seasons, with an exception perhaps of Kigoma, Bukoba and Mwanza stations whose accuracy indices in the two seasons are at variance with each other.

BIAS Score and Skill GHACOF

Figs 5(a) and 5(b) compares the bias scores for GHACOF seasonal rainfall forecast products for OND and MAM. In OND, 9 of the 16 stations have bias scores greater than 1.2 (Fig. 5(a)). Furthermore, 5 stations (Songea, Iringa, Kigoma, Mwanza and Musoma) have unbiased or slightly biased scores. Dodoma station is the only station in which rainfall amounts are under-forecasted (Bias score < 0.8). In general, seasonal rainfall in the majority of the stations in OND is over-forecasted.

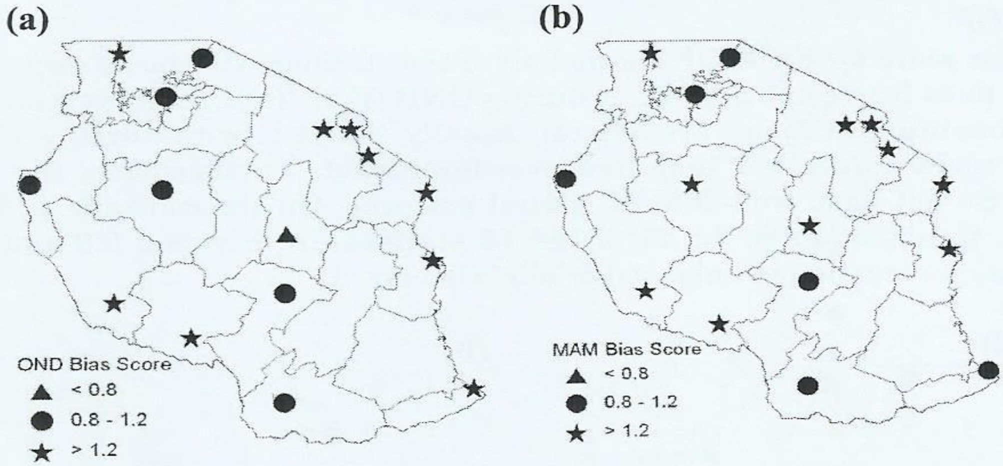


Figure 5: ***Bias statistic of the GHACOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for MAM.***

In MAM, Fig. 5(b) indicates that the rainfall amount in the southern and north-western parts is properly forecasted. However, in the north-eastern, central and south-western parts the rainfall amount is over-forecasted. As it was the case for the OND, the rainfall amount of the 5 stations (Songea, Iringa, Kigoma, Mwanza and Musoma) is unbiased.

The HSS statistic for GHACOF for OND and MAM are shown in Figs. 6(a) and 6(b). The skill levels of forecasts in OND vary significantly from one station to another. Seasonal forecasts for stations in the southern parts of Tanzania, including Tabora, Mwanza and Musoma, show no skill (HSS < -2). During MAM, the only station with some skill is Mtwara. The remaining stations show no skill.

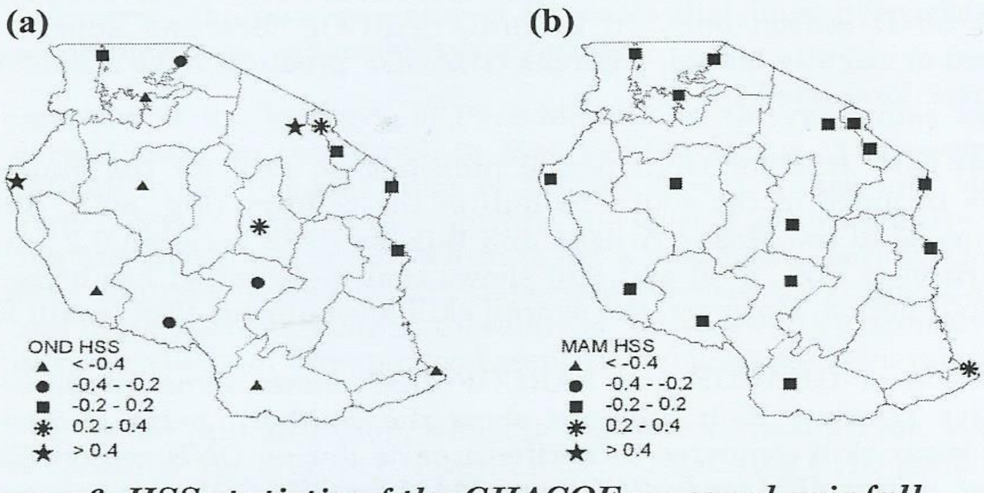


Figure 6: ***HSS statistic of the GHACOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for MAM.***

SARCOF

The bias score for SARCOF shows half of the stations with no or slight bias scores (bias between 0.8 and 1.2) during OND (Fig. 7(a)). The bias scores for the remaining stations are almost equally divided, with three stations being under-forecasted and five over-forecasted. Furthermore, the bias scores do not have well-defined spatial patterns. On the contrary, in JFM period, the bias scores for 11 of the 16 stations are between 0.8 and 1.2; meaning forecasting is unbiased or slightly biased.

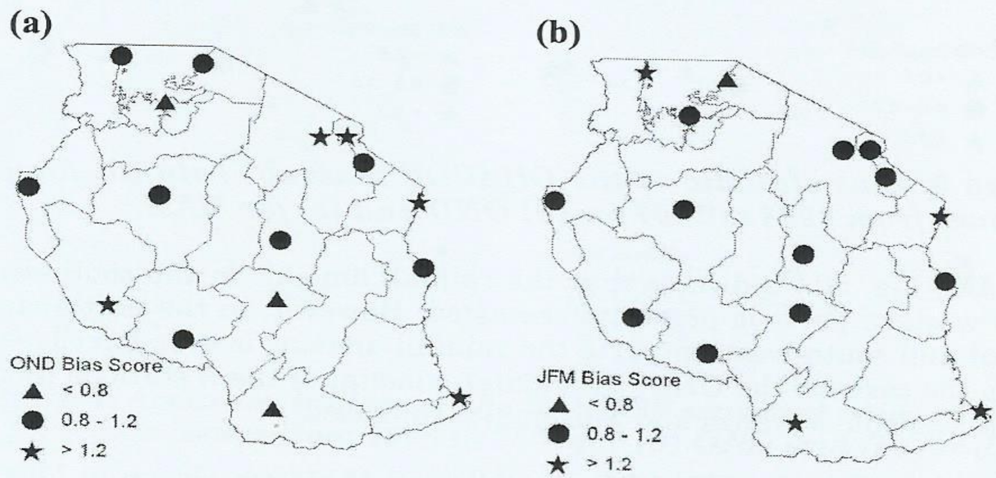


Figure 7: ***Bias statistic of the SARCOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for JFM***

Comparison of bias scores for GHACOF and SARCOF shows slight similarities for stations along the coast and north-eastern parts of Tanzania for the OND season only. In general, SARCOF forecasts appear to be unbiased or slightly biased, whereas GHACOF products have a tendency of being over-forecasted.

The SARCOF HSS for OND period indicates no skill for the majority of stations in much of the southern half of the country (Fig. 8(a)). Stations with some skill are Moshi, Arusha and Bukoba (HSS between 0.2 and 0.4). Comparison of Figs. 8 (a) and 8(b) shows that JFM period has better skill than OND period. However, the overall skill level during JFM is still low.

Comparison of GHACOF and SARCOF HSS shows some similarities in respective seasons. Both products show the southern parts of Tanzania having lower skill compared to northern parts during OND season. Skill of forecasts, during JFM for SARCOF and MAM for GHACOF, lies between -0.2 and 0.4. Overall, better skill is shown during JFM in the SARCOF forecasts.

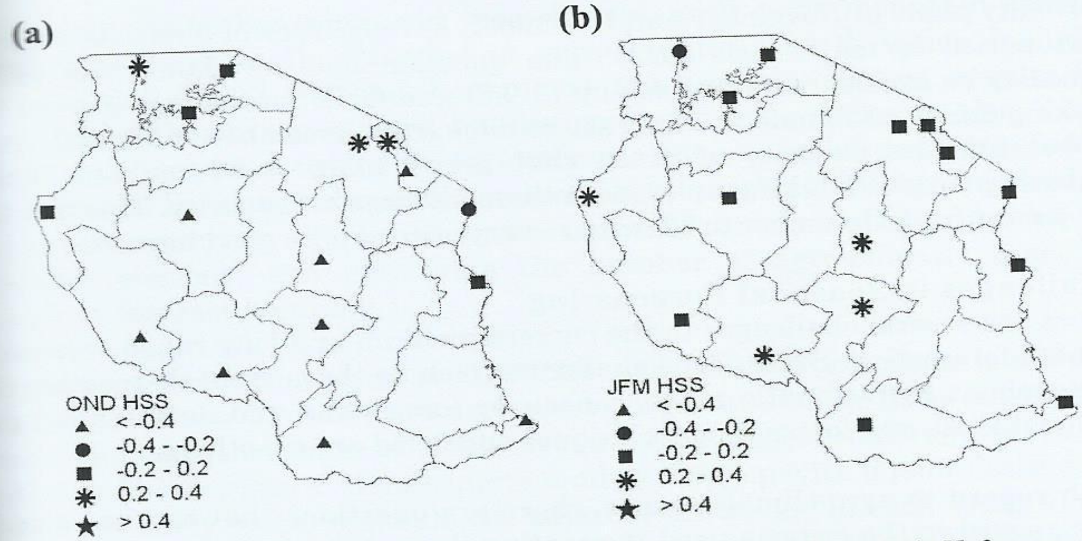


Figure 8: ***HSS statistic of the SARCOF seasonal rainfall forecasts issues from 1998 to 2007 for (a) OND and (b) for JFM.***

Usefulness of Forecasts for Agriculture

In Tanzania, rainfall starts during the October to December period. This period is more important in the bimodal areas compared to unimodal areas. Accurate prediction of rainfall in that period is extremely important in planning agricultural production to take advantage of opportunities or reduce risk. In the north-eastern parts of Tanzania—including Same and Mwanga Districts—this is the period in which runoff water from the Pare Mountains provide the most needed water for crop production through water harvesting. Farmers in the lowlands depend on this water for their survival rather than the rainfall they receive during the March to May period. However, the poor accuracy of forecasts that have been shown for this area implies more vulnerability for farmers.

With exception of the lowlands of Pare Mountains, the remaining bimodal areas depend more on the March to May rainfall season. The accuracy of MAM rainfall in the bimodal areas of Arusha, Moshi, Tanga and Musoma are extremely low (< 0.4). On the contrary, the level of accuracy during OND in Arusha and Moshi are better, which is not a very useful period. The need to improve accuracy indices is very important because of extreme events of floods and droughts that occur in these areas. These events extremely affect agricultural production, threaten food security and increase vulnerability.

In the uni-modal rainfall region, which is the central, western and southern parts of Tanzania, the accuracy of rainfall forecasts during OND period again is low (< 0.4), but reasonably high during JFM period. Since farmers normally plant in November and December, low accuracy of forecasts during that period is major risk factor. The question now is: should the JFM forecasts be considered (accuracy up to 0.8) and OND forecasts neglected in making decision? Should the forecast be done from December to March? This is because the majority of areas that grows maize tend to plant long maturing varieties, taking up or more than 120 days to maturity. This means the period from December to March are very critical for a good harvest.

Challenges in Seasonal Forecasting

There are several challenges in the current medium and long range seasonal rainfall forecasting. Some of the challenges include the current delineation of homogenous agro-climatic zones, consensus forecasting and downscaling at regional level, and forecasting techniques employed among others.

With regard to agro-climatic zones, there are questions that can be raised with regard to the criteria used in creating them. For example, in Mhita et al. (2003), Bukoba, Mwanza and Musoma are in the same agro-climatic zone (Fig. 9(a)). However, the rainfall characteristics of Bukoba and Musoma are quite different. Looking even at the level of accuracy indices, results for Bukoba and Mwanza seem to agree but disagree with those of Musoma. Recently reviewed agro-climatic zones have re-divided that zone separating Bukoba from Mwanza and Musoma (Fig. 9 (b)). This is likely to improve the accuracy of forecasts over Musoma.

(a) **(b)**

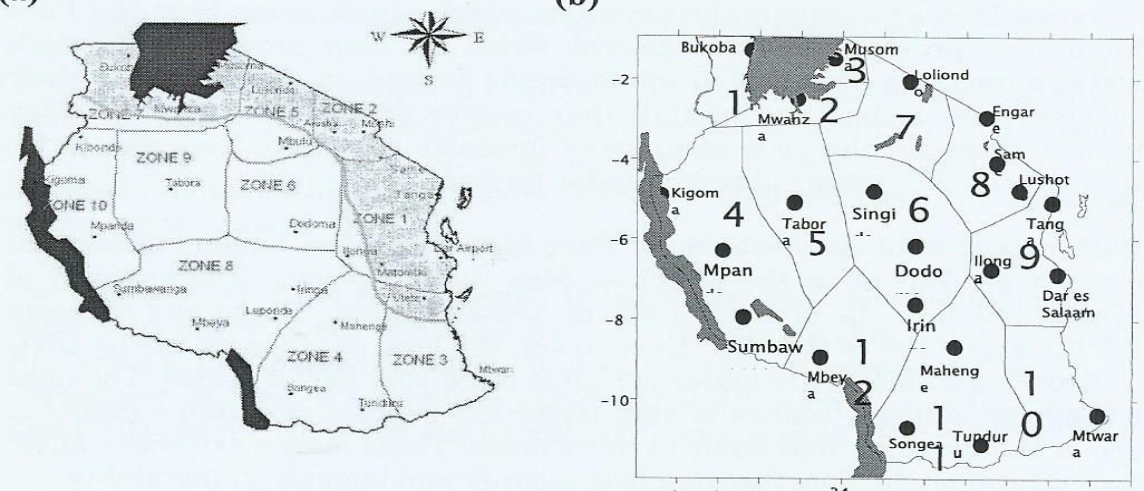


Figure 9: ***Map of Tanzania showing Agro-climatic zones (a) according to Mhita (2003) and (b) according to ICPAC (2003)***

Similarly, Same has semi-arid type climate, with some mountain ranges. This area is normally included in agro-climatic zone 2, which includes Arusha and Moshi stations. Looking at the accuracy indices, results for Arusha and Moshi agree more, but disagree with those of Same. Also, Same station cannot be included in agro-climatic zone 1, which includes Tanga and Dar es Salaam, because these are coastal stations. There is a need to increase resolution of agro-climatic zones by increasing the number of rainfall stations, and increasing the number of agro-climatic zones to improve forecast accuracy.

Consensus forecasting done at GHACOF and SARCOF meetings is another challenge. These forecasts are derived by consensus, where different experts meet and decide on the most likely scenario. The biggest challenge lies in the country's border zones. Here experts tend to come up with a joint decision on the most likely scenario should the adjacent zones, one in each country, end up with different forecast. Klopper and Landman (2003) and Atheru et al. (2001) observed that although the forecast models used are all scientifically sound, the compilation of the outlook remains subjective. They then proposed a method for combining seasonal forecasts for southern Africa.

Statistical forecasting techniques are still being employed to derive the current seasonal forecasts. However, it is well known that dynamical forecasting techniques are superior to statistical approaches. Factors that limit the application of dynamical forecasting techniques include human, software and hardware resources. Global, regional and national efforts are required to make it possible so that dynamic techniques will also be used together with statistical methods.

Conclusion

There appears to be a good agreement in the consensus forecasts of SARCOF and GHACOF in terms of spatial similarities in accuracy indices. For example, during OND, both forecasts show better accuracy indices in the northern parts of Tanzania compared to the southern parts.

Accuracy indices for stations in the central and southern parts of Tanzania are good compared to stations in the north. There is improved accuracy from OND to JFM: from poor to good accuracy for Dodoma, Iringa, Songea, Mbeya and Sumbawanga stations; and from medium to good accuracy for Kigoma station. The only station that maintained relevance for both OND and JFM is Kigoma. Therefore, the usefulness of SARCOF forecast from that of JFM is for stations having uni-modal rainfall characteristics.

A comparison of bias scores for GHACOF and SARCOF shows slight similarities for stations along the coast and north-eastern parts of Tanzania for the OND season only. In general, SARCOF forecasts appear to be unbiased or slightly biased, whereas GHACOF products have a tendency of being over-forecasted.

Also, a comparison of GHACOF and SARCOF Heidke Skill Scores shows some similarities in respective seasons. Both products show the southern parts of Tanzania having lower skill compared to northern parts during OND season. Skill of forecasts, during JFM for SARCOF and MAM for GHACOF, lies between -0.2 and 0.4. Overall, better skill is shown by SARCOF during JFM.

Since the accuracy indices are generally low (Accuracy < 0.4) for most of the stations investigated, their usefulness in agriculture is limited. Therefore, farmers should use forecasts cautiously.

There is a strong need to improve accuracy of the forecasts at regional (SARCOF and GHACOF forecasts) and national levels so as to reduce agricultural risks related to climate variability.

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