PERFORMANCE OF SEASONAL RAINFALL FORECASTS IN MALAWI

KEENNESS MANG'ANDA MTHIKO

I45/69984/2013

A REPORT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF POSTGRADUATE DIPLOMA IN METEOROLOGY

UNIVERSITY OF NAIROBI

DEPARTMENT OF METEOROLOGY

JULY, 2014

DECLARATION

This research project is my original work and has not been presented for a degree in any other university

Signature...Date 11/08/2014

Keenness Mthiko Mang'anda

Department of Meteorology

University of Nairobi

This research project has been submitted with our approval as university supervisors.

Signature...Date 11/08/2014

Prof. Ininda

Department of Meteorology

University of Nairobi

Signature...Date 11-8-2014

Dr. F. Opijah

Department of Meteorology

University of Nairobi

DEDICATION

To Nthanda Mang’anda, the bright morning star,

and Patrick Mang’anda my beloved husband, the favored of the Lord

ACKNOWLEDGMENT

My sincere acknowledgements and gratitude goes to my supervisors Dr. F. Opijah and Prof. J. Ininda for their tireless commitment, valuable advice and opinions that helped in the successful and timely completion of this project.

Special thanks to my dear husband, my family and my colleagues for their support and encouragement during this project.

My acknowledgement also goes to the Department of Climate Change and Meteorological Services for their support.

Above all, I would like to acknowledge the almighty God for being there with me all throughout and always.

ABSTRACT

This research evaluates the performance of seasonal rainfall forecasts in Malawi, which has consistently been issued since 2003. The main predictor indices are the El Nino southern oscillation (ENSO). While in some years the rainfall association has been observed to be in the predicted category, in some years the outcome has been on the contrary. However no comprehensive studies have been carried out to assess the success.

The objective of this study was to determine the skill of the forecast and also evaluate the suitability of the ENSO as predictor of seasonal rainfall over Malawi.

The forecast seasonal rainfall in Malawi generally did not perform well in terms of discrimination of events. Nonetheless it was observed that while the overall score over the years is low over the northern region, it was average over the southern region. The low skill in forecast over the northern part was attributed to the week relationship between ENSO and rainfall over the region. ENSO is positively correlated with the equatorial region and negatively correlated with the sub-tropical regions, however the northern part of Malawi is in the transition zone.

It is therefore recommended that further Research be conducted to identify other suitable predictors rather than depending on ENSO alone.

Table of Contents

List of Figures

List of Tables

List of acronyms

ADD	Agricultural Development Divisions
AMJ	April May June
CLIPS	Climate Information and Prediction Services
CPC	Climate Prediction Centre
CSC	Climate Services Centre
DCCMS	Department of Climate Change and Meteorological Services
ECMWF	European Centre for Medium Range Weather Forecasting
ENSO	El Nino Southern Oscillation
GDP	Gross Domestic Product
GHACOF	Greater Horn of Africa Climate Outlook Forum
IRI	International Research Institute
ITCZ	Inter-Tropical Convergence Zone
JAS	July August September
JFM	January February March
NCEP	National Centers for Environmental Prediction
NMHS	Meteorological and Hydrological Services
OND	October November December
RCOF	Regional Climate Outlook Forums
ROC	Relative Operating Characteristics
SADC	Southern Africa Development Community
SARCOF	Southern Africa Regional Climate Outlook Forum
WMO	World Meteorological Organization

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

The Malawian economy is agro-based and agriculture contributes 37.8 % to the country's GDP . about 90% of the foreign earnings come from agriculture and 85% of the population lives in rural and agriculture is their main livelihood. The amount of rainfall received determines the type of farming in a particular area. Therefore, the success or failure of the crops and water scarcity in any year is always viewed with the greatest concern. The inter- and intra-annual rainfall variability is the main factor responsible for fluctuations in yields and total production. By having a better understanding of the forecast and probabilities of rainfall, resources can be utilized more efficiently and effectively. In times of low, for example, rainfall there is a necessity for greater irrigation of crops, greater need for feed and water for livestock. In times of high temperature, animals will need shelter or increased water.

The Department of Climate Change and Meteorological Services (DCCMS) in Malawi is one of four departments in the Ministry of Environment and Climate Change Management. DCCMS began issuing rainfall seasonal forecasts every year in October 1997. These forecasts cover the rainfall season from October to March.

The forecasts for Malawi and southern Africa are released after The Southern Africa Regional Climate Outlook Forum (SARCOF) is held where Climate scientists from the National Meteorological Services within the SADC region, meet to come up with a consensus forecast for the rainfall seasons for the Southern Africa Development Community (SADC) region. The Climate scientists prepare this consensus forecast using national inputs. Additional contributions come from the SADC Climate Services Centre (CSC), International Research Institute for climate prediction (IRI, USA), European Centre for Medium Range Weather Forecasting (ECMWF, UK) and Climate Prediction Centre (CPC, USA).

Regional Climate Outlook Forums (RCOFs) were initiated in October 1996 as part of WMO's Climate Information and Prediction Services (CLIPS) project in partnership with the National

Meteorological and Hydrological Services (NMHSs), regional climate institutions and other agencies. Climate Information and Prediction Services (CLIPS) is a project of the World Meteorological Organization (WMO) designed to assist in the provision of climate information and predictions for improved economic and social decision making, and thereby support sustainable development. RCOFs stimulate the development of climate capacity in the NMHSs and facilitate end-user liaison to generate decisions and activities that mitigate the adverse impacts of climate variability and change and help communities to build appropriate adaptation strategies.

Regional Climate Outlook Forums (RCOFs) gained momentum as a regional response to the major El Nino event of 1997/98. Since that time they have rapidly become the main regional mechanism for the formulation and dissemination of seasonal climate forecasts to policymakers and other climate information users. The Forums bring together climate scientists, operational forecasters and climate information users to formulate climate outlook guidance and to discuss the implications of probable climate outcomes for climate-sensitive sectors. In the process a substantial amount of experience and knowledge has been gained in the generation, communication and application of seasonal climate information (Reid Basher et al. 2001). The SARCOF process has provided a vehicle for the reintegration and strengthening of meteorological expertise within the region (Edward 2003).

The standard forecast product, contains probabilities of occurrence for the three climatologically equi-probable categories of seasonal total precipitation; below, near, and above normal as defined by the 30-yr base period in use at the time.

1.2 STATEMENT OF THE PROBLEM

The Department of Climate Change and Meteorological Services (DCCMS) in Malawi, according to its mandate, aims at providing reliable, responsive and high quality weather, climate and climate change services to meet national, regional and international obligations through timely dissemination of accurate and up-to-date data and information for socio-economic development.

However, in many locations seasonal forecasts are not reliable enough to warrant changes in operating policies (Watkins and Wei 2008). As a result most users of such important information do not really rely on them. Moreover, During the review of the RCOF seasonal forecasts in 2008, the results indicated that Predictability in the vicinity of Malawi is known to be weak because of a transition between zones with distinct ENSO-tele-connection signals to the north-east (generally wet during warm episodes), and south-west (generally dry). This means that the skill of the forecast might be weak over Malawi and therefore the reliability and quality is also weak. However, seasonal Rainfall Forecasts for Malawi have so far not been comprehensively evaluated independently.

Unless there is an evaluation of the forecasts produced in Malawi, no improvement can be done on the models used. There is need for a detailed diagnostics in order to identifying the weaknesses in the forecasts. This should form a basis for adjustments to the forecast method help in order for the DCCMS in Malawi to improve on its seasonal forecast and to build confidence in areas it is doing well. Additionally, the existing and potential users need to be provided with a simple indication about the quality of these forecasts; Knowledge about the quality of the seasonal forecasts would help users to understand the risks and uncertainties involved when considering the information.

1.3 OBJECTIVES

The main objective of this research is to determine the performance of seasonal rainfall forecasts Issued by the Department of Climate Change and Meteorological Services in Malawi.

To help achieve this main objective, the following Specific objectives will be carried out:

1. Determine the skill of the seasonal forecasts
2. Determine the link between extreme rainfall events and global teleconnection

1.4 JUSTIFICATION

Seasonal rainfall forecasts for Malawi have so far not been comprehensively evaluated independently. However, there is a need to have some numerical measure of how well forecasts are performing otherwise there would be no objective of judging how changes in training, equipment or forecasting models affect the quality of forecasts.

The previous research of verification of RCOF forecast was conducted at a regional scale. However as it was indicated in this research that Malawi lies within a transition zone and therefore the Predictability is known to be weak, there is need for a specific evaluation of the forecast for Malawi to Identify the weaknesses and areas of improvement. The Department of Climate Change and Meteorological Services needs to know the weaknesses so that forecasts can be improved the scores produced by this verification can be used as a justification for improved training and equipment and for research into better forecasting models for Malawi.

The users of the forecast also need to have a clear indication on the reliability and quality of the seasonal forecasts. This would help them understand the risks and uncertainties involved when considering the information.

1.5 HYPOTHESIS

The performance of seasonal rainfall forecast in Malawi has not been very reliable to warrant changes in operating policies and their low skills have led to loss of confidence by the users of the forecast over the last decade

1.6 STUDY AREA

Malawi is situated in southeastern Africa. It is wholly within the tropics; from about 9°30S at its northernmost point to about 17°S at the southernmost tip. Topographically, Malawi lies within the Great Rift Valley system. Lake Malawi, a body of water some 580 km long and about 460 m (1,500 ft) above sea level, is the country's most prominent physical feature. The land forms high plateaus, generally between 900 and 1,200 meters (2,953 and 3,937 ft) above sea level. In the north, the Nyika Uplands rise as high as 2,600 meters (8,530 ft). South of the lake lie the Shire Highlands, with an elevation of 600–1,600 meters (1,969–5,249 ft), rising to elevations of 2,130 and 3,002 meters (6,988 and 9,849 ft) at the Zomba Plateau and mount Mulanje respectively. In the extreme south, the elevation is only 60–90 meters (197–295 ft) above sea level. The lowest point is on the southern border, where the Shire River approaches its confluence with the Zambezi at 37 m (121 ft) above sea level.

Malawi climate is strongly seasonal. It is largely influenced by the oscillations of the Inter-Tropical Convergence Zone (ITCZ), the converging of - and interaction between - the zonal Congo air mass and the meridional south-eastern trade winds and monsoonal northeastern winds. The warm-wet season stretches from October to April, during which 95% of the annual precipitation takes place. Extreme conditions include the drought that occurred in 1991/92 season and floods of 1988/89 season. The low-lying areas such as Lower Shire Valley and some localities in Salima and Karonga are more vulnerable to floods than higher grounds. A cool, dry winter season is evident from May to August with mean temperatures varying between 17 and 27 degrees Celsius, with temperatures falling between 4 and 10 degrees Celsius. In addition, frost may occur in isolated areas in June and July. A hot, dry season lasts from September to October with average temperatures varying between 25 and 37 degrees Celsius. Humidity ranges from 50% to 87% for the drier months of September/October and wetter months of January/February respectively.

This seasonal pattern is further influenced by the Indian Ocean's south western cyclonic weather patterns, and increasingly by the ocean's surface temperature variability which is especially responsible for annual variations, leading to abnormal weather effects. The effects of the El Nino Southern Oscillation in the north, and in common with the experience of east African countries, leads to increased precipitation and risk of flooding, while in the south, in line with its effects on southern African countries, has the opposite effect of less rain and increased risk of drought. In the event of the ocean's surface temperatures decreasing (La Nina), the reverse picture is true, the north drier, and the south wetter.

Malawi's climate is moderated by a high percentage of surface water, and by the fact that it possesses an altitudinal range of 500m (Lake Malawi and Liwonde) to peaks over 3000m high (Mt Mulanje). Spatially, precipitation levels increase south to north, with patches – rain shadow zones - receiving 600mm to 750mm, the majority of the country between 750mm and 1000mm and much of the coastal lake plains, the north and the highlands garnering between 1000mm and 2500mm.

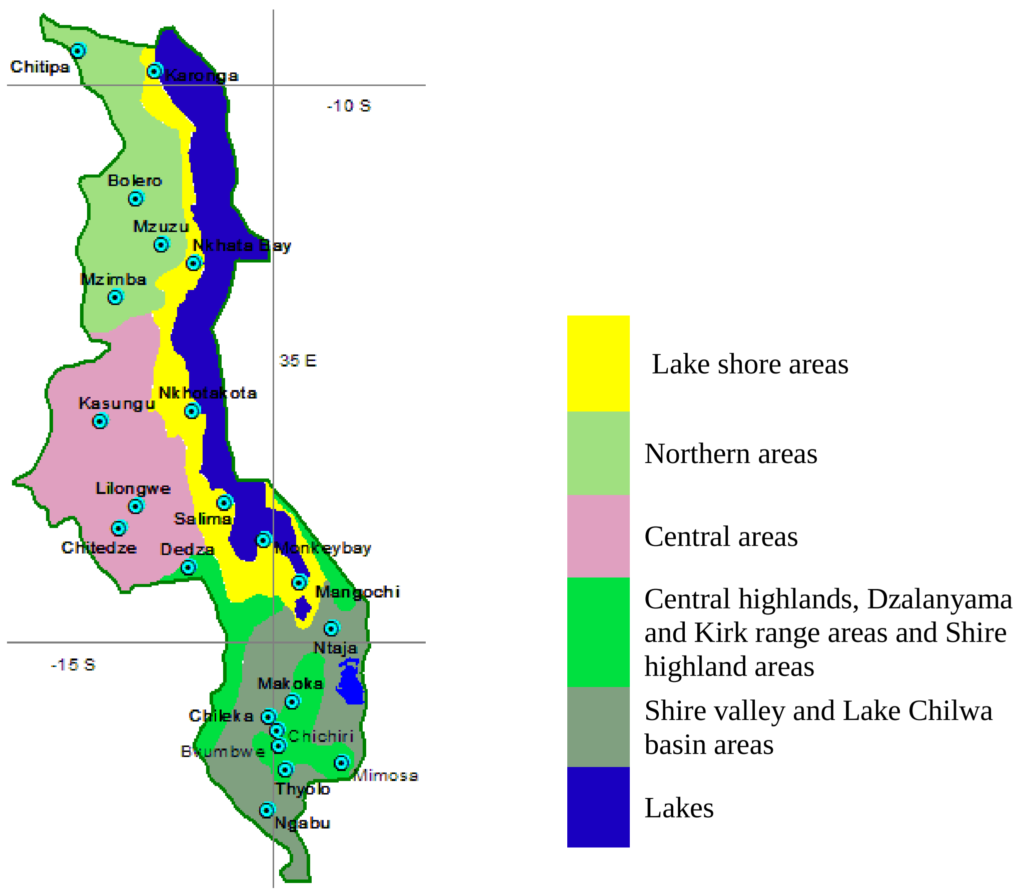


Figure 1.1 Map of Malawi showing main Meteorological stations and climatological zones

CHAPTER 2

LITERATURE REVIEW

2.1. The value of seasonal forecast

Climate variability poses a severe threat to subsistence farmers in southern Africa. Evidence suggests that Malawi's economy is among the most sensitive to climatic shocks of any in the region (Clay et al, 2003). Extreme climatic events such as droughts and floods which are becoming increasingly common and intense often affect food production negatively resulting in severe food shortages. In Malawi, for example, the 2002 drought left approximately 5 million people in need of emergency food aid which took a long time to be delivered.

Advance information in the form of seasonal climate forecasts alters the risk for agriculture and therefore food insecurity (Osgood et al. 2008). Food security in Southern Africa can be enhanced with weather-risk management techniques. This for the large systemic drought risk would allow operators at all levels to better manage their risk and improve investment decision-making (Hess et al. 2005).

There is no reason why countries such as Malawi should not be net exporters of food since agro-climatic conditions are relatively good, despite the volatility in rainfall patterns. Even farmers are particularly keen to choose and adapt approaches that give them immediate benefit (DFID 2010). A formal and comprehensive survey of potential users of climatic information had suggested a substantial and broad demand for forecast applications (Mkandawire et al. 1999). It is now recognized that forecast users range from individual end-users to intermediaries acting on behalf of large groups of end users (Basher et al. 2001).

The fragility of agriculture and the rural economy and society in Malawi, and perhaps elsewhere, are now more fully accepted. So there should be a greater interest in potentially useful information on the evolving weather situation. More specific information would be of use to more specific user groups, such as water system managers, commercial farmers and the public institutions and NGOs working with small farmers (clay et al. 2003).

2.2. Seasonal forecasts

A seasonal forecast refers to a forecast for average temperature and precipitation for a long period of up to several months. Predictability of the climate from season-to-season and year-to-year primarily arises from the interaction of the ocean and the atmosphere.

ENSO and other sea-surface temperature anomalies are known to influence global climate, altering rainfall and other climate variables throughout much of the tropics and sub-tropics and, in a few locations, in mid-latitudes. Seasonal climate prediction is based on the expectation of effects of these influences in the coming season. Seasonal outlooks are generated by combining dynamical and statistical climate model predictions, as interpreted by experts, to arrive at a consensus forecast.

Seasonal forecasts of climate variables such as rainfall and temperature are often presented as a probability of occurring within a certain category such as above or below average (two categories), or above, near, and below average (three-category tercile forecasts) (Zhang And Casey 1999). Terciles are used to represent three broad sectors of the probability distribution that are equally likely, climatologically. The terciles correspond to actual precipitation ranges, based on the set of historical observations. In using tercile forecasts, users need to know the ranges.

The probability of occurrence in each forecast category is usually expressed as a percentage probability figure with the total probability in all categories adding to 100%. A significant shift of the probability away from its average is indicated by corresponding changes in the probabilities in other categories (Zhang And Casey 1999). The ostensible reason for providing a probability value is because probabilistic forecasts have the advantage that they can convey the uncertainty associated with the forecasts in a quantitative way (Murphy 1977).

2.3. Malawi and ENSO

Climate zones do not follow national boundaries: Malawi lies between the core zones of South East Africa and Equatorial East Africa, indicating the difficulties of climate forecasting in Malawi. The transitional position of Malawi is also indicated by the less-close relationship between El Nino and drier years. Drought came in 1994 before the regional drought in 1995, whilst in 1997/8 there was no drought because of other influences. Malawi's location between these two core regions, with their differences in ENSO- rainfall associations, indicates the difficulties facing climate forecasting in Malawi (Clay et al. 2003).

There are micro variations in weather patterns associated with Malawi's location in the overlapping area of two climatic zones and also caused by the localized effects of Lake Malawi (Bohn 2002, Clay et al. 2003). In this view a more verifiable quantitative forecasting approach, as opposed to the consensus method needs to be developed

2.4. Importance of seasonal forecast evaluation

There is an important role for climatic forecasting in Southern Africa more generally and specifically in Malawi, because of considerable climatic variability (Clay et al. 2003). But the reliability of the forecasts needs to improve. There is an overwhelming case for investing in improving the spatial and temporal reliability of these (seasonal and within season) forecasts, and for establishing the necessary dissemination systems to ensure that these forecasts are effectively reaching potential users' (World Bank, 1996, p.14). According to Clay (2003), many users feel that the current reliability is not sufficient for them to make significant changes to their behavior. Lack of forecast verification is also an issue, as Users would like to have more information about how accurate past forecasts have been.

Improving the accuracy of quantitative precipitation forecasts is a primary goal of the National Centers for Environmental Prediction and the meteorological research community (Fritsch et al. 1998). There is substantial room to improve seasonal forecast, (Osgood et al 2008) and the need for better understanding of climatic information which implies a strengthening of management and planning capacity, so that forecasting is used to inform strategies for preparedness and the actual organization of public action. (Clay 2003).

The objectives for evaluating the quality of the forecasts were categorized by Brier and Allen (1951) as serving administrative, scientific and economic purposes and there is overlap between the three categories. From an administrative point of view, there is a need to have some numerical measure of how well forecasts are performing. Otherwise, there is no objective way to judge how changes in training, equipment or forecasting models, for example, affect the quality of forecasts" (Jolliffe and Stephenson 2003). For this purpose, a small number of overall measures of forecast performance are usually desired.

As well as measuring improvements over time of the forecasts, the scores produced by the verification system can be used to justify funding for improved training and equipment and for research into better forecasting models. More generally they can guide strategy for future investment of resources in forecasting. Measures of forecast quality may even be used by administrators to reward forecasters financially.

On the other hand , the scientific viewpoint is concerned more with understanding, and hence improving the forecast system A larger investment in more complex verification schemes will be rewarded with a greater appreciation of exactly where the deficiencies in the forecast lie, and with it the possibility of improved understanding of the physical processes which are being forecast.

Murphy (1997) distinguishes between verification measures, performance measures and scoring rules. A verification measure is any function of the forecasts, the observations, or their relationship, even though this is not concerned with the correspondence between forecasts and observations. Performance measures constitute a subset of verification measures that focus on the correspondence between forecasts and observations, either on an individual or collective basis, for example, conditional probabilities such as the *hit rate* and the *false alarm rate*.

2.5. Previous research

Frequently updated forecast evaluations, using multiple criteria, should be available to potential users of seasonal climate outlooks. (Hartmann et al 2002). The first decade of SARCOF, GHACOF and PRESAO forecasts review, based on satellite-based observational data, was conducted at the African Centre of Meteorological Application for Development (ACMAD) with support from IRI (Chidzambwa and Mason, 2008), In all three regions there was some evidence of positive skill in the forecast, an evidence of useful information that could have been beneficial but the forecasts had a clear evidence of systematic errors.

The SARCOF forecasts had more skills for above-normal category. On the other hand, the below-normal category from the forecasts has poor reliability and resolution, and for the normal category there is no skill at all. There was also a notable error hedging on the normal category contributed to the under-forecasting of the Below-Normal category as below-normal rainfall occurred more widely than suggested by the forecasts.

The general tendency of the forecasts over the ten-year verification period was incorrect. The lack of skill for the normal category is not exclusive to the SARCOF forecasts, or to those of the other African RCOFs, but is widely reported elsewhere (Wilks 2000; Wilks and Godfrey 2002). There is a possibility that the below-normal category is frequently given probabilities that are too low because of fear of causing alarm over the potential for drought.

In this review it was also noted that Predictability in the vicinity of Malawi is known to be weak because of a transition between zones with distinct ENSO-tele-connection signals to the north-east (generally wet during warm episodes), and south-west (generally dry). There is a stronger indication of a spatial distribution to the skill of the forecasts than for October – December, with better skill south of about 10°S. There is thus considerable scope for improvement.

CHAPTER 3

DATA AND METHODOLOGY

3.1 DATA

The rainfall data that has been used in this research was sourced from the Department of Climate change and meteorological service; Monthly Rainfall data, in millimeters, for the main Meteorological Stations for the years 2003 to 2013. The Data for 1961 to 1991 was also used, to calculate long term standard deviation and long term averages for calculating rainfall anomalies. Terciles were calculated to obtain the cut points between above, normal and below normal precipitation categories for JFM and OND. The Seasonal rainfall forecast for these years were also sourced from the Department of Climate change and Meteorological Services.

Figure 1.1 shows the Map of Malawi showing main Meteorological stations. The present network of meteorological stations comprise 22 full meteorological stations. Observations at main Meteorological stations are done by fully trained Meteorological Assistants who undergo an initial six months training course.

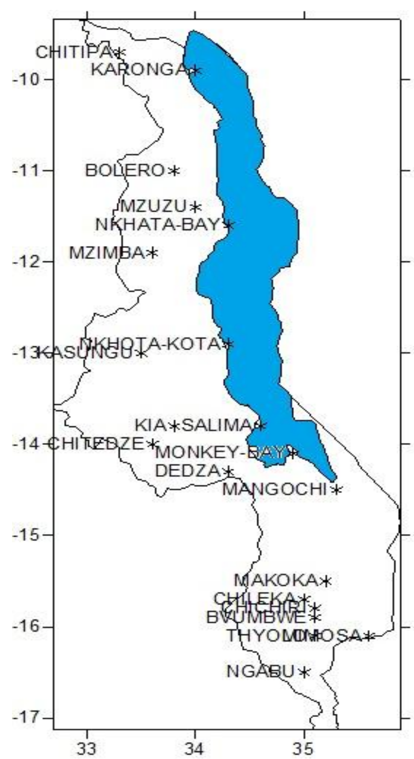


Figure 3.1 Map of Malawi showing main Meteorological stations

The data for Nino index was sourced from NCEP; seasonal Oceanic Nino index of AMJ, JAS, OND, JFM for the years 1961 to 2013.

Data Quality Control

Before the analysis, there was need to check the quality of the data. Data quality control is necessary if correct statistical inferences are to be made from the data. Data quality Control was performed using Cumulative mass curve method to check for homogeneity.

3.2 METHODOLOGY

3.2.1 Determining the skill of the forecasts

The most important attributes of a good forecast are Resolution, discrimination and also Reliability because they indicate whether the forecasts contain any useful information. These attributes were evaluated for the seasonal Rainfall forecasts in Malawi.

3.2.1.1 Resolution

One of the most basic attributes of a good set of probabilistic forecasts is that the outcome must be different if the forecast is different. If, on average, the same thing happens regardless of what the forecast is then the forecasts are completely useless (Mason 2009). Resolution can be determined by measuring how strongly the outcome is conditioned upon the forecast. If the outcome is independent of the forecast, the forecast has no resolution and is useless – it can provide no indication of what is more or less likely to happen. Resolution using the Hit score calculated as follows:

$$\bar{y}_k = 100 \times \frac{1}{n_k} \sum_{i=1}^{n_k} y_{k,i} \tag{1}$$

Where n is the of number of forecasts, and $y_{k,i}$ is the number of times the observation occurred in the category with the kth highest probability. The hit score ranges from 0% for the worst possible forecasts (the category with the highest probability never verifies) to 100% for the best possible forecasts (the category with the highest probability always verifies). The interpretation is simplified considerably if the categories are climatology ically equiprobable, in which case the score of no-skill forecasts will be one divided by the number of categories (33% in the case of the standard three-category tercile-based seasonal forecasts). If the categories are not climatologically equiprobable then the expected score of no-skill forecasts is equal to the climatological probability of the largest category.

The difference between the hit scores for the categories with the highest and lowest probabilities provides a simple indication of resolution. This skill score would range from 100% for forecasts that always identify the correct category, to 0% for forecasts with no resolution (the category with the lowest probability occurs just as often as the category with the highest probability), to -100% for forecasts with perfect resolution, but which consistently point to the wrong category.

3.2.1.2 Discrimination

To measure the discrimination for individual categories, the area beneath the Relative Operating If, on average, a forecaster issues the same forecast when rainfall is above-normal compared to when rainfall is below-normal the forecasts cannot "discriminate" between these different outcomes. Whereas resolution is concerned with whether the expected outcome differs as the forecast changes, "discrimination" is concerned with whether the forecast differs given different outcomes (Mason 2009). Measures of discrimination distinguish between potentially useful and useless forecasts. In measure discrimination the Relative operating Characteristics curve is recommended. The ROC curve is constructed by calculating hit and false-alarm rates for decreasing probability. If the forecasts have no useful information, the hit and false-alarm rates will be identical, but if the forecasts can discriminate the events, the hit rate will be larger than the false-alarm rate. The Hit Rates and False Alarm Rates are calculated as:

$$\text{Hit Rate} = \frac{Number\ of\ hits}{number\ of\ Events} \qquad (2)$$

False Alarm Rate = $\frac{Number\ of\ false-alarms}{number\ of\ non-Events}$

(3)

Whereas the area beneath the curve was then calculated as:

$$A = 0.5 \times \left[1 + \sum_{k=0}^{d}(y_k x_{k+1} - y_{k+1} x_k)\right]$$

(4)

where d is the number of discrete probability values, and $y1$ and $x1$ are the hit and false alarm rates for the highest probability value only, y_2 and x_2 are the rates for the highest and second highest probabilities, etc. The interpretation of the ROC area is that if the category of interest is above-normal, the score indicates the probability of successfully discriminating above-normal observations from normal and below-normal observations. The scaling has a score of 50% representing no skill, 100% indicating perfect discrimination, and 0% indicating perfectly bad discrimination.

3.2.1.3 Reliability

The purpose of issuing probabilistic forecasts is to provide an indication of the uncertainty in the forecast. The forecast probabilities are supposed to provide an indication of how confident the forecaster is that the outcome will be within each category, and so they could be interpreted as the probability that a deterministic forecast of each category will be "correct. Forecasts are reliable, or well-calibrated, if the observation falls within the category as frequently as the forecast implies (Murphy 1993). More often than not seasonal forecasts are unreliable. The commonest situation is that the forecasts are over-confident – increases and decreases in probability are too large. Overconfidence occurs when the forecaster thinks that the probability of a specific category is increased (or decreased), but over-estimates that increase (or decrease), and thus issues a probability that is too high (or too low). In other words reliability is the agreement between forecast probability and mean observed frequency.

$$\text{Reliability } = \frac{1}{n}\sum_{k=1}^{d} n_k [\bar{P}_k - \bar{y}_k]^2$$

(5)

In equation 3.5, n_k is the number of forecasts for the k^{th} probability value ($\bar{P}_k$), and $\bar{y}_k$ is the observed relative frequency for that value. The observed relative frequency is calculated as the number of events divided by the number of forecasts. The reliability score measures "errors" in the reliability of the forecasts, and so ranges from 0.0, for perfectly reliable forecasts, to a maximum value of 1.0 which is only possible if the forecasts were perfectly bad (Mason 2009).

3.2.1.4 Evaluation of the skill of the forecasts

This was been done by converting the forecast probabilities into an index using standard deviation in order to rate the forecasts. Although each category is given its distinct probability, the general forecast is usually stated considering the category with the highest probability and the category with the second highest probability, in the form Normal to above normal or below normal to Normal for example. The Standardized rainfall anomalies were used to come up with a forecast index. This has been done in order to interpret the skill of the forecast in an easy to understand format for user. Table 3.1 shows the forecast index and the forecast categories.

Table 3.1: the Forecast category and forecast index

Forecast category	Forecast index
Above Normal to Normal	1.5
Normal to Above Normal	0.5
Normal to Below Normal	-0.5
Below Normal to Normal	-1.5

This forecast index was used to rate the forecast into skills of either high skill, average, low skill and no skill. This skill was calculated as an average of the skill index which was generated by scoring the forecast if there was a hit in either one or both the categories with the highest and second highest probabilities.

A rainfall anomaly index was developed in order to convert the observed rainfall into the same format as the forecasts. Table 3.2 shows the Rainfall anomaly index and the observed rainfall category. Table 2 shows that when the observed Rainfall Anomaly Index(RAI) is greater than 1, it means that the observed rainfall category was above normal to normal, when it is between 0 and 1, the observed rainfall category was normal to above normal and so forth.

Table 3.2: Rainfall anomaly index and the observed rainfall category

Rainfall Anomaly Index (RAI)	Observed rainfall category
RAI $\geq$ 1.0	Above Normal to Normal
0 $\leq$ RAI $\leq$ 1.0	Normal to Above Normal
-1.0 $\leq$ RAI $\leq$ 0	Normal to Below Normal
-1 $\leq$ RAI	Below Normal to Normal

Table 3.3 shows the Scores that are awarded to the forecast based on the occurrence and the forecast. Table 3.3 shows that a full score of 1 is awarded when the observed category is the same as the forecasted category, a half score is awarded when a reversed paten of the forecasted category is observed, when only part of the forecasted category is observed a score of 0.25 is awarded and so forth.

Table 3.3: Forecast Score Index and Observed Category/ Occurrence

Observed Category/ Occurrence	Forecast Score Index			
Above Normal to Normal	AN to N =1	N to AN = 0.5	N to BN =0.25	BN to N= 0
Normal to Above Normal	N to AN =1	AN to N = 0.5	N to BN =0.25	BN to N= 0
Normal to Below Normal	N to BN =1	BN to N = 0.5	N to AN =0.25	AN to N = 0
Below Normal to Normal	BN to N =1	N to BN = 0.5	N to AN =0.25	AN to N = 0

The score index was then calculated as the average of the scores for all the forecasts as shown in equation 6. This was used to rate the forecasts as either having high skill, average skill, low skill or no skill as shown in Table 3.4.

$$\mathrm{SI} = \frac{1}{n}\sum_{i=1}^{n} FSI \tag{6}$$

Where FSI is the forecast score index SI is the score index and n is the number of years

Table 3.4: Score index and the associated skill

Score index (SI)	skill
SI ≥ 0.75	high skill
0.75 ≤ SI ≥ 0.5	average skill
0.5 ≤ SI ≥ 0.25	low skill
SI ≤ 0.25	no skill

3.2.2 Determine the link between extreme rainfall events and global teleconnection

In order to determine the Rainfall variability, the standardized rainfall anomaly index was calculated. This was performed using the following equation:

$$Z = \frac{x - \bar{x}}{\sigma} \tag{7}$$

In equation 3.1, Z is the standardized rainfall anomaly, x is the total precipitation for the season, $\bar{x}$ is the long term average, and $\boldsymbol{\sigma}$ is the standard deviation.

The seasonal rainfall anomalies were then correlated with the Nino index obtained from National Centers for Environmental Prediction (NCEP). These were seasonal index of AMJ, JAS, OND, and JFM.

Chapter 4

RESULTS AND DISCUSSIONS

Figure 4.1 shows an example forecast map for Malawi showing the two homogeneous zones. This figure shows that the country is divided into two homogeneous zones, namely Zone I and Zone II. These zones are divided using principal component analysis. The standard forecast product, contains probabilities of occurrence for the three climatologically equi-probable categories of seasonal total precipitation; below, near, and above normal as defined by the 30-yr base period in use at the time, the base period in this case being 1961 to 1991.

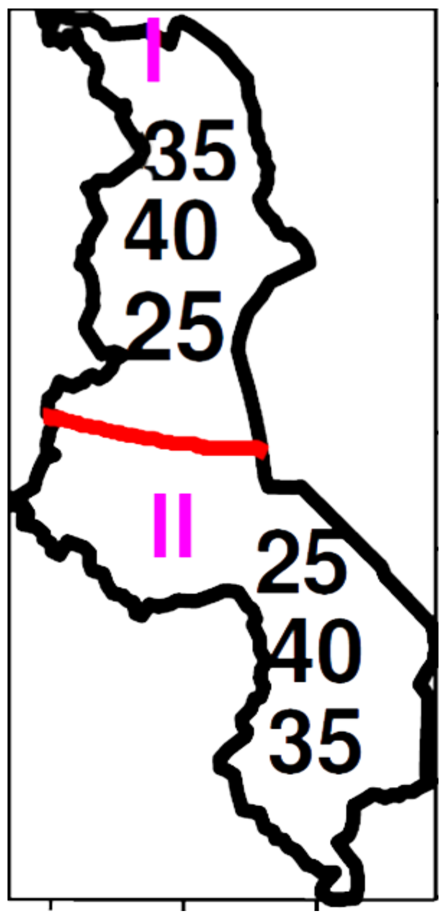


Figure 4.1 Example forecast map for Malawi showing the two homogeneous zones, Zone I and Zone II, and their forecast probability distribution

4.1 DETERMINATION OF SEASONAL RAINFALL FORECASTS SKILL

4.1.1 Reliability

Table 4.1 shows the results that were obtained after calculating reliability using the reliability equation (Eq 3. 6). The scores were calculated by pooling all the forecasts from both the two zones. Measuring reliability requires large samples, and so it is only viable to measure it by pooling the forecasts from different locations (Mason, 2009). The reliability score measures errors in the reliability of the forecasts, and so ranges from 0.0 for perfectly reliable forecasts, to a maximum value of 1.0 for perfectly bad forecasts. The reliability error is small, approximately less than 0.2 for all the categories. This means that the Reliability of the forecasts for all the Forecasts is good.

Table 4.1: results for reliability

CATEGORY	OND	JFM
Above Normal	0.02693	0.04750
Normal	0.08823	0.09333
Below Normal	0.04375	0.01563

4.1.2 Resolution

Table 4.2 shows the results that were obtained after determining the resolution of the forecast. In this table, Y1 refers to the category with the highest probability, Y2 refers to the category with the second highest probability and Y3 refers to the category with the third highest probability. The skill score is the measure for resolution defining the difference between the hit scores for the categories with highest and lowest probabilities. This is then compared with a score of no skill which is 33% in the case of the standard three-category tercile-based seasonal forecasts. When the skill score is less than 33% it then means that the resolution is not good.

Table 4.2 shows that the Hit scores for Zone I, during October to December rainfall season are 62.5%, 25% and 12.5% for the category with the highest, second highest and third highest probabilities respectively, and the skill score is 50%. The table also shows that the hit scores for this Zone during the January to March rainfall season are 75%, 12.5% and 12.5% for the category with the highest, second highest and third highest probabilities respectively, and that the skill score for this season is 62.5%. During both seasons, the Resolution score, in zone I, is above the score of no skill which is 33%. This means that the resolution was good for zone I during both October to December and January to rainfall seasons. The forecasts have been successful at indicating the most likely outcome

Table 4.2 shows that the Hit scores for Zone II, October to December rainfall season are 62.5%, 37.5% and 0% for the category with highest, second the highest and third highest probabilities respectively, and the skill score is 62.5%. The table also shows that the hit scores for this Zone during the January to March rainfall season are 25%, 62.5% and 12.5% for the category with highest, second highest and third highest probabilities respectively, with the skill score for this season being 62.5%.

For Zone II, during October to December Rainfall season, the resolution is good. But During January to march Rainfall season the category with highest probability has the lowest hit score while the one with the second highest probability has the highest score. This shows that there was a hedging on to the normal category. The hit score therefore is providing an indication of how the shift in the probability distribution towards above- or below-normal was informative. The skill score defining the difference between the hit scores for the categories with highest and lowest probabilities is 12.5%. This is lower than the score of no-skill forecasts (33%) indicating bad Resolution skill. The very low hit score for the category with the lowest probability indicates that the forecasts have been successful at indicating what is most likely not to happen, but have been less successful at indicating the most likely outcome.

Table 4.2: results for resolution

ZONE	Hit score for Y1	Hit score for Y2	Hit score for Y3	Skill score
ZONE I: OND	62.5%	25%	12.5%	50%
ZONE I: JFM	75%	12.5%	12.5%	62.5%
ZONE II OND	62.5%	37.5%	0%	62.5%
ZONE II: JFM	25%	62.5%	12.5%	12.5%

4.1.3 Discrimination

Discrimination is measured for individual categories as the area beneath the Relative Operating Characteristics curve. The ROC curve is constructed by calculating hit and false-alarm rates for decreasing probability. The score ranges from 0% to 100% with a score of 50% representing no skill, 100% indicating perfect discrimination, and 0% indicating perfectly bad discrimination. Scores of less than 50% indicate bad forecasts these are forecasts that can discriminate, but which indicate the wrong tendency, for example assigning a high forecast probabilities on below-normal to indicate a low probability that below-normal rainfall will actually occur, and can reach a lower limit of 0% given perfectly bad forecasts (Mason 2009).

The Figure 4.2 shows the ROC curves for categories which had no discrimination In Zone I and II. This figure shows that the curves during these seasons follow the 45° diagonal thus enclosing an area of 50%. This means that there was no discrimination for these categories. This was probably because of the perpetual forecasting of the same probabilities for these Categories. The perpetual forecasting of the same probabilities will select all or none of the observations at the same time since there is no basis for selecting some over others. The hit and false-alarm rates will then both be 1.0 if all the observations are selected, and both 0.0 when none of the events are selected, and the curve joining these points will follow the 45° diagonal, and enclose an area of 50%.

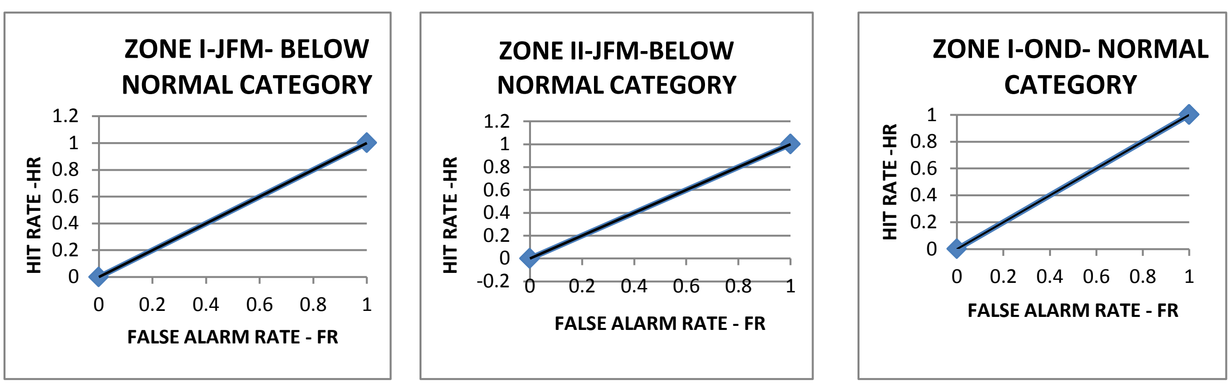


Figure 4.2 ROC curve for categories with no discrimination in ZONE I and II. Area under curve is 50%

For good forecasts, the hit rate will be initially much larger than the false-alarm rate, and so the graph should be fairly steep near the left hand corner. The more successfully the forecasts can discriminate the events, the steeper the curve will be near the left, and the shallower the curve will be near the right, and will thus embrace more area.

Figure 4.3 shows the ROC curves for categories with good discrimination in ZONE I and II. The area under the curve is above 50% for all the categories depicted in this Figure, especially the ZONE I (North) October to December season for the below normal category, which had a higher score of 83.3%, implying that there is a greater than 83% probability that the forecasts can successfully discriminate the below-normal season from other seasons. But the other categories shown in Figure 4.3 have curves slightly close to the 45° diagonal. These types of forecasts contain useful information only when the probabilities are low, and so the curve will be initially close to 45°, but will flatten out towards the top right (Mason 2009).

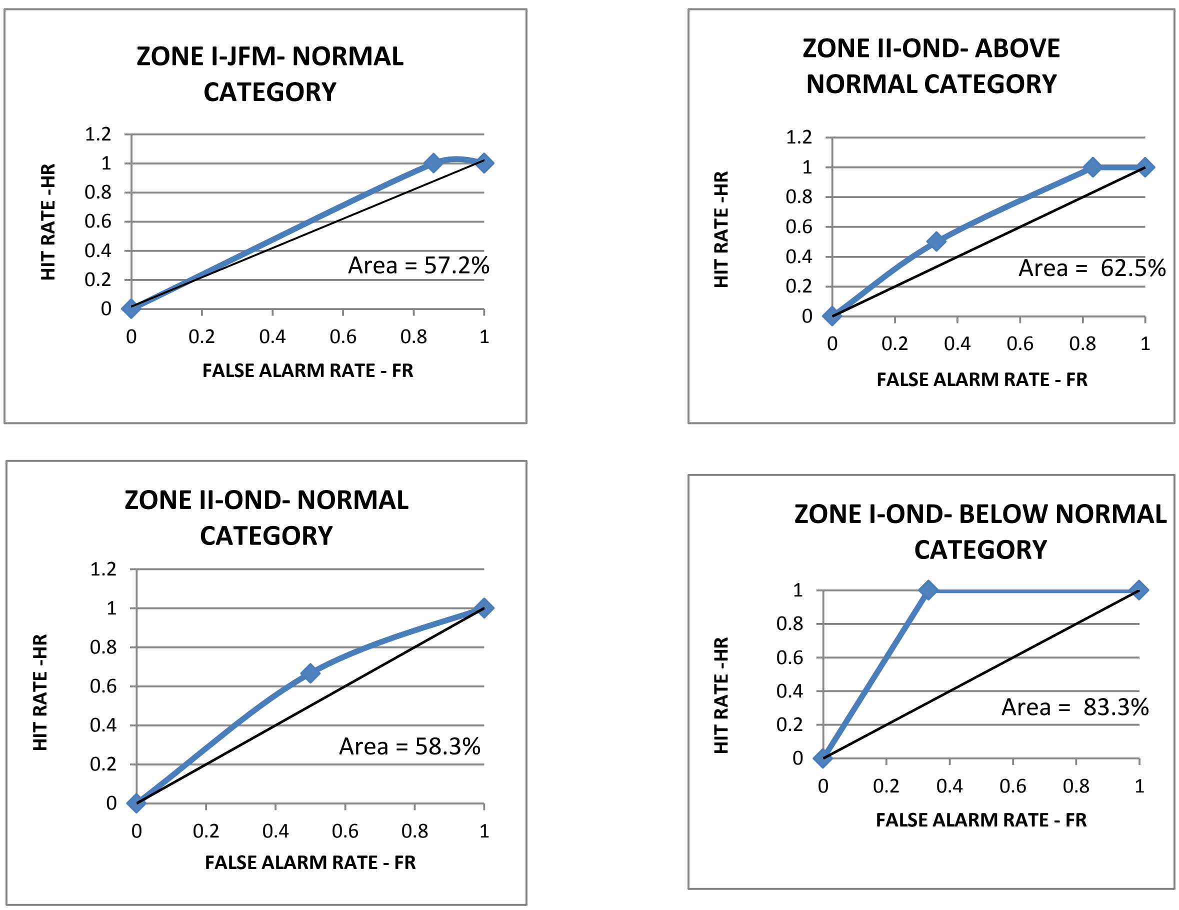


Figure 4.3 ROC curve for categories with good discrimination in ZONE I and II

Figure 4.4 shows the categories that had the area under the ROC curve below 50%. In this Figure, the categories have concave curves. If the forecasts are bad only relatively few events will be selected initially and the curves will therefore be concave (Maso 2009). Therefore categories shown in Figure 4.4 had bad discrimination.

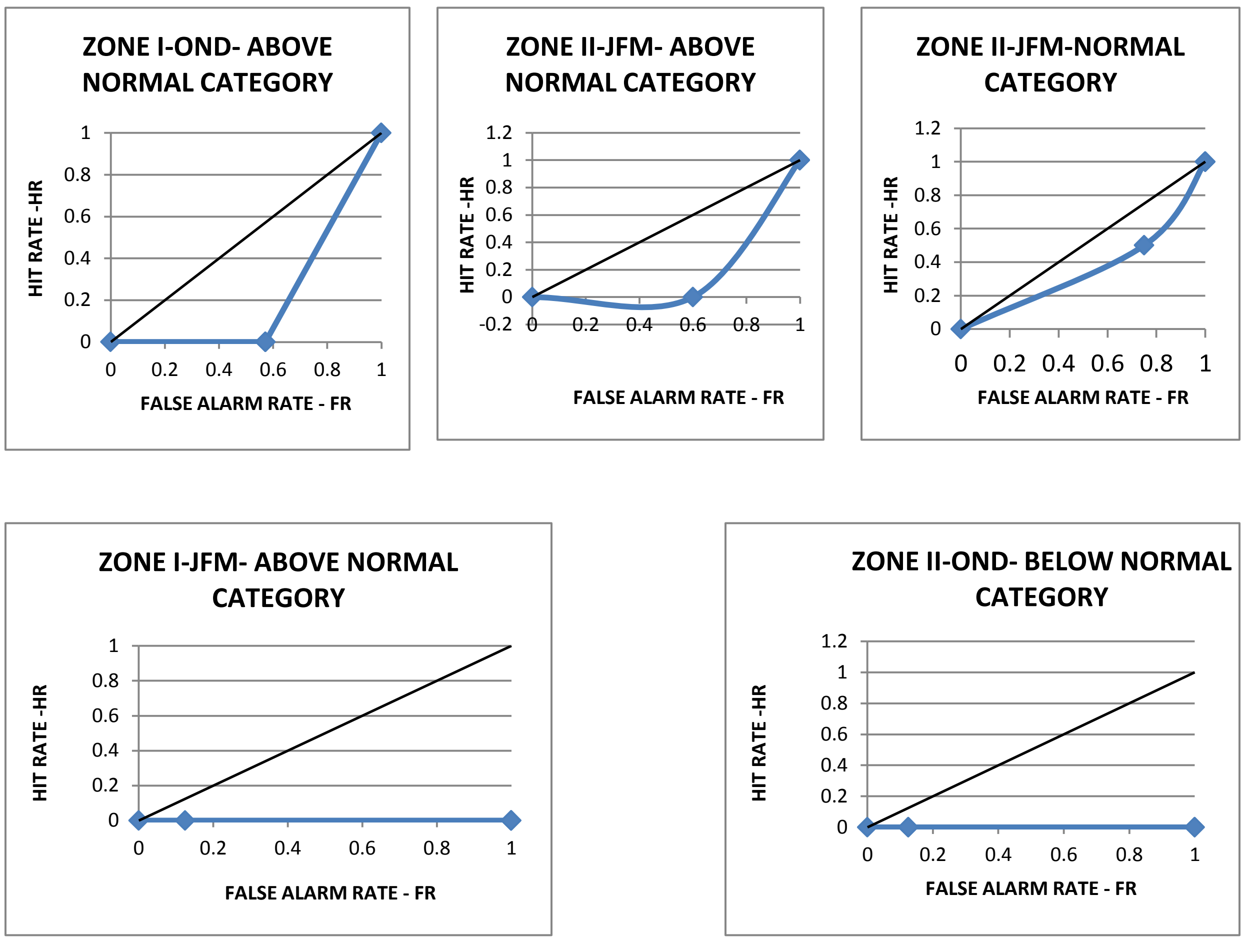


Figure 4.4 ROC curves for categories with the area under ROC Curve below 50% in ZONE I and II

4.1.4 Evaluation of the seasonal rainfall forecast skill

The results obtained from evaluating the skill of the forecast has shown that the overall skill of the forecast is low in zone I and average in zone II. Table 4.3 shows the average score index for each zone. The skill for zone I, during October to December season, is low while during January to March season there is no skill. In zone II, the skill is average for both seasons.

Table 4.3: Average score index for zone I and zone II

Season	**Skill**	**Evaluation**
Zone I: OND	0.41	Low skill
Zone I: JFM	0.22	No skill
Zone II: OND	0.59	Average skill
Zone II: JFM	0.66	Average skill

Figure 4.5 shows a graph of the forecast index and the rainfall anomalies. The Figure shows anomaly how the plot for the forecast index and the plot for observed rainfall anomaly index are tarrying. Figure 4.5 shows that in most of the forecasts, the forecast index and the observed rainfall index are not tarrying. On average the rainfall over zone I has been normal to below normal, but the forecasts were generally of normal to above normal, while in the south, zone II the forecasts and the rainfall both lie within normal to above normal rainfall category.

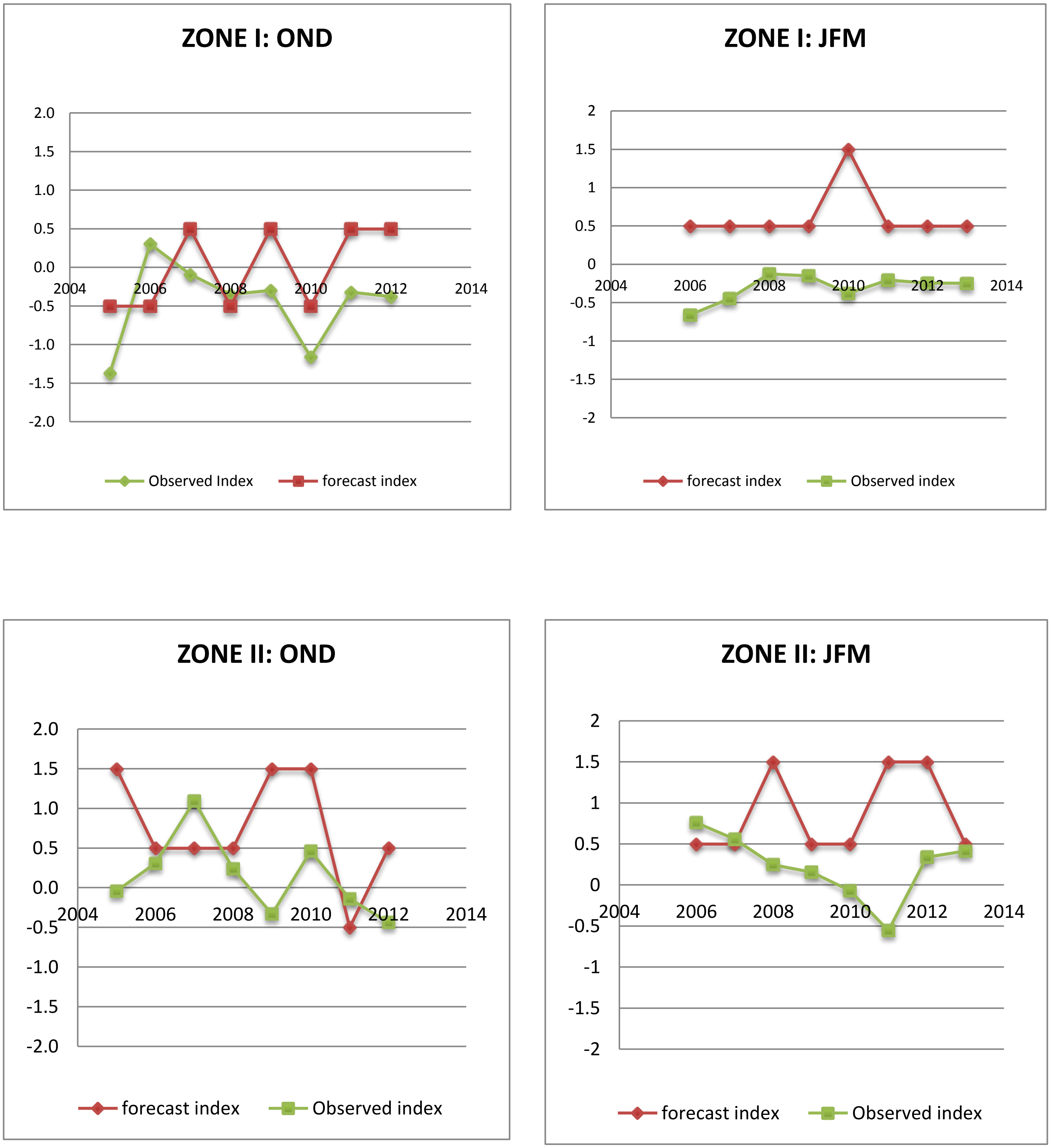


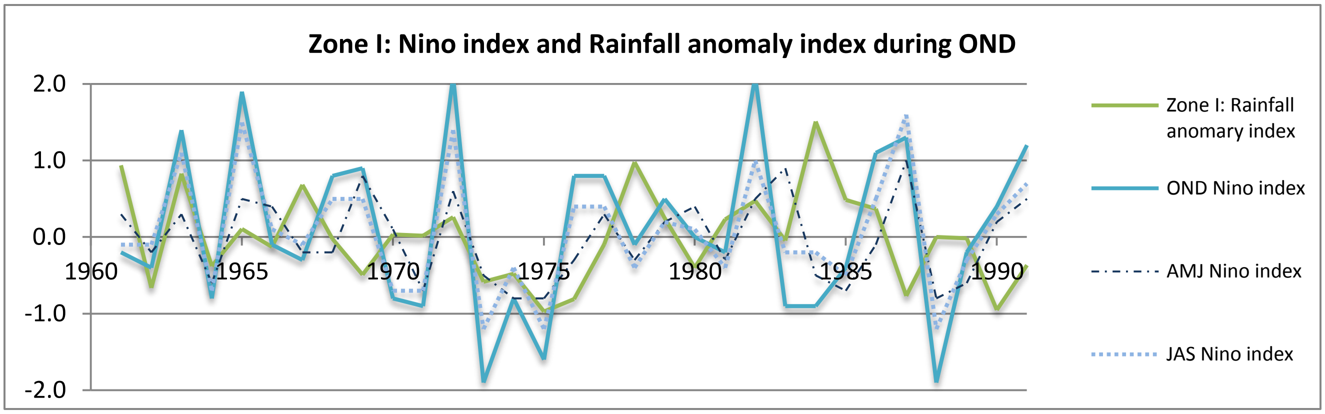
Figure 4.5 a plot of observed rainfall anomalies and forecast index.

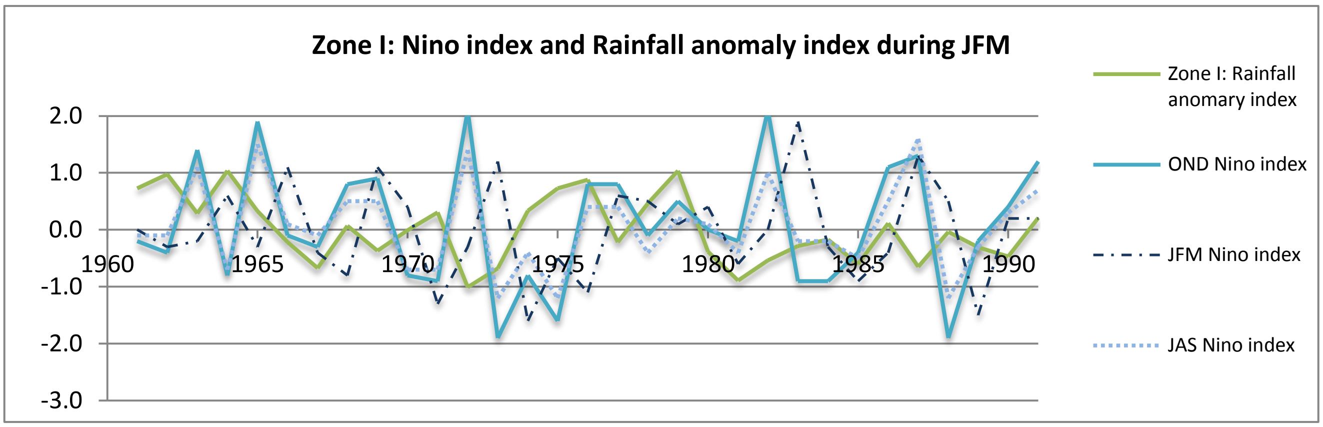
4.2 DETERMINE THE LINK BETWEEN EXTREME RAINFALL EVENTS AND GLOBAL TELECONNECTION

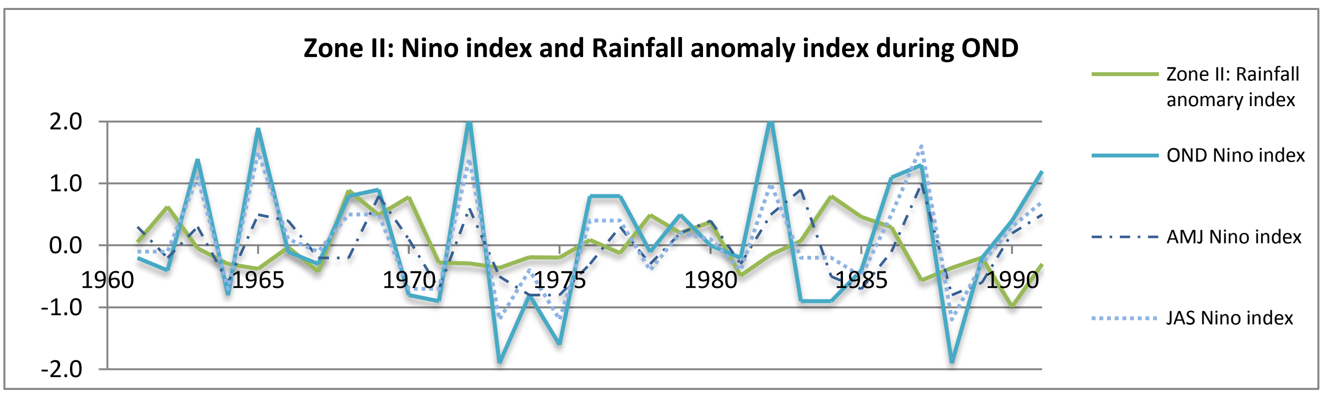
In order to determine the variation of the rainfall, monthly rainfall data for the years 1961 to 1991 was used. This evaluation has been done based on data from the 22 main meteorological stations. The totals mean and standard deviation of rainfall and the seasonal standardized rainfall anomaly for the main rainfall stations in Malawi were computed and correlated with the seasonal ENSO index obtained from NCEP.

Figure 4.6 shows a plot of Nino index and Rainfall anomaly index for Zone I and II from 1961 to 1991. This figure depicts graphically the relationship between rainfall in Malawi and ENSO. Taking into consideration the lag period that be available before the effect of ENSO reaches Malawi, Nino index have been plotted for AMJ, JAS, OND and JFM. The figure shows that zone I experiences high rainfall anomalies when there is a positive Nino index which is known as El Nino, and when there is La Nina, a negative Nino index, zone I experiences low anomalies in rainfall. However there are some instances where zone experienced high anomalies in rainfall during a La Nina episode and Low anomalies in rainfall during an El Nino episode, 1984 and 1991 for instance. Figures 4.6 also shows that in zone II high rainfall anomalies are experienced when there is a La Nina episode but near to normal rainfall is recorded when there is an El Nino episode. This means that the rainfall in Malawi does not depend entirely on ENSO although its effect may sometimes be felt.

In order to determine the relationship between ENSO and rainfall in Malawi, the correlation coefficients were computed using Microsoft Excel, statistical computer package. Rainfall anomaly index for OND and JFM in both zones but separately were correlated with Nino Index of AMJ, JAS, OND and JFM. The correlation coefficient is a number between -1 and 1 that indicates the strength of the linear relationship between two variables. The sign of the coefficient (+ or -) indicates the direction of the relationship between the two variables and how far away from zero it is indicates the strength of the relationship. P-value was used to test the probability that relationship found was by chance sampling error, t-test was also used to test the significance of the relationship.







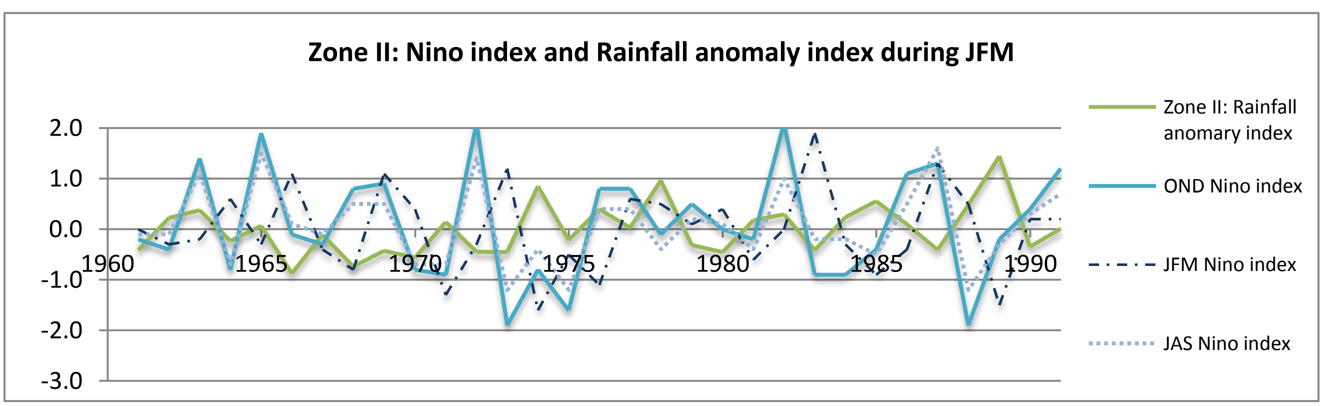


Figure 4.6 Nino index and Rainfall anomaly index for Zone I and II from 1961 to 1991

Here the null hypothesis is that there is no relationship between rainfall in Malawi and ENSO while the alternate hypothesis is that there is a significant relationship between rainfall in Malawi and ENSO.

Table 4.3 shows the results from the correlation of rainfall anomaly index with Nino index. The Table shows that the correlation coefficients in all the tests are close to zero, except for the correlation of zone II JFM rainfall anomaly index correlation with JFM Nino index, but the t-est for this relationship is 0.059 which is less than the critical value. Furthermore the T-test values for all the correlations tested were less than the critical value. This means that there was no significant relationship found in all the correlations that were tested between rainfall anomaly index for Malawi and Nino index of AMJ, JAS, OND, and JFM. Therefore there is no sufficient evidence to reject the null hypothesis. There is no significant relationship between rainfall in Malawi and ENSO.

Table 4.3 The results from the correlation of rainfall anomaly index with Nino index

Zone I: OND rainfall anomaly index correlated with			
	OND Nino index	**AMJ Nino index**	**JAS Nino index**
Pearson Correlation	0.099	-0.037	0.064
df	30	30	30
t Stat	-0.434	0.131	-0.364
P(T<=t) one-tail	0.334	0.448	0.359
t Critical one-tail	1.697	1.697	1.697
P(T<=t) two-tail	0.667	0.897	0.719
t Critical two-tail	2.042	2.042	2.042
Zone I: JFM rainfall anomaly index correlated with			
	JAS Nino index	**JFM Nino index**	**OND Nino index**
Pearson Correlation	-0.179	-0.197	-0.142
df	30	30	30
t Stat	-0.329	0.064	-0.396
P(T<=t) one-tail	0.372	0.475	0.348
t Critical one-tail	1.697	1.697	1.697
P(T<=t) two-tail	0.744	0.949	0.695
t Critical two-tail	2.042	2.042	2.042
Zone II: OND rainfall anomaly index correlated with			
	OND Nino index	**AMJ Nino index**	**JAS Nino index**
Pearson Correlation	-0.063	-0.054	-0.099
Degree of freedom	30	30	30
t Stat	-0.429	0.150	-0.371
P(T<=t) one-tail	0.335	0.441	0.357
t Critical one-tail	1.697	1.697	1.697
P(T<=t) two-tail	0.671	0.882	0.713
t Critical two-tail	2.042	2.042	2.042
Zone II: JFM rainfall anomaly index correlated with			
	JAS Nino index	**JFM Nino index**	**OND Nino index**
Pearson Correlation	-0.159	-0.561	-0.073
Degree of freedom	30	30	30
t Stat	-0.346	0.059	-0.417
P(T<=t) one-tail	0.366	0.477	0.340
t Critical one-tail	1.697	1.697	1.697
P(T<=t) two-tail	0.732	0.953	0.680
t Critical two-tail	2.042	2.042	2.042

Figure 4.7 shows the standardized rainfall anomalies in Malawi over the years 2003 to 2013 during OND. The figure depicts the rainfall variability over Malawi during this. The rainfall anomalies were high during the 2004/2005 OND rainfall season, in both the north and the South of Malawi. According to Meyers (2007), in 2004 a positive Indian Ocean dipole formed over the Indian Ocean.

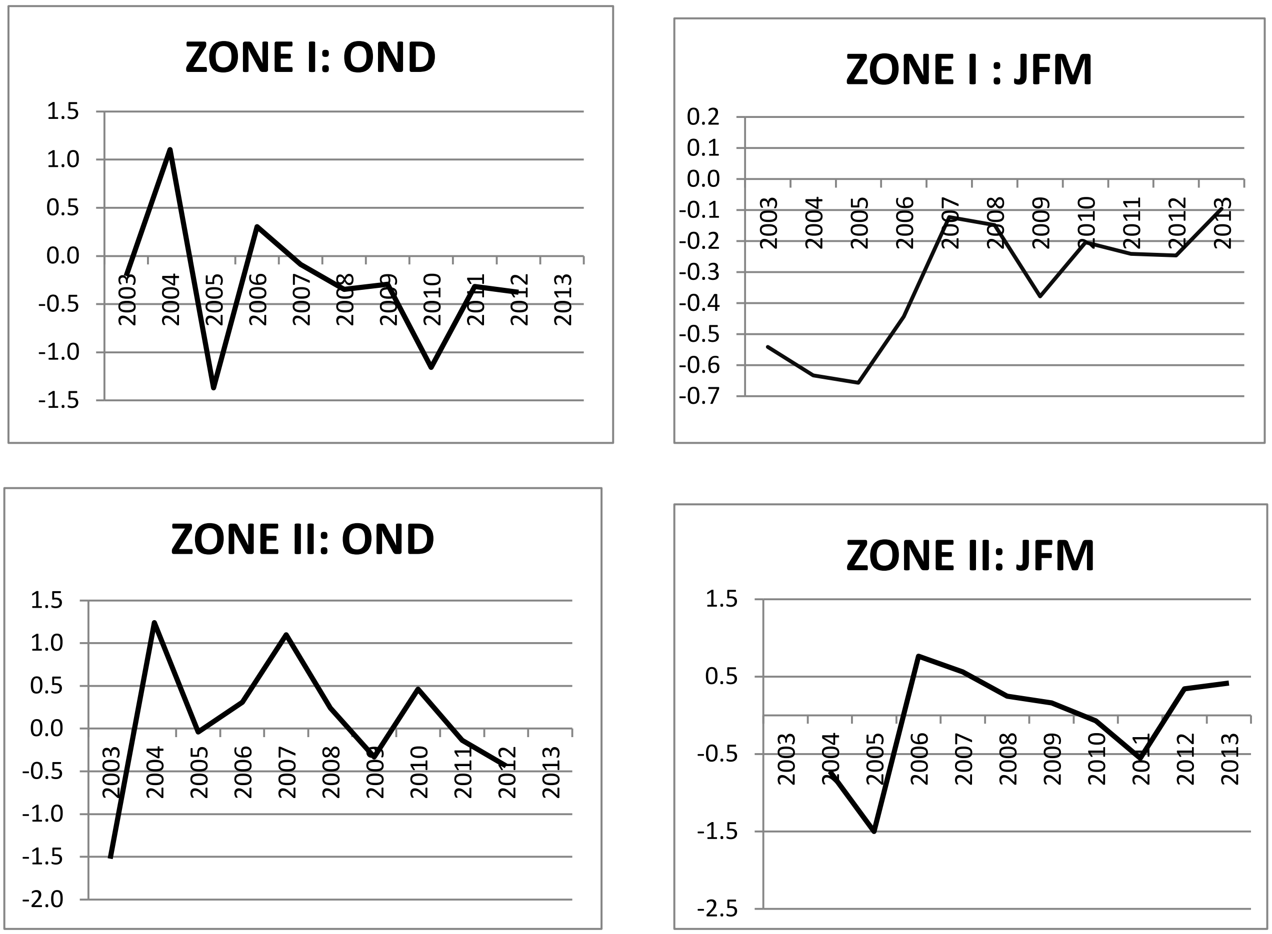


Figure 4.7: standardized rainfall anomalies for rainfall in Malawi over the years 2003 to 2013 during October to December.

The Indian Ocean Dipole (IOD) is an irregular oscillation of sea-surface temperatures in which the western Indian Ocean becomes alternately warmer and then colder than the eastern part of the ocean. A positive phase sees warmer sea-surface temperatures and greater precipitation in the western Indian Ocean region, with a corresponding cooling of waters in the eastern Indian Ocean—which tends to cause droughts in adjacent land. The negative phase of the IOD brings about the opposite conditions, with warmer water and greater precipitation in the eastern Indian

Ocean, and cooler and drier conditions in the west. There was more rainfall during this OND rainfall season due to the positive Indian Ocean Dipole in 2004. In 2010/2011 (NCEP), a negative IOD formed. Even though there was La Nina in 2010/2011 January to March rainfall season, less rainfall was recorded in the southern part, ZONE II because of the Formation of the IOD. On the other hand the north recorded low rainfall in October to December that year as both the Negative Indian Ocean Dipole and La Nina brought about drier conditions for the north.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Reliability is the agreement between forecast probability and mean observed frequency, Resolution can be determined by measuring how strongly the outcome is conditioned upon the forecast, and Discrimination is concerned with whether the forecast differs given different outcomes.

The Results have shown that the forecast probabilities that were used in the forecasts for Malawi are Reliable. The Resolution is good except for Zone II in January to March rainfall Season which had poor resolution. In zone II, during JFM, the resolution skill score was 12%.

The forecasts in most of the categories have scored poorly at Discriminating events. This can be attributed to perpetual forecasting of the same probabilities in these categories. Zone I-OND-below normal category has shown good discrimination skills, with a score of 83.3%, there was no perpetual forecasting of same probabilities in this category. Therefore these forecast had greater than 83% probability that the forecasts can successfully discriminate the below-normal season from other seasons. Where there was perpetual forecasting of the same probabilities, for example in Zone I during JFM, below normal category, the forecasts indicated no discrimination or bad discrimination. If, on average, a forecaster issues the same forecast when rainfall is above-normal compared to when rainfall is below-normal the forecasts cannot “discriminate” between these different outcomes.

The results from evaluating the overall skill of the forecast have shown that there is average skill in the southern part of Malawi, zone II, than in the northern part, zone I.

The results have shown that the northern part of Malawi zone I, and the Southern part of Malawi Zone II respond differently to El Nino and La Nina Episodes. This is in confirmation with Clay et al. (2003) who indicated that Malawi’s location between these two core regions, with their differences in ENSO- rainfall associations, indicates the difficulties facing climate forecasting. The transitional position of Malawi is also indicated by the less-close relationship between El Nino / La Nina and rainfall in Malawi. The results have shown that there is an insignificant relationship between Malawian rainfall and ENSO.

Although it is expected that when there Is La Nina there should be more rainfall experience in areas in the southern part of Africa, and drier conditions experienced during El Nino episodes, the results from this research have shown that in some years the Effects of La Nina can be counteracted by a negative Indian Ocean dipole. The results have also shown that Rainfall can also be enhanced by a positive Indian Ocean dipole in both Zones. This means that there are other signals that can be considered as predictors and not ENSO only.

The forecast for rainfall season forecast In Malawi generally did not perform well in terms of discrimination of events. The forecast have an overall average score of 0.47 which means low skill for the forecasts. This low skill in forecasts can be attributed to the insignificant relationship between Malawi and ENSO due to its location in transition zone between two teleconnection signals. This means that there is need for improvement in the forecasts.

5.2 Recommendations

The forecast are based on models that use scientifically established relationships between rainfall over Southern Africa and ENSO teleconection signals. However, the relationship between rainfall in Malawi and ENSO is insignificant. The low skill in forecasts can be attributed to the insignificant relationship between Malawi and ENSO due to its location in transition zone between two core regions, with their differences in ENSO- rainfall associations. Therefore further Research should be conducted to identify other suitable predictors rather than depending on ENSO alone.

The forecasts that were issued in the past ten years did not contain any information on the onsets and cessation of rainfall. A study in Malawi (clay et. al, 2003) showed that the users of the forecast information require this kind of information. This information is vital for agriculture.

It is also recommended that the forecasts be downscaled in older to capture the micro variation that is brought about by the location of Malawi and the localized effect of Lake Malawi and topography.

The probabilities are rounded to the nearest multiple of five without an attribute to any scientific basis. There is need for an explanation to this. This has adversely affected the quality of the forecasts. It is therefore recommended that study should be conducted on the new model of forecasting that will improve discrimination and resolution of the forecasts. This will help the forecasts to contain more useful information.

This research also recommends that a study be conducted on the onsets and cessation dates for Malawi so that such information should be included in the rainfall season forecasts to make the forecast contain more information and hence more useful

REFERENCES

Basher R., Clark C, Dilley M, Harrison M: 2001. Coping with the climate: a way forward; summary and proposals for action a multi-stakeholder review of Regional Climate Outlook Forums concluded at an international workshop, October 16 – 20, 2000, Pretoria, South Africa. IRI

Berri, G. J., Antico P. L., and Goddard L., 2005: Evaluation of the Climate Outlook Forums' seasonal precipitation forecasts of Southeast South America during 1998-2002. Int. J. Climatol. 25, 365-377.

Bohn, L.E. 2002. 'Climatic variability in Malawi .' Economic and financial impacts of natural disasters: an assessment of their effects and options for mitigation: Malawi Country Study, Background Paper, 3. London: ODI.

Chidzambwa, S. and Mason, S. J. 2008. Report of the evaluation of Regional Climate Outlook Forecasts for Africa during the period 1997 to 2007. ACMAD Technical Report.

Clay E, Bohn L, Blanco E, Armas, Kabambe S and Tchale H. 2003. Malawi and Southern Africa climatic variability and economic performance, Disaster Risk Management Working Paper Series, No. 7

Climate Prediction Center Internet Team: *Historical El Nino/ La Nina episodes (1950-present)* http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml, NOAA Center for Weather and Climate Prediction. 24/07/2014

Epstein, E. S., 1969: A scoring system for probability forecasts of ranked categories. J. Appl. Meteor., 8, 985–987.

Fritsch, J. M., and Coauthors, 1998: Meeting summary: Quantitative precipitation forecasts: Report of the Eighth Prospectus Development Team. U.S. Weather Research Program. Bull. Amer. Meteor. Soc., 79, 285–299.

Hartmann H.C. Pagano T.C, Sorooshian S., and Bales R., 2002. confidence builders, evaluating seasonal climate forecasts from user perspectives. American Meteorological Society

Hess, U. and Syroka, J. 2005. Weather-based Insurance in Southern Africa: The Case of Malawi. Washington, D. C

Jolliffe I.T. and Stephenson D.B., Forecast Verification. 2003: a practitioner's guide in atmospheric science, John Wiley and Sons, Chichester

Mason, S. J., 2009: Recommended Procedures for the Verification of Operational Seasonal Climate Forecasts. WMO technical publication.

Meyers, G.A., P.C. McIntosh, L. Pigot and M.J. Pook, 2007: The years of El Niño, La Niña and interactions with the tropical Indian Ocean. J. Climate, **20,** 2872-2880.

Mkandawire, Esnat, Ann-Marie Brouder and M. Neil Ward. 1999. 'Climate information user needs assessment survey in Malawi.' Malawi environmental management project: long lead climate forecasting component. Government of Malawi, ministry of transport and public works, meteorological department.

Murphy, A. H., 1969: On the ranked probability skill score. J. Appl. Meteor.,

Murphy, A. H., 1971: A note on the ranked probability score. J. Appl. Meteor.,

Murphy, A. H., 1977: The value of climatological categorical and probabilistic forecasts in the cost–loss ratio situation. Mon. Wea. Rev., 105, 803–816.

Osgood, D. E., Suarez, P., Hansen, J. W., Carriquiry, M. and Mishra, A. (2008). Integrating seasonal forecasts and insurance for adaptation among subsistence farmers: the case of malawi. World Bank Policy Research Working Paper No. 4651. Washington, DC.

Weigel A.P, Liniger M.A., and Appenzeller C, 2006: Federal Office of Meteorology and Climatology (MeteoSwiss), Zurich, Switzerland. 135, Washington, D.C

Wilks, D. S., 1995: Statistical Methods in the Atmospheric Sciences. International Geophysics Series, Vol. 59, Academic Press,467 pp.

Wilks, D. S., 2000: Diagnostic verification of Climate Prediction Center long lead outlooks, 1995–1998. J. Climate 13, 2389–2403.

Wilks, D. S., and C. M. Godfrey, 2002: Diagnostic verification of the IRI Net Assessment forecasts, 1997–2000. J. Climate 15, 1369–1377.

World Bank. 1996. 'Drought in Malawi: from crisis response to strategic management.' Working Paper.

Zhang T. and Casey H 1999, Verification Of Categorical Probability Forecasts Bureau Of Meteorology Research Centre, Melbourne, Victoria, Australia