STUDY ON RAINFALL TIME SERIES IN MALAWI; AN ANALYSIS OF THE TEMPORAL AND SPATIAL FLUCTUATION, LINKAGE WITH GLOBAL SEA SURFACE TEMPERATURE

マラウィにおける降雨量時系列に関する研究.

時間的空間的変動、全球海水面温度とのリンクの解析

CHISOMO PATRICK KUMBUYO

THE UNITED GRADUATE SCHOOL OF AGRICULTURAL SCIENCES,

TOTTORI UNIVERSITY

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CHISOMO PATRICK KUMBUYO

(D12A4001K)

Submitted in partial fulfilment of the requirement for the award of the doctoral degree (PhD) in the Division of Global Arid Land Sciences of the United Graduate School of Agricultural Sciences, Tottori University, Japan

Major Supervisor:

Dr Hiroshi Yasuda

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Emeritus Professor Yoshinobu Kitamura

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Declaration

I, CHISOMO PATRICK KUMBUYO, do hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Chisomo Patrick Kumbuyo

The United Graduate School of Agricultural Sciences,

Tottori University, Japan

Dedication

This research work is dedicated to the memories of Joe and Siyileni Kumbuyo.

"Many that live deserve death. And some that die deserve life. Can you give it to them? Then do not be too eager to deal out death in judgement. For even the very wise cannot see all ends."

J.R.R. Tolkien, *The Fellowship of the Ring*

Abstract

Rainfall is one of the most complex and variable climatic elements, both temporally and spatially. Rainfall is important for groundwater recharge, affects availability of water resources, and is mostly used for agriculture purposes in most countries around the world. An understanding of the temporal and spatial characteristics of rainfall is central to water resources assessments, water resources planning and management, agricultural planning, flood frequency analysis, flood hazard mapping, hydrological modelling, climate change impacts and other environmental assessments.

The intensity, amount and pattern of rainfall are expected to change, consequently extreme weather events, such as droughts and floods, are likely to occur more frequently.

Malawi has an agro-based economy where 90% of the agriculture is predominantly rainfed. About 90% of the rural population in Malawi are dependent on agriculture and the sector contributes nearly 33% of the country's export earnings and offers about 75% of the country's employment. In rainfed agricultural systems such as these, erratic rainfall has significant impacts on households, their livelihoods and economies. The pattern and amount of rainfall are among the most important factors that affect agricultural production. The rainfall in Malawi varies both seasonally and interannually. The country has one of the most erratic rainfall patterns with rainfall varying significantly between locations and with rainfall being unreliable every year. Floods are a major occurrence in low lying areas in southern Malawi, particularly the Lower Shire valley and the lakeshore areas. Since the economy of Malawi is dependent on rainfed agriculture, major floods and droughts have an impact of the performance of the economy.

Undertaking to understand the rainfall characteristics is an important step in agricultural planning and ensuring the country's sustained economic development. The analysis of rainfall for agricultural purposes must include information concerning the trends or changes

of rainfall, the start, end and length of the rainy season, the distribution of rainfall amounts through the year, and the risk of dry and wet spells.

Most of the extreme events like floods and droughts have been linked to climatic events such as El Niño, La Nina and Sea Surface Temperatures (*SST*) in the global oceans. The relationship between southern Africa rainfall and *SST* in the global oceans has been widely studied.

Understanding the teleconnections between Malawi rainfall and global *SST* is of paramount importance. Malawi relies heavily on rainfed agriculture and rainfall determined the type of farming and crops that can be grown. Knowledge on the linkage between Malawi rainfall and *SST* is important as it can help in the forecasting of Malawi rainfall. Forecasting of rainfall can help farmers and policy makers in having an insight into how much rainfall can be received, provide early warning for droughts and floods, and plan for mitigation measures accordingly. This helps in agricultural planning and hence economic development of the country.

Monthly rainfall data for the period 1980 to 2011 of nine rainfall stations in Malawi obtained from the Department of Climate Change and Meteorological Services (DoCCMS) were used in the study. The rainfall data were quality checked with respect to the World Meteorological Organization (WMO) standards to ensure that they were stationary, consistent, and homogeneous. *SST* data for the period 1975–2012 were obtained from the British Atmospheric Data Centre (BADC) and National Oceanic and Atmospheric Administration (NOAA).

Firstly a study on the interannual fluctuation of rainfall time series in Malawi was carried out using a 31 year time series from selected rain gauge stations with the aim of analyzing the spatial and temporal characteristics of rainfall in Malawi. Rainfall seasonality was assessed using the Seasonal Index (*SI*) while the seasonality of rainfall regime and heterogeneity of rainfall amounts was evaluated by using the Precipitation Concentration Index (*PCI*). Spectral analysis was carried out to evaluate the periodicity of the rainfall time series using the Maximum Entropy Method *(MEM)*. The study found strong interannual fluctuation of rainfall, with topography and location playing major roles in the annual rainfall distribution. The *SI* and *PCI* showed that rainfall is highly seasonal and highly concentrated with most stations receiving rainfall in three months, except for Nkhatabay which has seasonal rainfall. The interannual rainfall distribution was highly variable in time and space. Cross correlations among the stations and monthly rainfall distribution indicated two distinct zones, Zone 1 composed of Karonga and Nkhatabay in the north and Zone 2 composed of Bolero (in the north), Kasungu, Salima and Dedza (in the central region), Mangochi, Makoka and Ngabu (in the south). Spectral analysis of the rainfall time series revealed cycles at five to eight years, suggesting links with the El Niño Southern Oscillation (*ENSO)* and double the period of the Quasi Biennial Oscillation (*QBO*). Apart from the common cycles, the rainfall time series of the two zones showed periods of 10.06 and 13.64 years, respectively, which suggests links with the solar cycle. These cycles are consistent with those found in other Southern Africa (*SA*) countries.

Correlation between rainfall in Malawi and Global Sea Surface Temperature (*GSST*) were studied to elucidate the linkage between *SST* and rainfall. The study used *SST*s for the period 1979–2011 and rainfall data for 1981–2012 from nine stations, which were grouped into two zones on the basis of inter-station rainfall correlations. The Pearson correlation coefficient was used to test the hypothesis that the main influence on summer rainfall in Malawi was the Indian Ocean *SST* rather than the Pacific or Atlantic Ocean *SST*. The study found that summer rainfall was more strongly correlated with the Indian Ocean *SST* compared to the Atlantic and Pacific Ocean *SSTs*. The correlations were more significant for the Zone 1, northern stations than the Zone 2, central and southern stations. These results agree with other findings, the suggestion being that different climatic drivers influence the climate of different parts of Malawi. Northern areas are strongly influenced by the *SST* Indian Ocean dipole, whereas central and southern areas are strongly linked to the *SST* in the subtropical Indian Ocean. The results reveal that *SST* in the Atlantic Ocean off South Africa also affects Malawi rainfall. We conclude that the Indian Ocean *SST*, including in particular the *SST* dipole strongly influences the rainfall in Malawi.

Prediction of Malawi rainfall from global *SST* using a simple multiple regression model was studied. Links between Malawi rainfall and *SST* based on statistical correlations were evaluated and selected as predictors for the model. Monthly rainfall data from nine stations in Malawi grouped into two zones on the basis of inter-station rainfall correlations were used in the study. The predictors for Zone 1 model were identified from the Atlantic, Indian and Pacific oceans while those for Zone 2 were identified from the Indian and Pacific Oceans. The correlation between the fit of predicted and observed rainfall values of the models were satisfactory with r = 0.81 and 0.54 for Zones 1 and 2 respectively (significant at less than 0.01). The results of the models are in agreement with other findings that suggest that *SST* anomalies in the Atlantic, Indian and Pacific oceans have an influence on the rainfall patterns of Southern Africa. We conclude that *SST* in the Atlantic, Indian and Pacific Oceans is correlated with Malawi rainfall and can be used to predict rainfall values.

Overall the study has revealed that rainfall in Malawi is strongly affected by El Niño and La Niña events in the equatorial Pacific Ocean. Sea surface Temperature in the Indian and Pacific Oceans also significantly influence the rainfall season in Malawi. The study revealed that *SST* can be successfully used to predict the rainfall in Malawi.

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First and foremost, I would like to extend my sincere gratitude to Professor Yoshinobu Kitamura, for accepting to host me in his laboratory after I was given a scholarship to pursue my Masters degree which led to this journey. I would like to also recognize his contribution in way of supervision during the period of my Doctorate degree studies. Your input shaped the outcome of this research. I am greatly indebted to Associate Professor Dr Hiroshi Yasuda, my main supervisor for his tireless efforts, support and guidance during the entire research period. The confidence that you showed in me and my abilities, inspired, and motivated me greatly to work hard even during hard times. I also sincerely thank Dr Katsuyuki Shimizu, Professor Yasuomi Ibaraki of Yamaguchi University and Professor Tsugiyuki Masunaga of Shimane University for their contribution to this work. Members of the Water Use and Management Laboratory from 2010 to 2015 are also recognized for helping me in the course of my study and stay in Tottori, Japan. I would also like to thank Dr Cosmo Ngongondo of Chancellor College, Malawi for providing some of the rainfall data that was used in the study. The British Atmospheric Data Center (BADC) is also acknowledged for providing some of the rainfall data used in the study. The National Oceanic and Atmospheric Administration (NOAA), National Weather Service Climate Prediction Center is also acknowledged for providing Sea Surface Temperature (*SST*), Southern Oscillation Index (*SOI*) and North Atlantic Oscillation data.

The Government of Japan through the Ministry of Education, Culture, Sports, Science and Technology (Monbukagakusho) is greatly acknowledged for the financial assistance through the Monbukagakusho Scholarship which financed my studies. My sincere thanks also goes to the Government of Malawi through the Department of Irrigation Services for allowing me to take a study leave and further my education and the support rendered to me while on training.

Last, but not least, I would like to thank my wife Yvonne and son, Colin who have been with me throughout the period of my study. I know that you guys have endured some lonely days when I seemed to focus all my energy on my studies. I acknowledge your enduring spirit and may God bless you abundantly. To my mother, Hilda Kumbuyo, thank you for your unwavering and untiring support during the course of my education. You have made great sacrifices in your life to make sure that I am where I am now. Your prayers were of great help in the course of my studies. I pray that God bless you abundantly. My brothers and sisters also are acknowledged for their moral and spiritual support.

CHISOMO PATRICK KUMBUYO

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List of Abbreviations

AIC	Akaike Information Criterion (*AIC*)
AGCM	Atmospheric General Circulation Models
BADC	British Atmospheric Data Center
CRU	Climate Research Unit
CV	Coefficient of variation
CAB	Congo Air Boundary
DJF	December, January, February
DoCCMS	Department of Climate Change and Meteorological Services
PhD	Doctor of Philosophy
ENSO	El Niño Southern Oscillation
FMA	February, March, April
GDP	Gross Domestic Product
GSST	Global Sea Surface Temperature
IFPRI	International Food Policy Research Institute
IPCC	InterGovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
MEM	Maximum Entropy Method
MR_{Z1}	Malawi Rainfall for Zone 1
MR_{Z2}	Malawi Rainfall for Zone 2
NDJ	November, December, January
NOAA	National Oceanic and Atmospheric Administration
PCI	Precipitation Concentration Index
QBO	Quasi Biennial Oscillation

r	Correlation Coefficient
RMSE	Root Mean Square Error
SA	Southern Africa
SST	Sea surface temperature
SI	Seasonal Index
SADC	Southern Africa Development Community
SARCOF	Southern Africa Regional Climate Outlook Forum
SOI	Southern Oscillation Index
TS	Time Series
WMO	World Meteorological Organization
WB	World Bank

Chapter 1 General Overview

1.1 General Introduction

Rainfall is one of the most complex and variable climatic elements, both temporally and spatially. Rainfall is important for groundwater recharge, affects availability of water resources, and is mostly used for agriculture purposes in most countries around the world. Rainfall is an important climatic variable that underlies both droughts and floods (Coscarelli and Caloiero, 2012). An understanding of the temporal and spatial characteristics of rainfall is central to water resources assessments, water resources planning and management, agricultural planning, flood frequency analysis, flood hazard mapping, hydrological modelling, climate change impacts and other environmental assessments (Michaelides *et al.*, 2009).

Many studies on the temporal and spatial characteristics of rainfall around the world have been conducted and the literature in readily available (Zhang *et al.*, 2008,; Turks, 1996; De Luís *et al.*, 2000; Gonzalez-Hildago *et al.*, 2001; Cannarozzo *et al.*, 2006; Chu *et al.*, 2010).

The intensity, amount and pattern of rainfall are expected to change, consequently extreme weather events, such as droughts and floods, are likely to occur more frequently. The forth Intergovernmental Panel on Climate Change (IPCC, 2007) report confirmed an increase in rainfall for the period 1900–2005, north of 30^{o}latitude, due to global warming (IPCC, 2007). It also confirmed a decrease in the rainfall from 1970 in tropical areas and an increase in land affected by drought in tropical and subtropical areas from the 1970s (IPCC, 2007). Fauchereau *et al.* (2003) reported that rainfall variability in Southern Africa (SA) has experienced significant modulations, especially in recent decades. In particular, droughts have become more intense and widespread. New *et al.* (2006) reported a decrease in average rainfall intensity and an increase in dry-spell length from 1961 to 2000. In addition, the IPCC reported an increasing trend in rainfall amount from 1901 to 2005 from the equator to tropical eastern Africa but a declining trend south of 20ºS on the African continent. The study reports that dry periods in SA have become longer and more intense. If these phenomena are occurring as suggested, then the rainfall amount and intensity in the wet season may have increasing trends (Morishima and Akasaki, 2010).

A positive correlation between rainfall in Malawi and Ethiopia was reported by Nkhokwe (1996) who also found associations with the Southern Oscillation Index (*SOI*) and stratospheric *QBO*. Naujokat (1986) reported that a change in the zonal wind in the equatorial stratosphere from easterly to westerly with a period of about 28 months affects Malawi rainfall.

The climate of SA is influenced by the position of the subcontinent in relation to the major circulation features of the atmosphere of the southern hemisphere (Torrance, 1972). SA is under the influence of a sub-tropical anticyclone throughout the year and experiences a unimodal rainy season from October to April and the distribution of rainfall is erratic both temporally and spatially (Mwafulirwa, 1999). According to Lindesay and Harrison (1986), the Intertropical Convergence Zone (*ITCZ*), Southern Oscillation, El Niño Southern Oscillation (*ENSO*), Sea Surface Temperature (*SST*) and Walker Circulation strongly influence rainfall variability over SA. Generally, rainfall is below normal over SA during El Niño years and above normal during La Niña years (Nicholson and Entekhabi, 1986; Lindesay, 1988).

Malawi has an agro-based economy where 90% of the agriculture is predominantly rainfed. About 90% of the rural population in Malawi are dependent on agriculture and the sector contributes nearly 33% of the country's export earnings and offers about 75% of the country's employment. In rainfed agricultural systems such as these, erratic rainfall has significant impacts on households, their livelihoods and economies. The pattern and amount of rainfall are among the most important factors that affect agricultural production. The climate of Malawi is highly variable and has a significant influence on the amount, timing, and frequency of rainfall events and runoff patterns, which results in frequent recurrent droughts and floods (World Bank, 2009). The rainfall in Malawi varies both seasonally and interannually. The country has one of the most erratic rainfall patterns with rainfall varying significantly between locations and with rainfall being unreliable every year as evidenced by the fact that between 1967 and 2003, the country has experienced about six major droughts. Floods are a major occurrence in low lying areas in southern Malawi, particularly the Lower Shire valley and the lakeshore areas of Lake Malawi. Since the economy of Malawi is dependent on rainfed agriculture, major floods and droughts have an impact of the performance of the economy. Droughts and floods on average in Malawi together reduce the total Gross Domestic Product (GDP) by about 1.7% per year (IFPRI, 2010). Damages, however, vary considerably across weather events with total GDP declining by at least 9% during a severe 1-in-20 year drought. The expectation of variability and the unpredictability of rainfall and runoff constrain opportunities for growth by encouraging risk averse behaviour and discouraging investments in land improvements, advanced technologies, and agricultural inputs. An unreliable water supply due to hydrological variability is a significant disincentive to investments in industry and services, slowing the diversification of economic activities.

Undertaking to understand the rainfall characteristics is an important step in agricultural planning and ensuring the country's sustained economic development. The analysis of rainfall for agricultural purposes must include information concerning the trends or changes of rainfall, the start, end and length of the rainy season, the distribution of rainfall amounts through the year, and the risk of dry and wet spells. Studies of rainfall change are typically complicated by factors such as missing values, seasonal and other short-term fluctuations and by lack of homogeneity of the data (Ngongondo *et al.*, 2011). Studies on characteristics of rainfall in Malawi are limited. Some of the documented studies on Malawi's rainfall characteristics were carried out by Jury and Mwafulirwa (2002), Jury and Gwazantini (2002), Johnson *et al.* (2001), .Ngongondo (2006), Mbano *et al.* (2008) and Tadross *et al.* (2007). Munthali and Ogallo (1986) analyzed Malawi annual rainfall time series from selected locations and observed 17 major negative rainfall anomalies. Kamdonyo (1993) using percentiles characterized two droughts in Malawi. A normalized annual rainfall departure for the period 1922–1992 for seven locations showed negative departures with two of them in 1948/49 and 1991/92 standing out. These two droughts had a 30% departure from the normal and are some of the most severe experienced in Malawi. These droughts had negative impacts on agriculture, livestock, wildlife, tourism, water resources and hydroelectric power generation. The impact on the country's economy cannot be overemphasised.

Most of the extreme events like floods and droughts have been linked to climatic events such as El Niño, La Niña and Sea Surface Temperatures (*SST*) in the global oceans. The droughts of 1953/54, 1972/73, 1991/92 seasons among others were as a result of El Niño while the droughts of 1958/59, 1959/60 and 1967/68 seasons occurred when the *SST* in the eastern central equatorial Pacific Ocean were neutral. Rocha and Simmonds (1997a) found that rainfall tends to increase by about 10–25 percent around equatorial eastern Africa and lower in southeast Africa during warm El Niño Southern Oscillation (*ENSO*) events. Latif *et al.* (1999) showed that wet anomalies over eastern Africa of December to February 1997/98, which was a strong El Niño year, were a result of contemporaneous warm *SST*s over the Indian Ocean. Helpert and Ropelewski (1992) reported that good summer rainfall for SA (La Niña), which includes Malawi, are experienced when below normal surface temperatures occur from June to August while above normal temperature during the same period proceed El Niño years.

The relationship between SA rainfall and *SST* in the global oceans has been widely studied.

Nicholson and Entekhabi (1987), Ogallo (1987), Nyenzi (1988) and Walker (1989) are some of the notable researchers that have undertaken these studies. Walker (1989) reported that the rainfall in South Africa is enhanced when *SST* in the subtropical belt of eastern Agulhas current before La Niña years is above normal. Mason (1992) reported that rainfall in South Africa is strongly influenced by *SST* in the central South Atlantic Ocean, south Atlantic subtropical convergence region and western equatorial Indian Ocean. A correlation between central Indian Ocean *SST* and SA rainfall was reported by Pathack (1993). The correlations were as high as -0.6 at 3 and 6 months lag time. Nicholson and Entekhabi (1987) found that enhanced rainfall over East Africa is associated with a warm central Indian Ocean. Jury and Mwafulirwa (2002) reported a positive correlation between *SST* southeast of Madagascar in Indian Ocean and tropical Atlantic Ocean and Malawi rainfall is associated with above normal rainfall. Negative correlations were reported in the West Indian Ocean. The correlations were at 3 and 6 months lag time.

Folland *et al.* (1986) found a strong statistical relationship between seasonal rainfall in the Sahel and global *SST* but argued that the discovery of relationships between *SST* and African rainfall should not preclude the importance of local effects from the earth's surface on the seasonal time scale. Walker (1989) reported that South African plateau rainfall is enhanced when *SST* in the subtropical belt of the eastern Agulhas current is above normal during and prior to La Niña years. It was observed that in normal years significant correlation is found between rainfall with Benguela and Agulhas *SST*. Decreasing *SST* in central south Atlantic and increasing *SST* off the coast of southwestern African can lead to a demonstrable increase in daily rainfall and rainfall extremes over SA (Williams *et al.*, 2008). According to Misra (2003), patterns of regional linkage between dominant mode of SA precipitation variability and *SST* anomalies over eastern Indian Ocean is influenced by variations of Pacific Ocean *SST*. The nature of the linkage between SA precipitation and eastern Indian Ocean *SST* is apparent only when the Pacific Ocean *SST* variability is excluded. Other researchers who have done work on the influence of *SST* on SA rainfall include Mason and Tyson (1992), Enfield and Mayer (1997).

Mason (1992) performed correlation analysis on rainfall and *SST* with easterly (westerly) Quasi Biennual Oscillation (*QBO*) and found that the Ocean region associated with greatest rainfall response was south east of SA in the Indian Ocean (*QBO* easterly), followed by south Atlantic Subtropical Convergence region with westerly *QBO* and lastly Benguela system (South East Tropical Atlantic) with westerly *QBO*. According to Jury and Pathack (1991) the correlation between *SST*s and convection (Outgoing Longwave Radiation) shows that a warming of waters within the cyclogenesis region northeast of Madagascar triggers decreased rainfall in Southeast Africa. According to Jury *et al.* (1991), the increased low level westerly anomalies off the northern tip of Madagascar reduces the inflow of moisture and subsequently limits rainfall over SA. Likewise low-level easterly anomalies south of Madagascar in the region 25–35°S and 40–55°E, result in cyclonic circulation centered over Madagascar in dry summers and oppose convective outflows. Strong convective activity across equatorial eastern Africa, northeast Madagascar and the Southwest Indian Ocean matches with below normal convective activity across SA. Other researchers that have done work on how variability of African rainfall is related to *SST* over the Atlantic, Indian and Pacific Oceans are: Hirst and Hastenrath (1983), Nicholson and Entekhabi (1987) and Nyenzi (1988).

The literature on linkage between *SST* and summer rainfall in Malawi is sparse. Notable previous studies have been in the area of climate variability and have included Ngongondo *et al.* (2011), Jury and Nkosi (2000), Mason (1997) and Nkhokwe (1996).

Nicholson and Entekhabi (1997) reported that an enhanced rainfall over East Africa was linked with a warm central Indian Ocean and that there were weak correlations with *SOI* and *QBO*. Jury and Mwafulirwa (2002) found negative correlations between dry summers and *SST*s in the West Indian Ocean and positive correlations between dry summers and *SST*s in the East Atlantic and Agulhas region. They reported an apparent north–south gradient of *SST* in the subtropical West Indian Ocean.

Understanding the teleconnections between Malawi rainfall and global *SST* is of paramount importance. Malawi relies heavily on rainfed agriculture and rainfall determined the type of farming and crops that can be grown. Knowledge on the linkage between Malawi rainfall and *SST* is important as it can help in the forecasting of Malawi rainfall. Forecasting of rainfall can help farmers and policy makers in having an insight into how much rainfall can be received, provide early warning for droughts and floods, and plan for mitigation measures accordingly. This helps in agricultural planning and hence economic development of the country.

Jury and Mwafulirwa (2002) using the stepwise multivariate linear regression approach forecasted Malawi rainfall using a three-predictor model. The model predictors were three area *SST* index, air pressure over the East Indian Ocean and stratospheric zonal wind anomaly. Long term forecasting of rainfall in Malawi remains a challenge due to a lack of technical, human and financial resources among other factors. Some of the problems associated with rainfall forecasting in Malawi are;

- Spatial scale of the forecast is not detailed enough
- The level of detail about the distribution of rainfall within the wet season is inadequate. Most forecasts produce information about the distribution of rainfall for over a period of 3 months.
- Inadequate information about the start and end of the rain season
- Poor reliability of the forecasts
- Lack of forecast verification

Malawi relies on the Southern Africa Regional Climate Outlook Forum (SARCOF), a regional grouping of Southern Africa Development Community (SADC) member states which develops consensus probabilistic seasonal rainfall forecasts for the Southern Africa region. The forecast is based on dynamic and statistical models that use scientifically established relationships between rainfall over southern Africa and *SST*. Malawi therefore needs to enhance its technical capacity to forecast rainfall at the local level.

1.2 Research Area

Malawi, which is located in SA (Figure 1.1) is a land-locked country located between latitudes 9 and 17°S and longitudes 32 and 36°E. With a total area of 118,480 km^2, the country varies in altitude from near sea level to more than 2,000 m above mean sea level. Water bodies dominated by Lake Malawi occupy 20 percent of the total area. The country is also part of the Great Rift Valley. Lake Malawi has a surface area of around 28,760 km^2 and has a big influence on the country's water balance. Mean annual rainfall over the lake is estimated at 1,549 mm. The total inflow into the Lake is calculated at 920 m^3/s, of which 400 m^3/s is from within Malawi, 486 m^3/s from Tanzania and 413 m^3/s from Mozambique. Shire River is the only outlet from the Lake and has an average annual outflow of 395 m^3/s. Lake Malawi has a mean lake level of 474.4 m above sea level (Kaluwa *et al.*, 1997).

Malawi has a sub-tropical climate, which is relatively dry and strongly seasonal. From November to April the country experiences the warm-wet season during which 95% of the annual rainfall takes place. Mean annual rainfall range from 725mm to 2,500mm. The Intertropical Convergence Zone (*ITCZ*), Congo Air Boundary (CAB), Semi permanent anti-cyclones, tropical cyclones and easterly waves are the main rain bearing systems that dominate over the country. The teleconnection link amongst upper air flow, low pressure cell over Botswana, southeast trades, northeast monsoons and mid latitude pressure system influences rainfall distribution in space and time. The climate of Malawi is highly variable which results in a significant influence on the amount, timing, and frequency of rainfall events. The rainfall in Malawi varies considerably both seasonally and interannually resulting in drought and floods. Notable droughts include those that occurred in 1948/49, 67/68, 72/73, 82/83, 91/92 seasons amongst others. Floods occur persistently in southern Malawi particularly in low lying areas and lake shore areas of Lake Malawi. A cool, dry winter season is evident from May to August with mean day temperatures varying between 17 and

27 degrees Celsius and night 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.

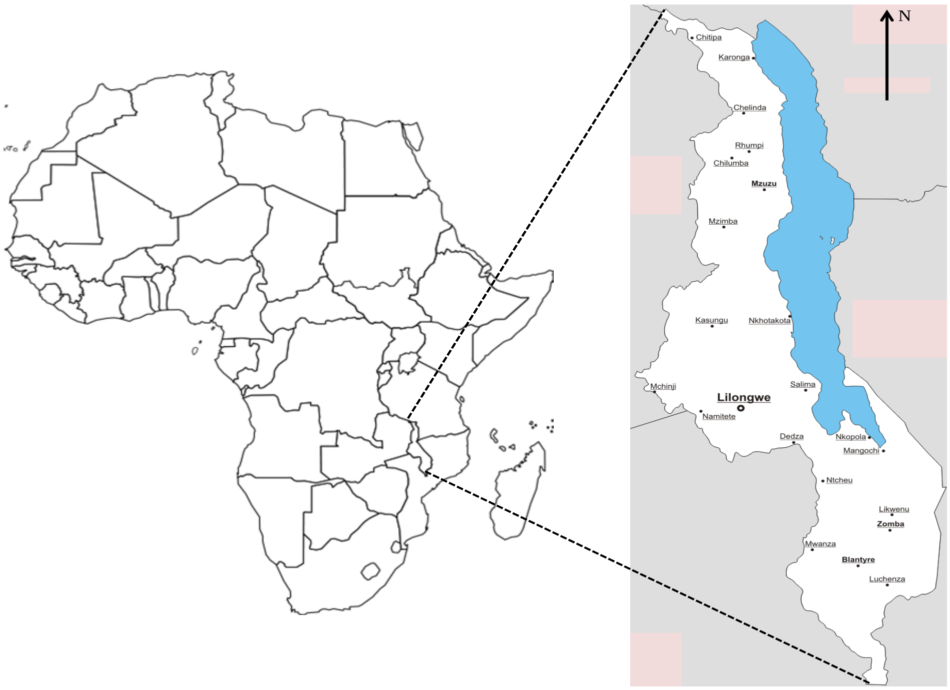


Figure 1.1 Map of Africa showing the location of Malawi (left) and Map of Malawi showing location of some cities and towns (right)

1.3 Data and Sources

Monthly rainfall data for the period 1980 to 2011 of nine rainfall stations (Figure 1.2) in Malawi obtained from the Department of Climate Change and Meteorological Services were used in the study. The stations used in the study were Karonga, Nkhatabay, Salima and Mangochi along the shores of Lake Malawi, Bolero in the northern highlands; Kasungu in the central plains; Dedza in the central highlands near Lake Malawi and Ngabu located in Lower Shire River valley which has a high risk of flooding most of the time.

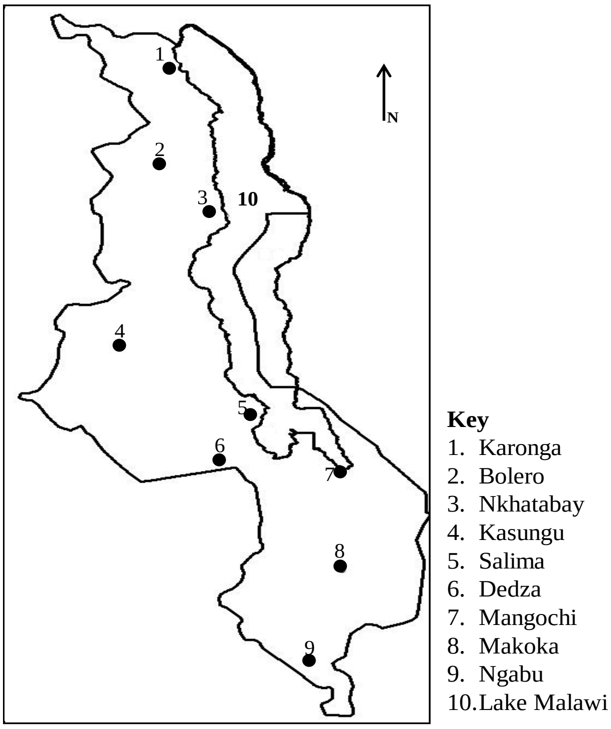


Figure 1.2 Map of Malawi showing location of study areas

The rainfall data were quality checked with respect to the World Meteorological Organization (WMO) standards to ensure that they were stationary, consistent, and homogeneous. The nine rainfall stations were later zoned into two on the basis of inter-station rainfall correlations.

Table 1.1 Rain gauge stations used in the study.

Station No.	Station Name	Zone	Latitude (°S)	Longitude (°E)	Altitude (m)	Mean annual rainfall (mm)	*CV*
1	Karonga	1	9.88	33.95	529	942	0.23
2	Bolero	2	11.02	33.78	1,100	626	0.22
3	Nkhatabay	1	11.60	34.30	500	1,570	0.21
4	Kasungu	2	13.03	33.46	1,036	784	0.22
5	Salima	2	13.75	34.58	512	1,207	0.26
6	Dedza	2	14.32	34.27	1,632	947	0.16
7	Mangochi	2	14.43	35.25	482	805	0.31
8	Makoka	2	15.52	35.22	1,029	1,003	0.21
9	Ngabu	2	16.50	34.95	102	826	0.29

Nkhatabay station has the highest mean monthly rainfall of 1,570 mm experienced in March with a *CV* of 0.21. Bolero, with a mean monthly rainfall of 626 mm and *CV* of 0.22, experiences the lowest rainfall among the stations.

SST data for the period 1975–2012 were obtained from the British Atmospheric Data Center (BADC). The BADC HadISST 1.1 dataset (http://badc.nerc.ac.uk/view/badc.nerc.ac.uk_ATOM_dataent_hadisst), which consists of global sea-ice coverage and *SST* data was used. HadISST 1.1 contains global 1° × 1° grids of monthly mean *SST*, which are updated monthly.

1.4 General Research Objectives

The economy of Malawi is strongly dependent on rainfall and agriculture accounts for about one-third of Malawi's GDP. Failure of rainfall in a season or year has adverse agricultural and economic effect. Major floods and droughts have a significant impact on national economic performance. The GDP and in growth rates of agricultural and non-agricultural sector products are sensitive to water shocks. Additionally, predictability of rainfall helps farmers in agricultural planning and deciding which cropping systems to pursue. The objectives of this study are;

i. Analyze the fluctuation in space and time of rainfall time series at 9 stations in Malawi through understanding the rainfall variability and factors that affect the variability. The understanding of the periodical fluctuation is significant in Malawi because being an agro-based economy rainfall is an important aspect in economic development. Increased trend in rainfall may trigger floods and erosion of top soil while on the other hand increased rainfall means increased water available for irrigation purposes.

ii. Investigate the linkage between Malawi rainfall and global *SST*. This will help in understanding of the precursors of rainfall in Malawi and help in forecasting of rainfall.

iii. Develop rainfall forecasting models using simple multiple regression models that can be used to predict rainfall in Malawi. The models will be developed by looking at the relationship between Malawi rainfall and *SST* in the global oceans and use these as predictors in the models.

1.5 Methodology

This study used secondary data in conducting the analysis. Rainfall data were from the Department of Climate Change and Meteorological Services (DoCCMS) and grid rainfall data from the British Atmospheric Data Center (BADC). The monthly data were quality checked to make sure they were consistent, homogenous and stationary.

SST data were obtained from the BADC. The BADCs HadI*SST* 1.1 dataset (available from http:// badc.nerc.ac.uk/view/badc.nerc.ac.uk_ATOM_dataent_hadisst), which consists of global sea-ice coverage and *SST* data was used. The Seasonal Index (*SI*) was used to assess the aspect of rainfall seasonality while the Rainfall Concentration Index (*PCI*) was used to evaluate the seasonality of rainfall regime and heterogeneity of rainfall amounts. To evaluate the periodicity of the rainfall time series, spectral analysis was used.

Spectral analysis was applied to the annual time series of rainfall. The method used was the Maximum Entropy Method (*MEM*) which presents higher resolution of power spectrum and is based on the principle of entropy maximization. The Akaike Information Criterion (*AIC*) was used to optimize the obtained frequencies.

The Pearson correlation coefficients between rainfall and monthly *SST* were computed to gauge the statistical relationship between rainfall and *SST* and the student t test was used to evaluate the significance of the correlations. The Surfer Golden software was used to produce the correlation maps between *SST* and rainfall. The multiple regression was used to model rainfall. The step-wise multiple regression method was used within the *R* software package (available from http://cran.r-project.org). Malawi rainfall was the target objective and *SST* was used as the predictor. The models were validated using the correlation coefficient (*r*), bias (*BIAS*) and *RMSE* between observed and predicted summer rainfall.

1.6 Thesis Organization

The organization of this thesis takes into consideration the studies that have been undertaken during the three year course of the Doctor of Philosophy (PhD) research program at the United Graduate School of Agricultural Sciences, Tottori University in Japan from April 2012 to March 2015. The studies have been arranged in three main chapters.

Chapter 1 gives an overview of the whole research in terms of the introduction to the different studies, the reasons behind undertaking of the studies, the methodology used and the area where the studies were conducted.

In Chapter 2, results on a study on the interannual fluctuation of rainfall time series in Malawi are presented. The study was conducted using a 31 year time series from selected rain gauge stations with the aim of analyzing the spatial and temporal characteristics of rainfall in Malawi. The study found strong interannual fluctuation of rainfall, with topography and location playing major roles in the annual rainfall distribution. The seasonal index and precipitation concentration index showed that rainfall is highly seasonal and highly concentrated with most stations receiving rainfall in three months, except for Nkhatabay which has seasonal rainfall. The interannual rainfall distribution was highly variable in time and space. Cross correlations among the stations and monthly rainfall distribution indicated two distinct zones, Zone 1 composed of Karonga and Nkhatabay in the north and Zone 2 composed of Bolero (in the north), Kasungu, Salima and Dedza (in the central region), Mangochi, Makoka and Ngabu (in the south). Spectral analysis of the rainfall time series revealed cycles at five to eight years, suggesting links with the *ENSO* and double the period of the Quasi Biennial Oscillation (*QBO*). Apart from the common cycles, the rainfall time series of the two zones showed periods of 10.06 and 13.64 years, respectively, which suggests links with the solar cycle. These cycles are consistent with those found in other southern Africa countries.

In Chapter 3 Correlation between rainfall in Malawi and global sea surface temperature (G*SST*) were studied to elucidate the linkage between *SST* and rainfall. The study used *SST*s for the period 1979–2011 and rainfall data for 1981–2012 from nine stations, which were grouped into two zones on the basis of inter-station rainfall correlations. The Pearson correlation coefficient was used to test the hypothesis that the main influence on rainfall in Malawi was the Indian Ocean *SST* rather than the Pacific or Atlantic *SST*. We found that summer rainfall was more strongly correlated with the Indian Ocean *SST* compared to the Atlantic and Pacific Ocean *SST*s. The correlations were more significant for the Zone 1, northern stations than the zone 2, central and southern stations. These results agree with other findings, the suggestion being that different climatic drivers influence the climate of different parts of Malawi. We conclude that the Indian Ocean *SST*, including in particular the *SST* dipole strongly influences the rainfall in Malawi.

In chapter 4, this study deals with a way of predicting Malawi rainfall from G*SST* using a simple multiple regression model. Links between Malawi rainfall and *SST* based on statistical correlations were evaluated and selected as predictors for the model. The predictors for Zone 1 model were identified from the Atlantic, Indian and Pacific oceans while those for Zone 2 were identified from the Indian and Pacific Oceans. The correlation between the fit of predicted and observed rainfall values of the models were satisfactory and significant at less than 0.01. The results of the models are in agreement with other findings that suggest that *SST* anomalies in the Atlantic, Indian and Pacific oceans have an influence on the rainfall patterns of Southern Africa. We conclude that *SST* in the Atlantic, Indian and Pacific Oceans is correlated with Malawi rainfall and can be used to predict rainfall values.

Chapter 5 presents the overall summary and significant findings of each study and the general conclusions of the thesis.

Chapter 2 Fluctuation of Rainfall Time Series in Malawi: An Analysis of Selected Areas

2.1 Introduction

An aspect of climate change that requires thorough investigation is the time distribution of rainfall and its historical changes. Rainfall is an important climatic variable that underlies both droughts and floods (Coscarelli and Caloiero, 2012). An understanding of the temporal and spatial characteristics of rainfall is central to water resources assessments, water resources planning and management, agricultural planning, flood frequency analysis, flood hazard mapping, hydrological modelling, climate change impacts and other environmental assessments (Michaelides *et al.*, 2009).

Many studies of the temporal and spatial characteristics of rainfall have been conducted around the world and in Malawi as well. A positive correlation between rainfall in Malawi and Ethiopia was reported by Nkhokwe (1996) who also found associations with the *SOI* and stratospheric *QBO*. Naujokat (1986) reported that a change in the zonal wind in the equatorial stratosphere from easterly to westerly with a period of about 28 months affects Malawi rainfall.

The objective of this study was to conduct an analysis of the fluctuations in space and time of rainfall time series from nine stations in Malawi over a 31 year period.

2.2 Data Processing and Quality Control

The monthly data were screened to make sure they were consistent, homogenous and stationary. Spearman rank correlation was used to test for the absence of trends; F test for stability of variance was used to test for stability of variance and mean and serial correlation coefficient was used to test for absence of persistence (Dahmen and Hall, 1990). Mean monthly and annual values were calculated with the corresponding coefficient of variation.

2.2.1 Test of homogeneity

Buishand (1982) analyzed some methods for testing the homogeneity of rainfall records. The methods that were analyzed are; the Von Neumann ratio test, cumulative deviations, Worsely's likelihood ratio test and Bayesian procedures. Other methods that are used in testing homogeneity of rainfall data are; Kohlers double mass analysis, the standard normal homogenization test and the residual test by the WMO. In this study the Von Neumann ratio was used owing to its simplicity and ease of interpretation.

Given a rainfall time series data set n, with values from Y_i, Y_{i+1}……Y_n, the Von Neumann ratio is defined by:

$$N = \frac{\sum_{i=1}^{n-1}(Y_i - Y_{i+1})^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} \qquad (2.1)$$

In which N is the Von Neumann ratio, Y stands for the values in data set n and $\overline{Y}$ is average of the data set values Y.

Under the null hypothesis of a constant mean, it can be shown that E (N) =2. For a non homogeneous record the mean of N tends to be smaller than 2 (Buishand, 1982).

2.2.2 Test of absence of trend

According to Dahmen and Hall (1990), after plotting the time series, there is need to ensure that there is no correlation between the order in which the data was collected and increase (or decrease) in magnitude of those data. It is therefore important to test the whole series for absence of trends. The Spearman rank correlation which is a simple and distribution free method was used. The method is based on the Spearman rank correlation coefficient, R_{sp}, which is defined as;

$$R_{sp} = 1 - \frac{6 \times \sum_{i=1}^{n} (D_i \times D_i)}{n \times (n \times n - 1)} \tag{2.2}$$

where n is the total number of data, D is difference, and i is the chronological order number. The difference between rankings is computed with;

$$D_i = Kx_i - Ky_i \tag{2.3}$$

where Kx_i is the rank of the variable, x, which is the chronological order number of the observations. The series of observations, y_i, is transformed to its rank equivalent, Ky_i, by assigning the chronological order number of an observation in the original series to the corresponding order number in the ranked series, y. The null hypothesis that $R_{sp} = 0$ (there is no trend) is tested against the alternate hypothesis that $R_{sp} < > 0$ (there is a trend), with the test statistic;

$$t_t = R_{sp} \sqrt{\left[\frac{n-2}{1 - R_{sp} \times R_{sp}}\right]} \tag{2.4}$$

where t_t has students t distribution with $v = n - 2$ degrees of freedom. At a significance level of 5 percent (two tailed), the two sided critical region, U, of t_t is bounded by;

$$\{-\infty, t\{v, 2.5\%\}\} U \{t\{v, 97.5\%\}, +\infty\} \tag{2.5}$$

and the null hypothesis is accepted if t_t is not contained in the critical region. In other words, the time series has no trend if;

$$t\{v, 2.5\%\} < t_t < t\{v, 97.5\%\} \tag{2.6}$$

If the time series has a trend, the data cannot be used for frequency analyses or modelling.

In addition to testing the time series for absence of trend, the *F* test for stability of variance and the *t* test for the stability of mean to split, non–overlapping, sub sets of the time series were applied. This is done because if the variance is unstable, it implies that the time series is not stationary and not suitable for use. Secondly, the test for stability of mean is much simpler if one can use a pooled estimate of the variances of the two subsets (Dahmen and Hall, 1990). The distribution of the variance ratio of samples from a normal distribution is known as the F or Fisher distribution. Even if samples are not from a normal distribution, the *F* test will give an acceptable indication of stability of variance (Dahmen and Hall, 1990). Thus the test statistic reads;

$$F_t = \frac{S_1^2}{S_2^2} \qquad (2.7)$$

where S^2 is variance. The null hypothesis for the test, $H_0{:}S_1^2 = S_2^2$, is the equality of the variances, the alternative hypothesis is $H_1{:}S_1^2 <> S_2^2$. The rejection region is bounded by:

$$\{0, F\{v_1, v_2, 2.5\%\}\} \cup \{F\{v_1, v_2, 97.5\%\}, +\infty\} \qquad (2.8)$$

where $v_1=n_1-1$ is the number of degrees of freedom for the numerator, $v_2=n_2-1$ is the number of degrees of freedom for the denominator, and n_1 and n_2 are the number of data in each subset. This means that the variance of the time series is stable, and can use the sample standard deviation if:

$$F\{v_1, v_2, 2.5\%\} < F_t < F\{v_1, v_2, 97.5\%\} \tag{2.9}$$

2.2.3 Test of randomness and persistence

Precipitation data for agriculture and water management studies should be stationary, consistent, homogeneous and with absence of persistence. In this study the serial correlation coefficient was used to test for absence of persistence. According to Box and Jenkins (1976), the lag one serial correlation coefficient given as r_1 is defined as;

$$r_1 = \frac{\sum_{i=1}^{n-1}(x_i-\overline{x})\times(x_{i+1}-\overline{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{2.10}$$

where x_i is an observation, x_{i+1} is the following observation, $\overline{x}$ is the mean of the time series and n is the number of the data series. After computing r_1, the hypothesis H_0: $r_1=0$ was tested against the alternate hypothesis, H_1:$r_1 < >0$ and the critical region U, at 5% level of significance was defined according to Anderson (1942) as:

$$\left\{\frac{-1,\left(-1-1.96(n-2)^{0.5}\right)}{n-1}\right\} \cup \left\{\frac{\left(-1+1.96(n-2)^{0.5}\right)}{n-1}+1\right\} \tag{2.11}$$

2.3 Methodology

2.3.1 Rainfall seasonality

To assess the aspect of rainfall seasonality, the *SI* designed by Walsh and Lawler (1981) was used in this study as given by:

$$SI = \frac{1}{R}\sum_{n=1}^{12}\left|X_n - \frac{R}{12}\right| \qquad (2.12)$$

where; X_n, is rainfall of month *n* and *R* is annual rainfall.

SI permits quantification of the variability of rainfall through the year, but should be complemented by a detailed analysis of monthly rainfall (Sumner *et al.*, 2001). For this reason, we calculated the mean monthly rainfall and coefficient of variation (*CV*) for each station. The index does not provide information on when and how much precipitation occurs and relies simply on the summation of monthly differences from an assumed equal monthly mean that represent an even distribution of precipitation throughout the 12 months in a year.
The index varies from zero, if all the months have equal rainfall, to 1.83 if all the rainfall occurs in a single month. The detailed descriptions of the *SI* are given as equal rainfall ($SI<0.19$); equal rainfall but with definite wet season ($0.20<SI<0.39$); seasonal with short dry season ($0.40<SI<0.59$); seasonal ($0.60<SI<0.79$); markedly seasonal with long dry season ($0.80<SI<0.99$); most rain in 3 months or less ($1.00<SI<1.19$); and extreme seasonality with almost all rain in 1 to 2 months ($SI\geq1.20$).

2.3.2 Precipitation Concentration Index (PCI)

The seasonality of rainfall regime and heterogeneity of rainfall amounts was evaluated by using the *PCI* as described by Oliver (1980):

$$PCI = \frac{\left(\sum_{i=1}^{12} Pi^2\right)}{\left(\sum_{i=1}^{12} Pi\right)^2} \times 100 \qquad (2.13)$$

Where; P_i is the rainfall amount of the month i.

The *PCI* is related to the *CV* by means of the following equation:

$$PCI = \frac{100}{12} \times \left[1 + \left(\frac{CV}{100}\right)^2\right] \qquad (2.14)$$

The *PCI* defines the temporal aspect of rainfall distribution. It was derived by Oliver (1980) from the Index of Employment Diversification (Gibbs and Martin, 1962). When the rainfall in each month of the year is the same (complete evenly distribution), the *PCI* equals 8.3 (*CV*=0); when all the rainfall of the year occurs in one single month, the *PCI* equals 100 ($CV=100\sqrt{11}$). The detailed description of *PCI* is described as uniform (*PCI*=8.3–10), moderately seasonal (*PCI*=10–15), seasonal (*PCI*=15–20), highly seasonal (*PCI*=20–50) and irregular (*PCI*=50–100).

Elagib (2011) used *SI* and *PCI* in his study of changing rainfall seasonality and erosivity in the hyper-arid zone of Sudan.

2.3.3 Spectrum Analysis and Fourier fit

To evaluate the periodicity of the rainfall time series, spectral analysis was used. Spectral analysis is applied to the annual time series of rainfall. While the classical way of spectrum analysis is the Fourier transfer, the *MEM* which presents higher resolution of power spectrum distribution and avoids aliasing was used in this study. The *MEM* seeks to extract as much information from a measurement as is justified by the data's signal to noise ratio. The *MEM* is based on the principle of entropy maximization. According to Burg (1967) and Smylie *et al.* (1973), power spectrum by the *MEM* is given by:

$$S(f) = \frac{P_{m+1}}{2f_n\left|1+\sum_{j=1}^{m}\lambda_j e^{-12\pi fi}\right|^2} \qquad (2.15)$$

where $S(f)$ is the spectral estimate at frequency f, P_{m+1} is the prediction error mean square (power) of a filter of length $m+1$, and λ_j are the coefficients of the filter. The denominator will be bounded only if the roots of the filter lie outside the unit circle. A filter with its roots outside the unit circle is called the minimum-phase filter. Therefore the spectral estimation problem based on maximum entropy reduces to estimating the filter coefficients of a minimum-phase filter and the power of the error sequence (P_{m+1}).

To extract peaks of frequencies, a Fortran code program was composed and used. We incorporated a computer subroutine by Press *et al.* (1992) to the code program. Obtained frequencies were applied to the Fourier series to fit to the original rainfall time series:

$$r(t) = a_0 + \sum_{i=1}^{n}[a_i \cos 2\pi f_i t + b_i \sin 2\pi f_i t] \qquad (2.16)$$

where; a, b: the Fourier coefficient of term i, f_i: frequency of term i, t: time, n: number of terms.

On the way of the fitting process, combinations of obtained frequencies were optimized by the Akaike Information Criterion (*AIC*) given by;

$$AIC = m * \ln(\sigma) + 2n \tag{2.17}$$

where; σ: fitting error variation, m: number of rain data, n: number of coefficients of the Fourier series. In cases where analyses are based on more conventional least squares regression for normally distributed errors, one can compute the *AIC* by using the following formula:

$$AIC = n\log\left(\widehat{\sigma^2}\right) + 2K \tag{2.18}$$

where $\widehat{\sigma^2} = \frac{\sum_{i=1}^{n}[r_i - \hat{r}_i]^{2}}{n}$ (2.19)

where n is the sample size, r_i: observed rainfall, $\hat{r}_i$: estimated rainfall and k is total number of unknown parameters. Since the variance is estimated, it must be included in the count of parameters. The *AIC* has been used for model optimization (e.g. Lee and Ouarda, 2011). The minimum value of the *AIC* presents the optimal model (the optimal combination of the parameters). The *AIC* deals with the tradeoff between the goodness of fit of the model and its complexity. The *AIC* seeks to find a model that has a better fit to the truth but with fewer parameters.

The *AIC* of all combinations of frequencies was calculated for the optimization.

2.4 Results and Discussion

2.4.1 Data processing and quality control

Table 2.1 below shows the results of the data quality control and homogeneity procedures that the data was subjected to before analysis.

Table 2.1 Results of data quality control procedures

Station	Karonga	Bolero	Nkhatabay	Kasungu	Dedza	Salima	Mangochi	Makoka	Ngabu
N	2.00	1.60	2.00	2.49	2.20	1.70	2.00	1.50	1.80
R_{sp}	0.25	0.03	0.08	-0.13	-0.30	0.23	-0.02	0.08	-0.11
F_t	0.82	1.07	0.96	1.11	0.90	1.26	0.83	0.99	0.94
r_1	0.00	0.15	0.02	-0.31	-0.11	0.17	0.00	0.24	0.17

where N is the Von Neumann ratio, R_{sp} is Spearman rank correlation coefficient, F_t is F test for stability of variance and r_1 is the test for absence of persistence. Two stations, Kasungu and Dedza had suspected homogeneity as their Von Neumann ratio was above 2. However when the other tests were applied, the results were normal, therefore no further action was taken and the data was used as it was. The limit for spearman rank correlation (R_{sp}) was $-0.385 < Rsp < 0.307$; for stability of variance (F_t), it was $0.301 < F_t < 3.43$; and absence of persistence (r_1) it was were $0.385 < r_1 < 1.318$.

2.4.2 Annual rainfall time series

The mean annual rainfall for all the stations is given in Table 2.2 Nkhatabay had the highest mean annual rainfall of 1,570 mm and a *CV* of 0.21. Nkhatabay is located along the lake shore, which lies in the rift valley and on the windward side of Viphya plateau such that it receives both convectional and topographic rainfall. Bolero, in the rain shadow area of Nyika plateau, had the lowest annual rainfall of 626 mm and a *CV* of 0.22. Six stations had mean annual rainfall between 600 to 1,000 mm and three stations had mean annual rainfall greater than 1,000 mm. These were Makoka (1,003 mm), Salima (1,207 mm), and Nkhatabay (1,570 mm). Salima and Nkhatabay are located along the lake shore plains near the rift valley escarpment, giving them a tropical type of climate which favors rainfall. Makoka is in the Shire highlands within the Lake Chilwa basin.

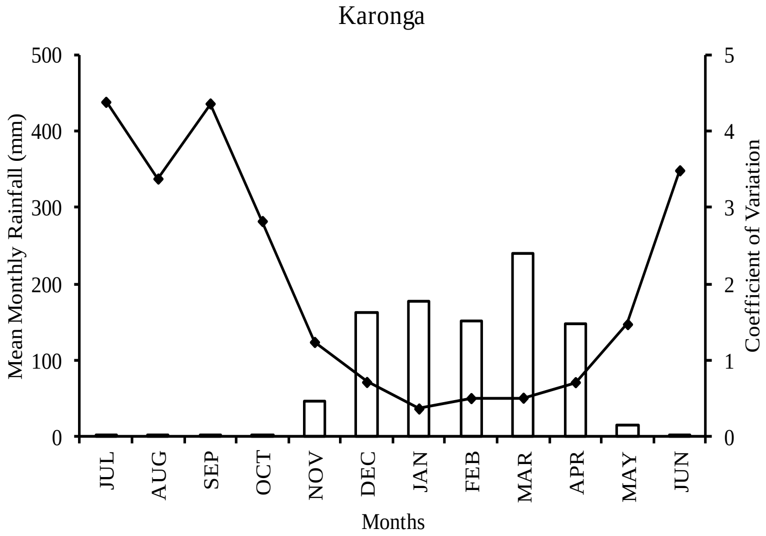
Table 2.2 Mean annual rainfall and coefficient of variation (*CV*)

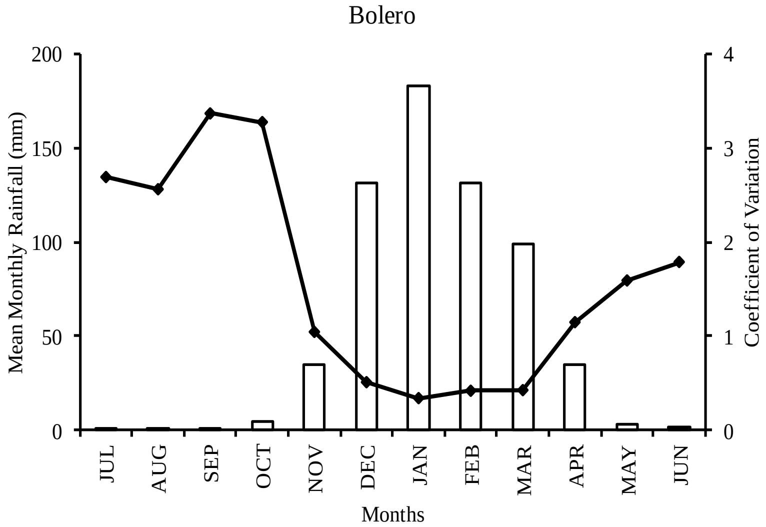
Station / Items	Karonga	Bolero	Nkhatabay	Kasungu	Salima	Dedza	Mangochi	Makoka	Ngabu
Rainfall(mm):	942	626	1,570	784	1,207	947	805	1,003	826
CV	0.23	0.22	0.21	0.22	0.26	0.16	0.31	0.21	0.29

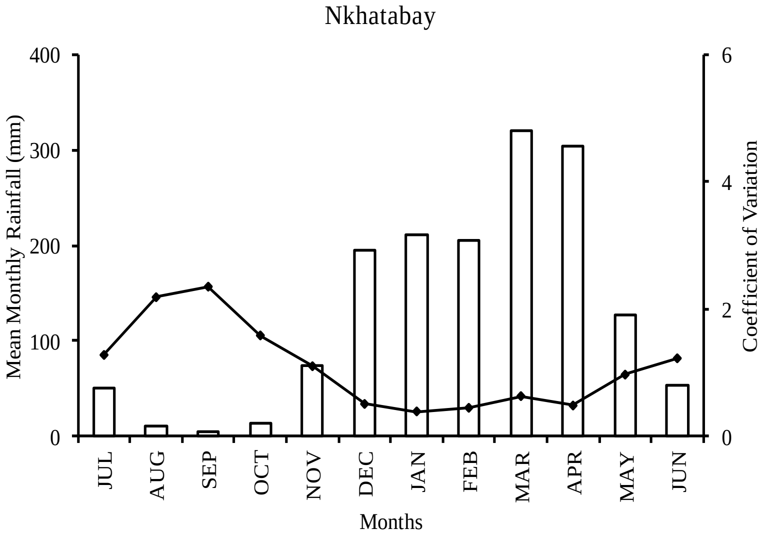
2.4.3 Mean monthly rainfall

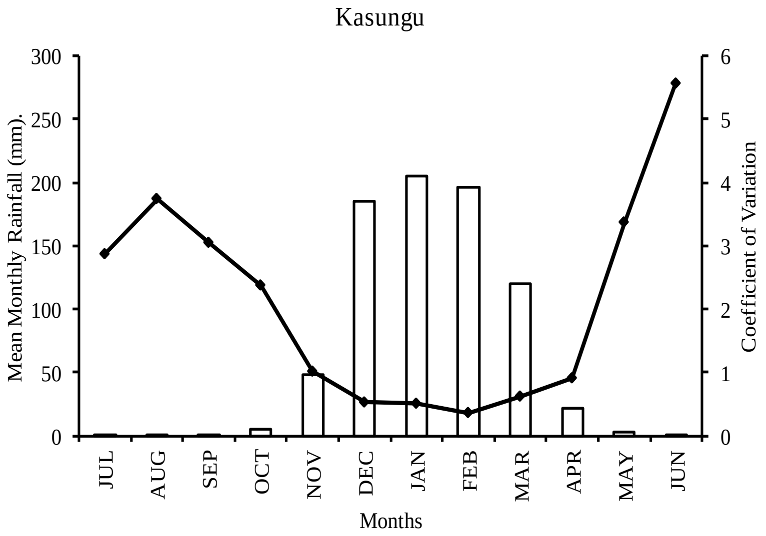
The mean monthly rainfall and *CV* for all stations were calculated as shown in Figure 2.2. January had the highest mean monthly rainfall for seven stations with a mean value of 225 mm and *CV* of 0.40. At Karonga and Nkhatabay the highest mean monthly rainfall was recorded in March with a value of 280 mm and *CV* of 0.57. The lowest mean monthly rainfall for all stations was in September with a mean value of 2.2 mm and *CV* of 2.8. The most significant result of this analysis was that rainfall was mainly concentrated between November and April for all stations with a peak in January except for two stations, Nkhatabay and Karonga which had bimodal rainfall patterns with peaks in January and March. For Nkhatabay, the mean rainfall was 211 mm for January and 320 mm for March and for Karonga, mean rainfall was 176 mm for January and 240 mm for March. The climate of Malawi depends on the *ITCZ*, the subtropical high pressure belt in the south between latitudes 25° and 35°S, and its topography (Torrance, 1972). The *ITCZ* enters the country from the north during its southwards movement to its southern limit in February and then moves back to the north. The other main rain bearing system for Malawi during the rainy season is the Congo Air Boundary (CAB), which marks the confluence between the Indian Ocean southeast trades and recurved the South Atlantic air that reaches Malawi as north westerly air mass through the Democratic Republic of Congo. This system brings well-distributed rainfall over the country and floods may occur in some areas especially in association with *ITCZ* (Jury and Mwafulirwa, 2002). These two rainfall systems account for the bimodal pattern of monthly rainfall in Karonga and Nkhatabay. Most equatorial countries in east Africa (e.g., Kenya, Tanzania and Uganda) experience the bimodal seasonal distribution of rainfall, the rains from October to December being called short rains and those from March to May being called long rains (Nicholson, 1996).

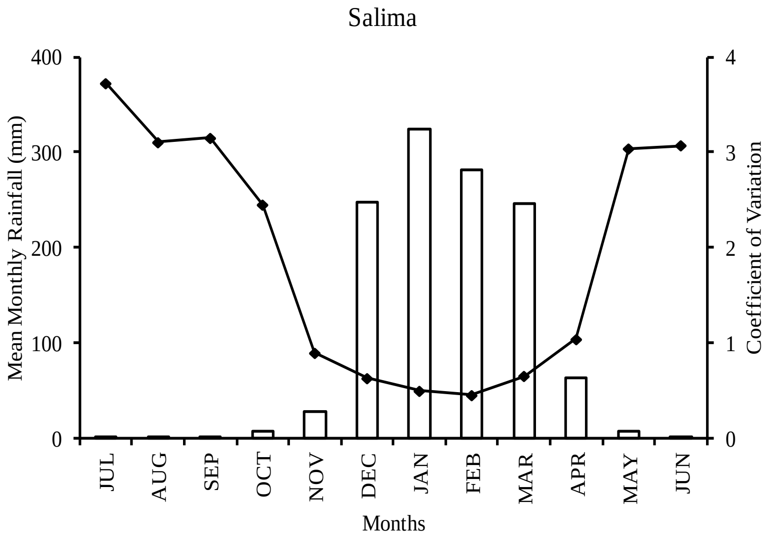
Figure 2.1 shows the results of the mean monthly rainfall and *CV* for all the stations

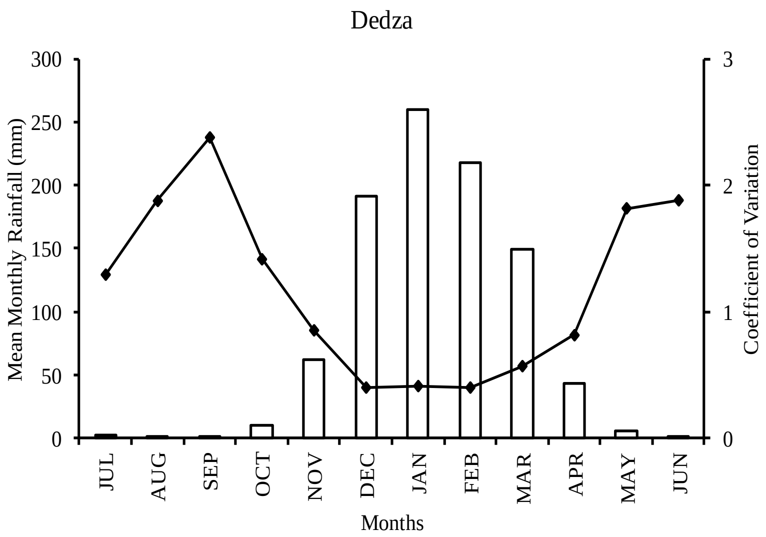

Karonga
Mean Monthly Rainfall (mm)
Coefficient of Variation
Months
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN


Bolero
Mean Monthly Rainfall (mm)
Coefficient of Variation
Months
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN


Nkhatabay
Mean Monthly Rainfall (mm)
Coefficient of Variation
Months
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN


Kasungu
Mean Monthly Rainfall (mm).
Coefficient of Variation
300
250
200
150
100
50
0
6
5
4
3
2
1
0
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN
Months


Salima
Mean Monthly Rainfall (mm)
Coefficient of Variation
400
300
200
100
0
4
3
2
1
0
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN
Months


Dedza
Mean Monthly Rainfall (mm)
Coefficient of Variation
300
250
200
150
100
50
0
3
2
1
0
JUL
AUG
SEP
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN
Months

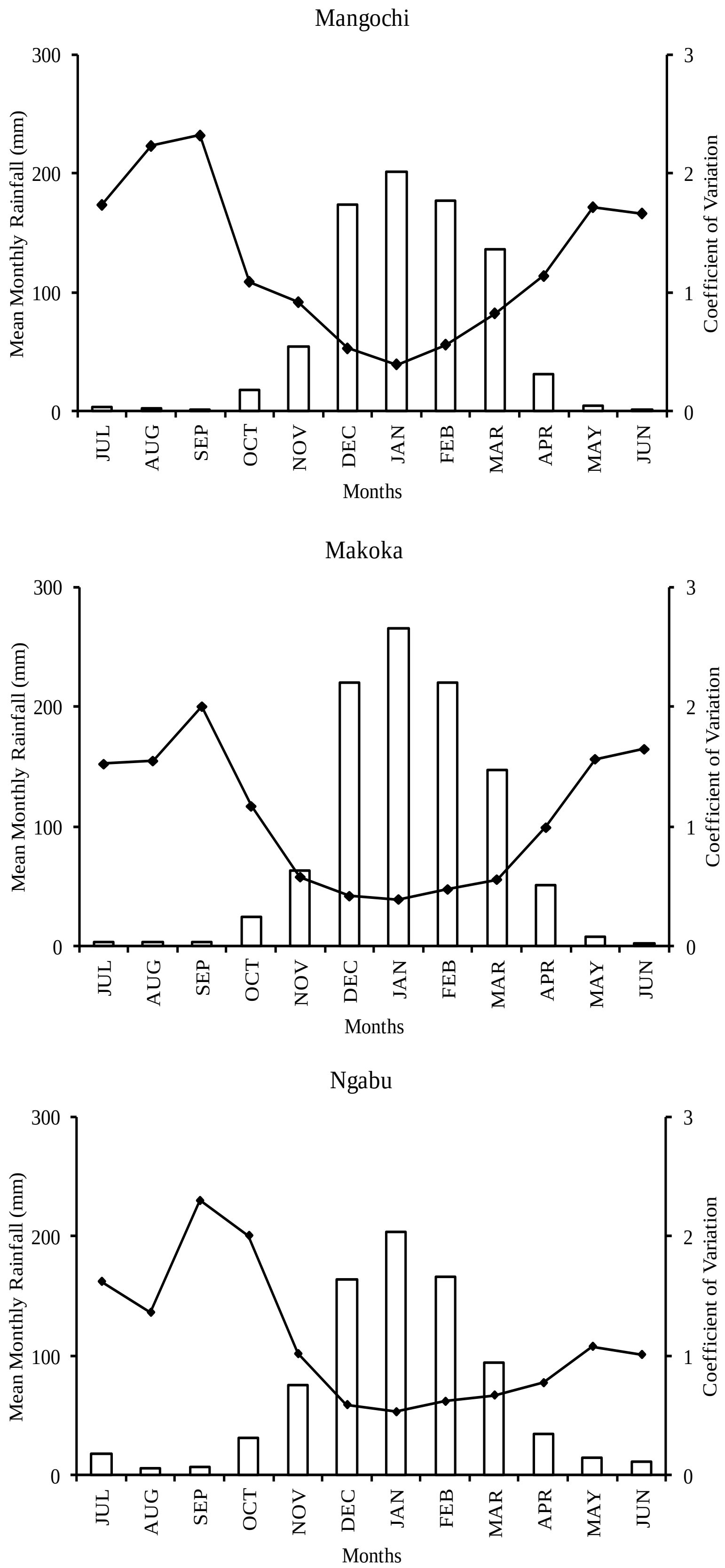


Figure 2.1 Monthly mean rainfall (left axis) and coefficient of variation (*CV*) (right axis)

2.4.4 Rainfall seasonality

The results of the seasonality analysis show that Nkhatabay with an annual *SI* of 0.74 was the only station with rainfall classified as seasonal (Table 2.3). Monthly rainfall at Nkhatabay (Figure 2.2) which receives both convectional and topographical rainfall and has a long rainfall season is more evenly distributed than at other stations. The dry season is short, from August to October, and there is significant rainfall from May to July, when rain is rare at other stations. Topographical rains occur due to southeasterly winds particularly during cool dry months (May-July) and transitional periods. Ngabu, with an annual *SI* of 0.87, has a markedly seasonal rainfall pattern with a long dry season. Ngabus location at the end of the rift valley escarpment in the rain shadow area of the lower Shire valley accounts for the long dry season. The rest of the stations had *SI* values ranging from 1.03 to 1.15 classifying them as receiving most rain in three months or less.

Table 2.3 Seasonal Index (*SI*) of the rainfall stations

Station / Items	Karonga	Bolero	Nkhatabay	Kasungu	Salima	Dedza	Mangochi	Makoka	Ngabu
Annual *SI*	1.03	1.08	0.74	1.13	1.15	1.06	1.04	1.03	0.87
Description	most rain in 3 months or less		Seasonal	most rain in 3 months or less					markedly seasonal

The decadal *SI* for the rainfall stations was also calculated. Table 2.4presents the results of the calculations. The decadal *SI* did not show significant changes in the rainfall seasonality. Only Karonga showed a significant change in the decadal *SI*. The decadal *SI* for 1980-90 period was 0.99 which shows markedly seasonal rainfall with a long drier season as compared to most rain in 3 months or less for the other decades. From the annual rainfall time series of Karonga (Figure 2.2), it can be seen that there is a significant drop in annual rainfall between 1990 and 2000 which could have impacted on the decadal *SI*. Analysis of the annual rainfall time series of Nkhatabay shows that the 1991-2000 and 2001-2010 had high inter- annual variability of rainfall which could have contributed to the changes from markedly seasonal rainfall with a long drier season as compared to most rain in 3 months or less. It suggests decadal meteorological fluctuation.

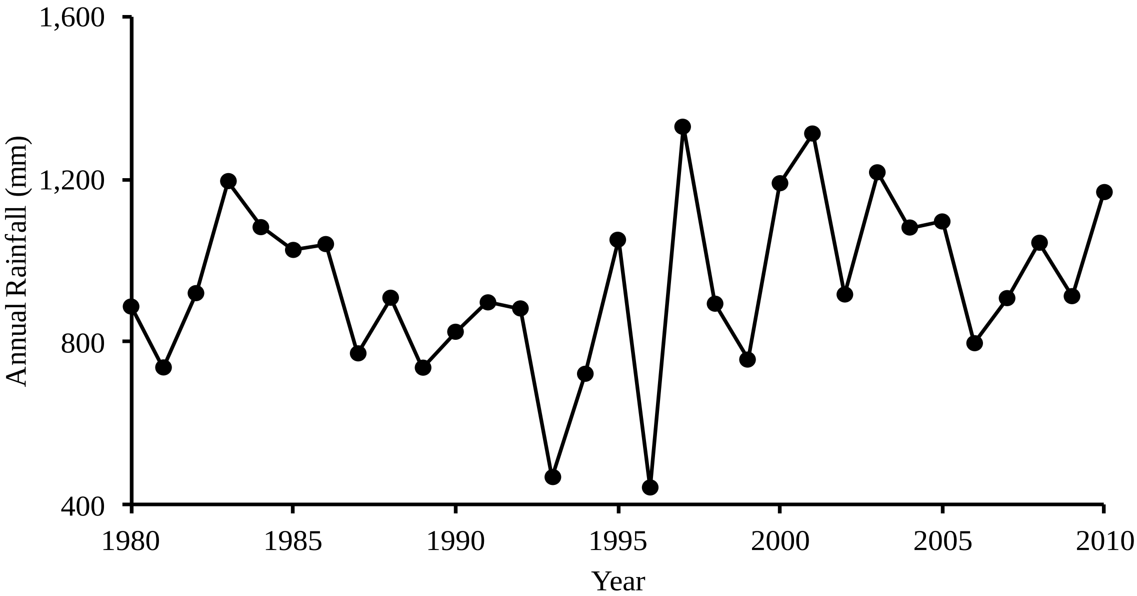


Figure 2.2 Annual rainfall time series for Karonga

Table 2.4 Decadal Seasonal Index (*SI*) of rainfall stations

Station / Items	Karonga	Bolero	Nkhatabay	Kasungu	Dedza	Salima	Mangochi	Makoka	Ngabu
Annual *SI*	1.03	1.075	0.74	1.13	1.06	1.15	1.04	1.03	0.87
SI (1980-90)	0.99	1.037	0.77	1.10	1.07	1.17	1.08	1.03	0.88
SI (1991-00)	1.03	1.105	0.76	1.13	1.03	1.12	1.06	1.04	0.88
SI (2001-10)	1.08	1.091	0.75	1.18	1.12	1.17	1.00	1.01	0.87

PCI of the rainfall stations varied from 14 to 21 (Table 2.5). Only Nkhatabay, with a *PCI* value of 14, had moderately seasonal rainfall concentration. Ngabu, Makoka, Mangochi and Karonga, with *PCI* values of 17 to 19, had seasonal rainfall concentration. The other four stations had *PCI* values greater than 20, or highly seasonal rainfall concentration. The *PCI* was calculated from mean monthly rainfall data averaged over 31 years. The temporal *PCI* is calculated from the rainfall data of individual years averaged over 31 years. On this metric, Nkhatabay station had a seasonal rainfall concentration while the rest of the stations with temporal *PCI* values ranging from 21 to 27 had a highly seasonal rainfall concentration. The results for *SI* and *PCI* both indicate that rainfall time series at all stations have pronounced seasonality. Nkhatabay showed notably less seasonality than the other stations. Monthly rainfall distribution at Karonga and Nkhatabay indicated a bimodal rainfall pattern suggesting that the meteorological dynamics at these stations are different from the others.

Table 2.5 Precipitation concentration index (*PCI*) of rainfall stations

Station Items	Karonga	Bolero	Nkhatabay	Kasungu	Salima	Dedza	Mangochi	Makoka	Ngabu
PCI	18	21	14	21	21	20	19	19	17
Description	Seasonal	highly seasonal	moderately seasonal	highly seasonal		Seasonal			
Temporal *PCI*	23	24	18	25	27	23	24	23	21
Description	highly seasonal		seasonal	highly seasonal					

2.4.5 Zoning of the stations

Rainfall from November to April was extracted from the rainfall time series of the nine stations and cross-correlation coefficients among the stations were calculated as shown in Table 2.6. The stations were classified in one of two zones on the basis of the strength of the correlations. Jury and Mwafulirwa (2002) used the same approach in their analysis of climate variability in Malawi.

Karonga and Nkhatabay had low correlation with the other stations. Especially Nkhatabay had very low correlations ($r < 0.1$) with stations in the south (Mangochi, Makoka and Ngabu). The correlation coefficient between Karonga and Nkhatabay was 0.535. Monthly average rainfall of Karonga and Nkhatabay showed the bimodal distribution suggesting that these stations experienced different meteorological mechanisms from the rest of the stations. These two stations were grouped into Zone 1. The other seven stations showed high correlations ($r > 0.47$ significance at 0.01 level) and were grouped into Zone 1. Normalized (standardized) values of rainfall for the rainy season of each zone were calculated by subtracting the mean annual rainfall of the time series of each zone from the rainfall of the i^{th} year and dividing by the standard deviation of the rainfall time series of each zone. Figures 2.3 and 2.4 show the normalized rainfall of the two zones over the study period.

Table 2.6 Cross-correlation coefficient for November to April rainfall among the rainfall stations

Stations / Stations	Karonga	Bolero	Nkhatabay	Kasungu	Salima	Dedza	Mangochi	Makoka	Ngabu
Karonga	1.000								
Bolero	0.358*	1.000							
Nkhatabay	0.535**	0.220	1.000						
Kasungu	0.197	0.652**	0.122	1.000					
Salima	0.403*	0.531**	0.270	0.634**	1.000				
Dedza	0.290	0.613**	0.137	0.675**	0.728**	1.000			
Mangochi	0.209	0.596**	0.081	0.614**	0.664**	0.686**	1.000		
Makoka	0.192	0.511**	0.085	0.542**	0.624**	0.670**	0.675**	1.000	
Ngabu	0.153	0.491**	0.071	0.558**	0.535**	0.588**	0.616**	0.630**	1.000

*$r \geq 0.36$ at 0.05 level of significance and **$r \geq 0.47$ at 0.01 level of significance

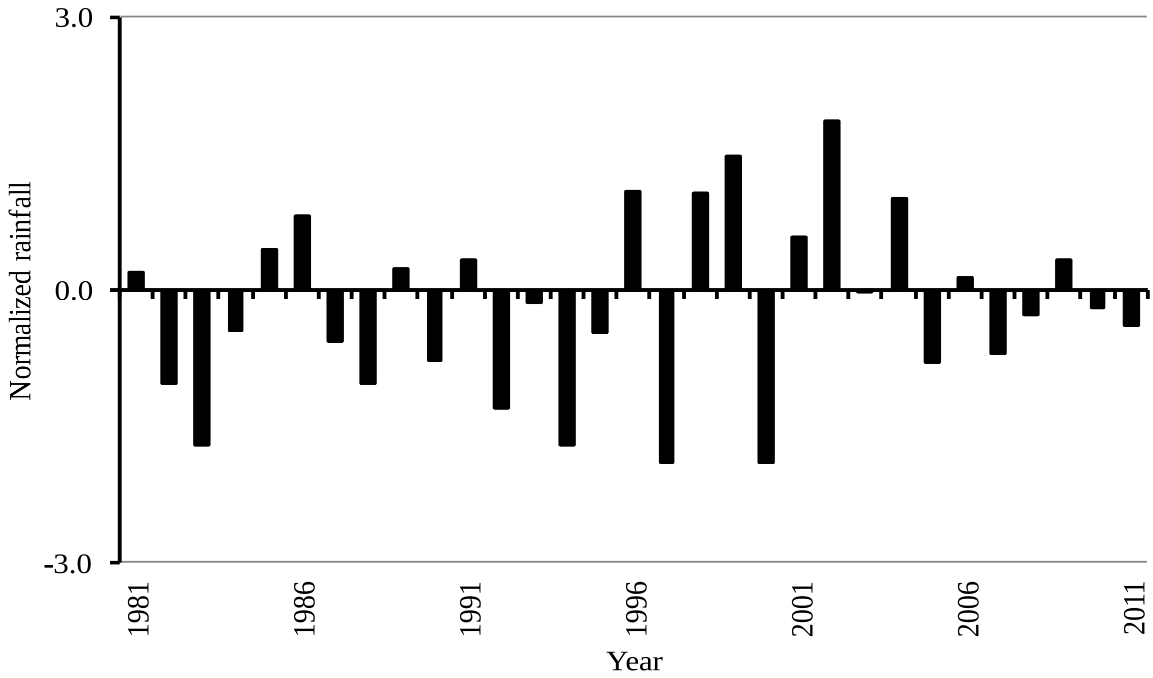


Figure 2.3 Normalized annual rainfall of Zone 1

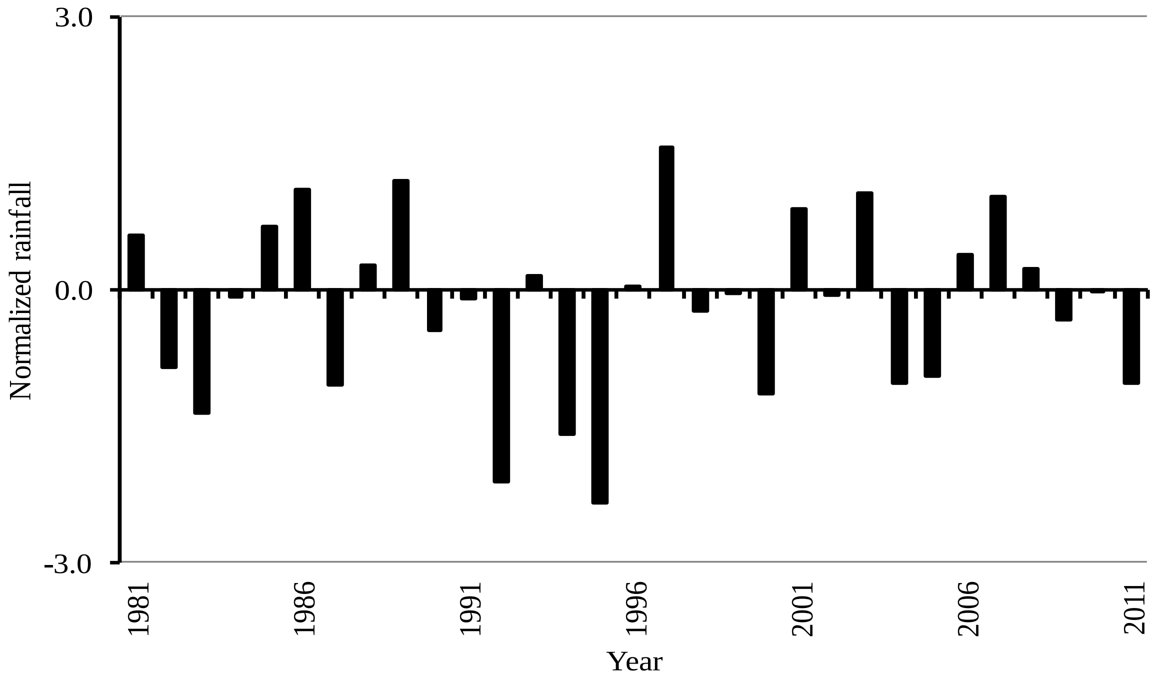


Figure 2.4 Normalized annual rainfall of Zone 2

Figures 2.3 and 2.4 show that the annual rainfall has a tendency for years with high rainfall to be followed by years with low rainfall. Zone 1 had the least annual rainfall between 1992 and 1995 and Zone 2 had the least rainfall in the years 1983, 1994, 1997 and 2000. Malawi experienced drought during these years which adversely affected crop production.

2.4.6 Spectrum analysis and Fourier fit

Spectral analysis was carried out on the rainfall time series to determine the periods and frequencies at which climatic events like drought and floods are likely to occur at the stations

The power spectrum (Figure 2.5) for Zone 1 rainfall shows strong peak between 0 and 0.15 and between 0.25 and 0.40 with smaller peaks at higher frequencies

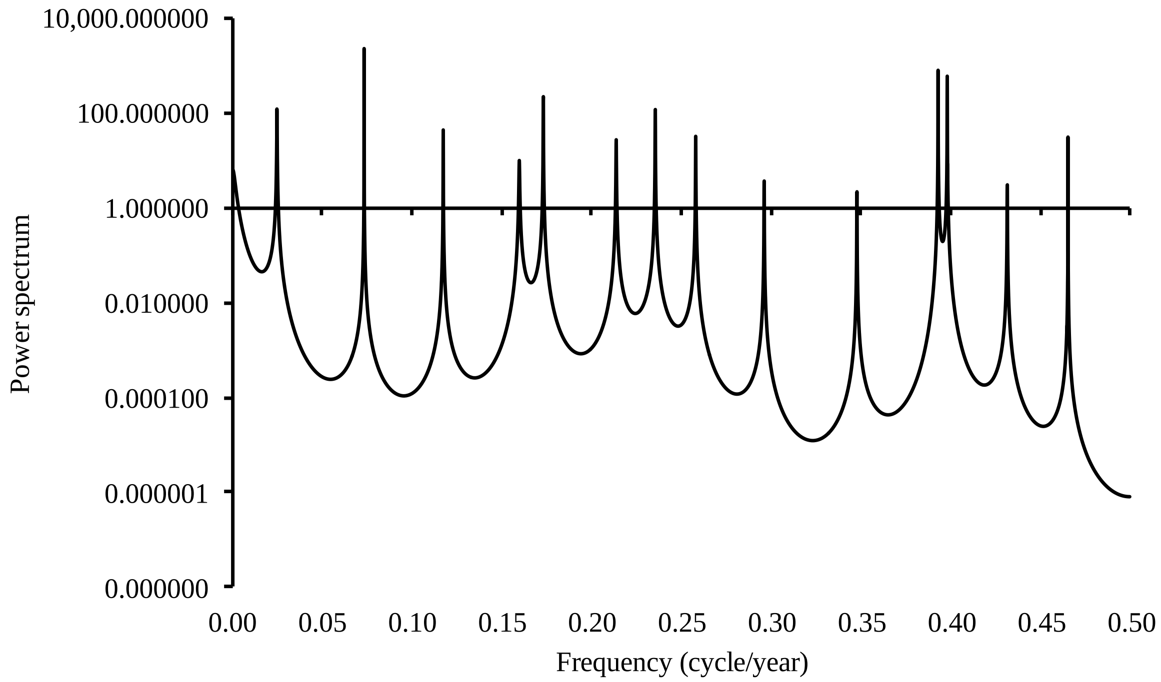


Figure 2.5 Power spectrum and frequency for spectral analysis for Zone 1

The maximum entropy spectrum (Figure 2.6) for Zone 2 rainfall shows strong peak between 0 and 0.40 with smaller peaks at higher frequencies in between.

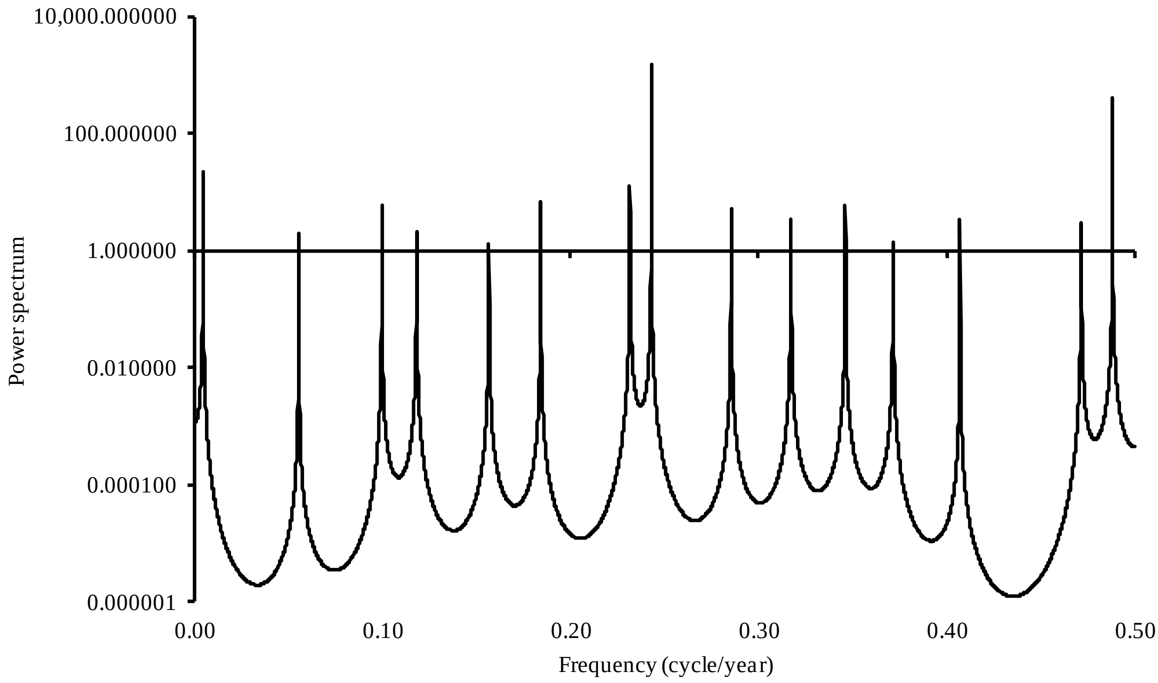


Figure 2.6 Power spectrum and frequency for spectral analysis for Zone 2

The detected frequencies from the initial calculation were further scrutinized to choose the optimized combination of the frequencies. The model optimization was performed considering combination of frequencies and fit with observed data. A way of optimization was the *AIC*. The *AIC* was used to optimize the Fourier fitting with the observed values. Table 2.7 presents the results of the analysis.

Table 2.7 Optimized frequencies (*f*): and corresponding periods (*T*) by the *AIC*

		Optimized frequencies and corresponding periods									
Zone 1	*f*(cycle/year):	0.4656	0.3983	0.3932	0.2581	0.2356	0.2138	0.1732	0.1174	0.0733	0.0247
	T (years):	2.15	2.51	2.54	3.87	4.24	4.68	5.77	8.52	13.64	40.49
Zone 2	*f*(cycle/year):	0.4885	0.3462	0.2855	0.2429	0.2315	0.1840	0.0994			
	T (years):	2.05	2.89	3.50	4.12	4.32	5.43	10.06			

The optimization of the spectral analysis of the rainfall time series revealed cycles between 2.15 and 40.49 years for stations in Zone 1 and between 2.05 to 10.06 for stations in Zone 2. There were suggested links with *ENSO*, *QBO* and solar cycle in both zones. Jury and Mwafulirwa (2002) found similar cycles in their study of climate variability in Malawi whilst Jury and Makarau (1997) also found similar cycles in rainfall records over Zimbabwe and South Africa. Jury and Mpeta (2005) reported 3-8 years as the annual cycle of climate in Africa. Figures 2.7 and 2.8 present the results of the Fourier fit. The correlation coefficients of the fit were larger than 0.78 for Zone 1 and 0.81 for Zone 2, respectively. The optimized Fourier fit follows the general tendency of the original rainfall time series.

Goddard and Graham (1999) evaluated the significance of the *ENSO* influence by analyzing the correlation among stations with *ENSO* in Malawi. The analysis showed there was high significant correlation among stations in the south of Malawi and the correlation became weaker in northern Malawi. They suggested that the correlation was weaker in the north because the north lies near the transition zone of *ENSO* influence with opposing centers of action in southern and eastern Africa.

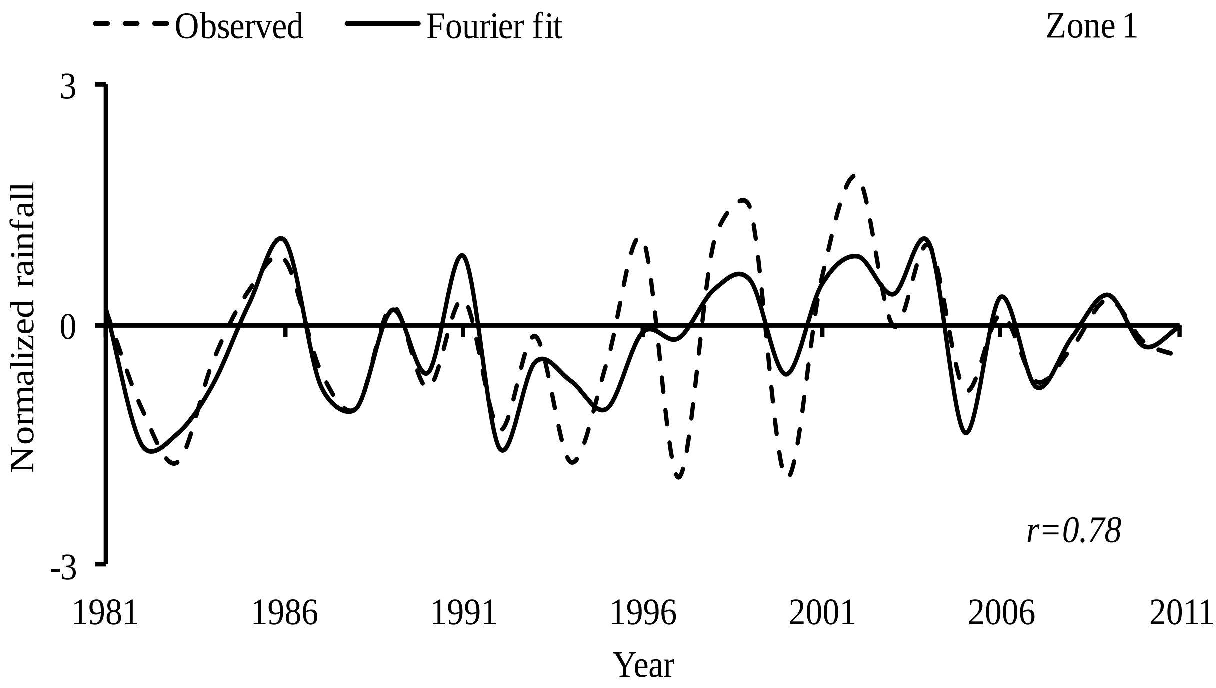


Figure 2.7 Fit of optimized Fourier series with the original time series for Zone 1

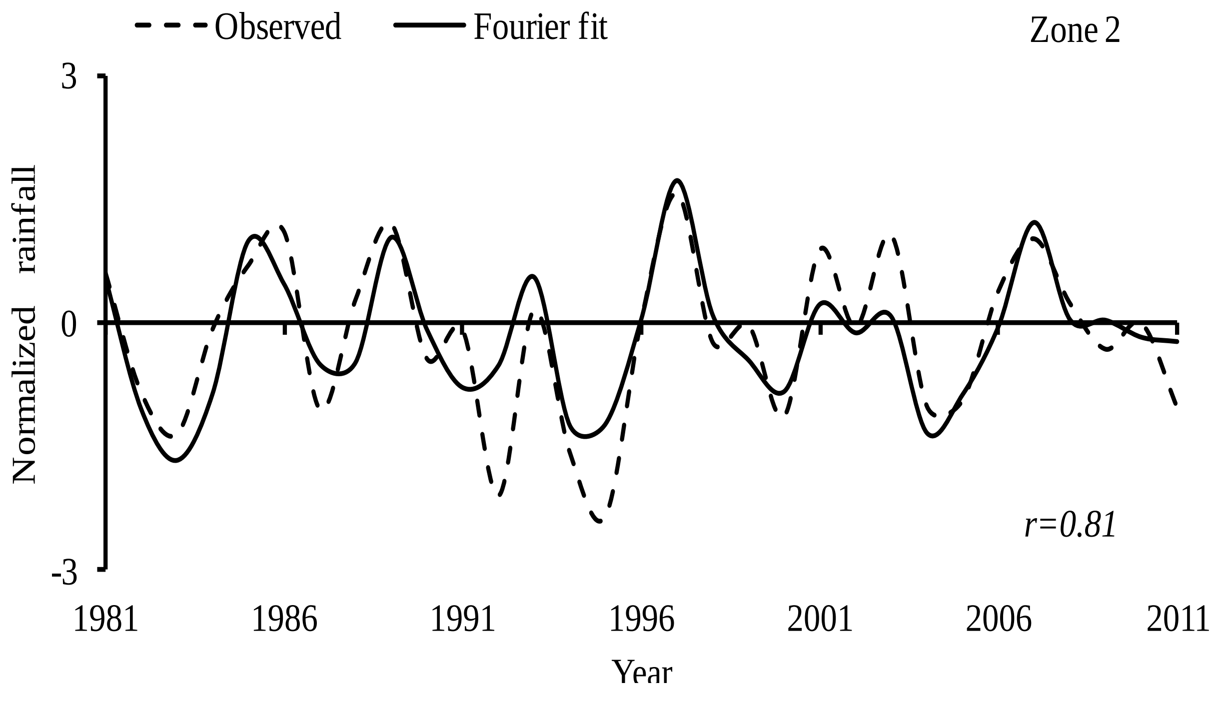


Figure 2.8 Fit of optimized Fourier series with the original time series for Zone 2

2.5 Conclusions

The interannual fluctuation of monthly rainfall over 31 years period was studied for nine locations in Malawi. The analysis of this time series revealed the following points:

- There was a high spatial variability of both monthly and annual rainfall. Rainfall season was from November to March with peaks in January, except for Karonga and Nkhatabay stations, which had dual peaks in January and March. The rainfall pattern in Malawi suggests that geographical factors like topography and location have a dominant role in the spatial distribution of rainfall.
- On the basis of seasonal indices, *SI* and *PCI*, rainfall time series of all stations except Nkhatabay indicated apparent seasonality (rainfall received in 3 months or less in *SI*, seasonal to highly seasonal rainfall concentration in *PCI*). Only Nkhatabay experienced less seasonality.
- Spectrum analysis of the rainfall time series revealed cycles at 2.15 to 40.49 years for Zone 1 and 2.05 to 10.06 for Zone 2. There were suggested links with the *ENSO*, *QBO* and solar cycle. These results are consistent with those found in other southern African countries.
- All parts of Malawi displayed strong seasonality and interannual fluctuation in rainfall. Given the importance of rainfall to agriculture in Malawi, these variations need to be applied to the planning of water resources management.

Chapter 3 Linkage between Malawi Rainfall and Global Sea Surface Temperature

3.1 Introduction

The climate of southern Africa is influenced by the position of the subcontinent in relation to the major circulation features of the atmosphere of the southern hemisphere (Torrance, 1972). Southern Africa (SA) is under the influence of a sub-tropical anticyclone throughout the year and experiences a unimodal rainy season from October to April and the distribution of rainfall is erratic both temporally and spatially (Mwafulirwa, 1999). According to Lindesay and Harrison (1986), the Intertropical Convergence Zone (*ITCZ*), Southern Oscillation, El Niño Southern Oscillation (*ENSO*), Sea Surface Temperature (*SST*) and Walker Circulation strongly influence rainfall variability over SA. Generally, rainfall is below normal over SA during El Niño years and above normal during La Niña years (Nicholson and Entekhabi, 1986; Lindesay, 1988).

Many studies have related African rainfall variability to *SST* over the Atlantic, Indian, and Pacific Oceans. Folland *et al.* (1986) found a strong statistical relationship between seasonal rainfall in the Sahel and global *SST* but argued that the discovery of relationships between *SST* and African rainfall should not preclude the importance of local effects from the earth's surface on the seasonal time scale. Walker (1989) reported that South African plateau rainfall is enhanced when *SST* in the subtropical belt of the eastern Agulhas current is above normal during and prior to La Niña years. It was observed that in normal years significant correlation is found between rainfall with Benguela and Agulhas *SST*. Decreasing *SST* in central south Atlantic and increasing *SST* off the coast of southwestern African can lead to a demonstrable increase in daily rainfall and rainfall extremes over SA (Williams *et al.*, 2008). According to Misra (2003), patterns of regional linkage between dominant mode of SA precipitation variability and *SST* anomalies over eastern Indian Ocean is influenced by variations of Pacific Ocean *SST*. The nature of the linkage between SA precipitation and eastern Indian Ocean *SST* is apparent only when the Pacific Ocean *SST* variability is excluded. Other researchers who have done work on the influence of *SST* on SA rainfall include Mason and Tyson (1992), Enfield and Mayer (1997).

The literature on linkage between *SST* and summer rainfall in Malawi is sparse. Notable previous studies have been in the area of climate variability and have included Ngongondo *et al.* (2011), Jury and Nkosi (2000), Mason (1997), and Nkhokwe (1996).

Nicholson and Entekhabi (1987) reported that an enhanced rainfall over East Africa was linked with a warm central Indian Ocean and that there were weak correlations with southern oscillation index (*SOI*) and Quasi Biennual Oscillation (*QBO*). Jury and Mwafulirwa (2002) found negative correlations between dry summers and *SST*s in the West Indian Ocean and positive correlations between dry summers and *SST*s in the East Atlantic and Agulhas region. They reported an apparent north–south gradient of *SST* in the sub-tropical West Indian Ocean.

The aim of this study is to conduct an analysis on the linkage between Malawi rainfall and *GSST*. The motivation is to find out how *GSST* influences rainfall in Malawi and how the peak rainfall in the months of January and March is related to *GSST*. The study utilized Zone 1 and Zone 2 rainfall as described in the first study. Secondly, grid rainfall data from across Malawi were used to test the relationship between peak rainfall in January and March with *GSST*. Grid data covers most parts of Malawi unlike the rain gauge station data which was from nine stations only.

3.2 Methodology

Mean monthly rainfall for the grid stations was calculated. The rainy season varies from November to April with most grids receiving maximum rainfall in January, with an average of 238 mm and coefficient of variation (*CV*) of 0.10. However some stations, notably in northern and central Malawi exhibited dual peaks of rainfall (bimodal), with high average rainfall amounts received in January, 246 mm with a *CV* of 0.22 and March, 302 mm and *CV* of 0.19 (Figure 3.1). The bimodal pattern of rainfall mostly characterize rainfall in equatorial east Africa (e.g. Uganda, Kenya, Tanzania). The *ITCZ* and CAB influences the bimodal rainfall in north Malawi (Kumbuyo *et al.*, 2014). The other stations indicated a single peak observed in January. Mean monthly rainfall values were also calculated for all the grid stations across Malawi.

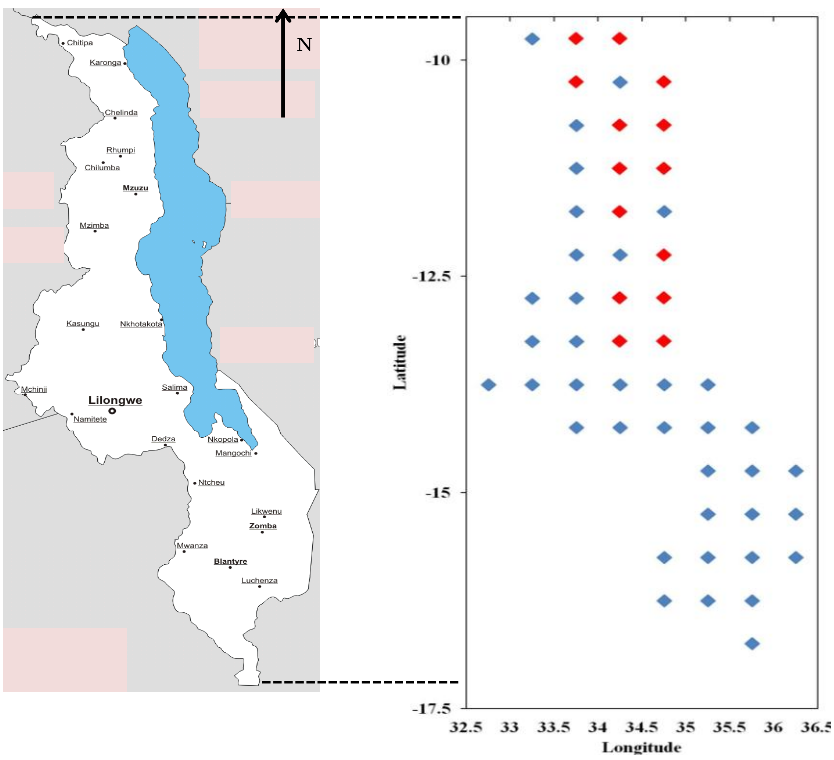


Figure 3.1 Map of Malawi showing location of grid stations. Red dots show stations with bimodal rainfall pattern

The grids were also divided into two zones (Zone 1 and Zone 2) with Zone 1 (Figure 3.2, clear graph) covering areas of the bimodal rainfall pattern (double peak) with peak rainfall in January and March; and Zone 2 (Figure 3.2, shaded graph) covering areas of single rainfall peak in January respectively and the stations with high rainfall in January only into Zone 2.

Cross correlations between rainfall and monthly *SST* were computed to gauge the statistical relationship between rainfall and *SST*. Two-month averages of *SST* and monthly rainfall were cross-correlated with each other for Zone 1, and three-month averages were used for Zone 2. We assigned March-April and December-January-February rainfall lag times of zero for Zones 1 and 2, respectively. The correlation coefficients ranged from 0.36 to 0.47; these r values corresponded to Type I error rates (p) of 5% and 1%, respectively.

As for the grid stations, November to April rainfall for Zone 1, was divided into two parts. The first part was November to January (NDJ) and the second part was February to April (FMA). These were then correlated with monthly *SST*. *SST* in November was assigned as Lag 0 for the first part and that in February was assigned as Lag 0 for the second part. We wanted to examine how the two peaks correlate with the *GSST* separately. For Zone 2, interannual time series of three months average rainfall from December to February (DJF) was extracted and correlated with monthly *SST*. This was done because the peak rainfall is in January. *SST* in December was assigned as Lag 0.

Correlations of the peak rainfall (NDJ and FMA for Zone 1 and DJF for Zone 2) with *GSST* were obtained and evaluated. Correlation coefficients equal to 0.36, 0.45 and 0.52 corresponding to the significance levels of 0.05, 0.01, and 0.001 respectively were extracted and evaluated.

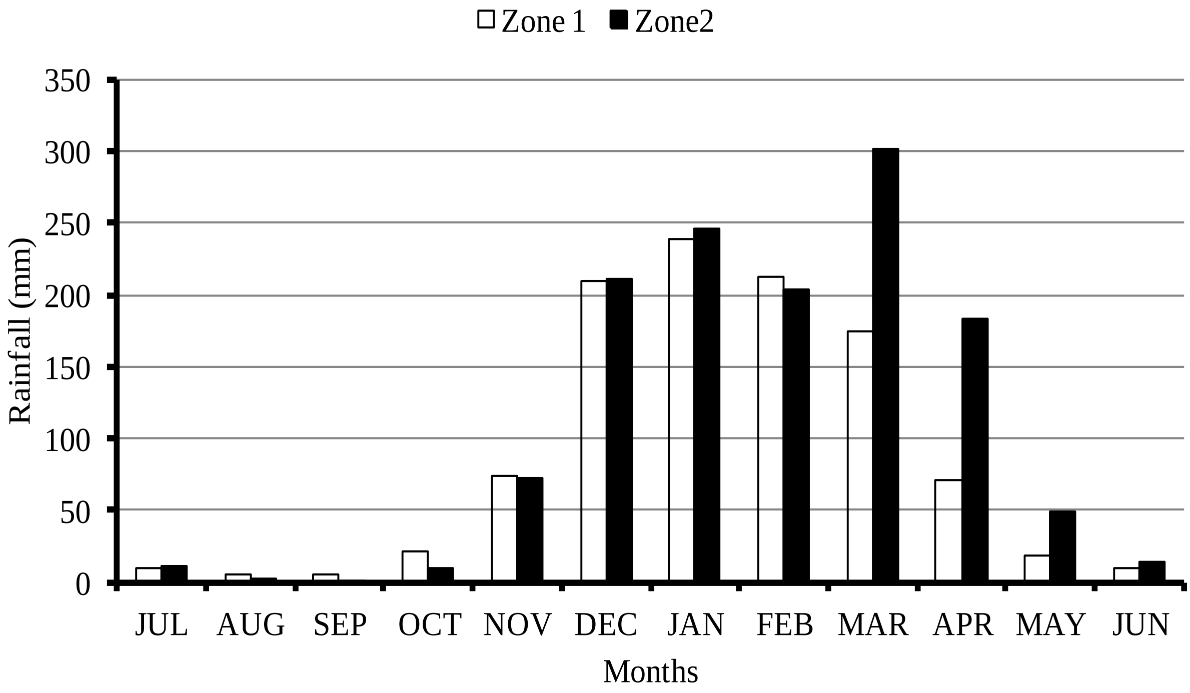


Figure 3.2 Mean monthly rainfall for Zone 1 and Zone 2 for grid stations

3.3 Results and Discussion

3.3.1 Analysis of relationship between SST and Zone 1 rainfall (using rain gauge data)

In the South Atlantic Ocean, significant positive correlations between *SST* and summer rainfall in Malawi were observed off the southwest coast of SA at lags 1–4 months (Figure 3.3). The correlations were more pronounced at lag 4 months. Decreasing *SST* in the central South Atlantic (lag 1–2 months) and increasing *SST* off the coast of southwestern Africa (lag 3–4 months) have been found to lead to a demonstrable increase of daily rainfall and rainfall extremes over SA (Williams *et al.*, 2008). Furthermore, they reported that these relationships reflected local effects, such as a change in Walker cell circulation. We believe that Malawi, being in SA, is affected by these phenomena, and that these effects explain the positive correlations observed (Figure 3.3). Also, Rouault *et al.* (2003) noted that the occurrence of warm events in the tropical southeastern Atlantic during the late austral summer can amplify local atmospheric instability, evaporation, and rainfall; leading to above-average rainfall, the effects of which extend further than usual into SA. In the South Atlantic Ocean off the coast of Brazil, *SST*s were positively correlated with Malawi rainfall at lags of 4–5 months, and 7–8 months (Figure 3.4). According to Nicholson (1997), the *ENSO* signal in African rainfall variability is a result of the influence of the *ENSO* on *SST* in the Atlantic and Indian Oceans, which, in turn, influences rainfall. He reported that cold (La Niña) and warm (El Niño) phases of the *ENSO* cycle relate correspond to improved and decreased rainfall over the African continent. However, the onset of the warming and cooling in the south and equatorial Atlantic occurs progressively later from south to north; thus the signal propagates northward.

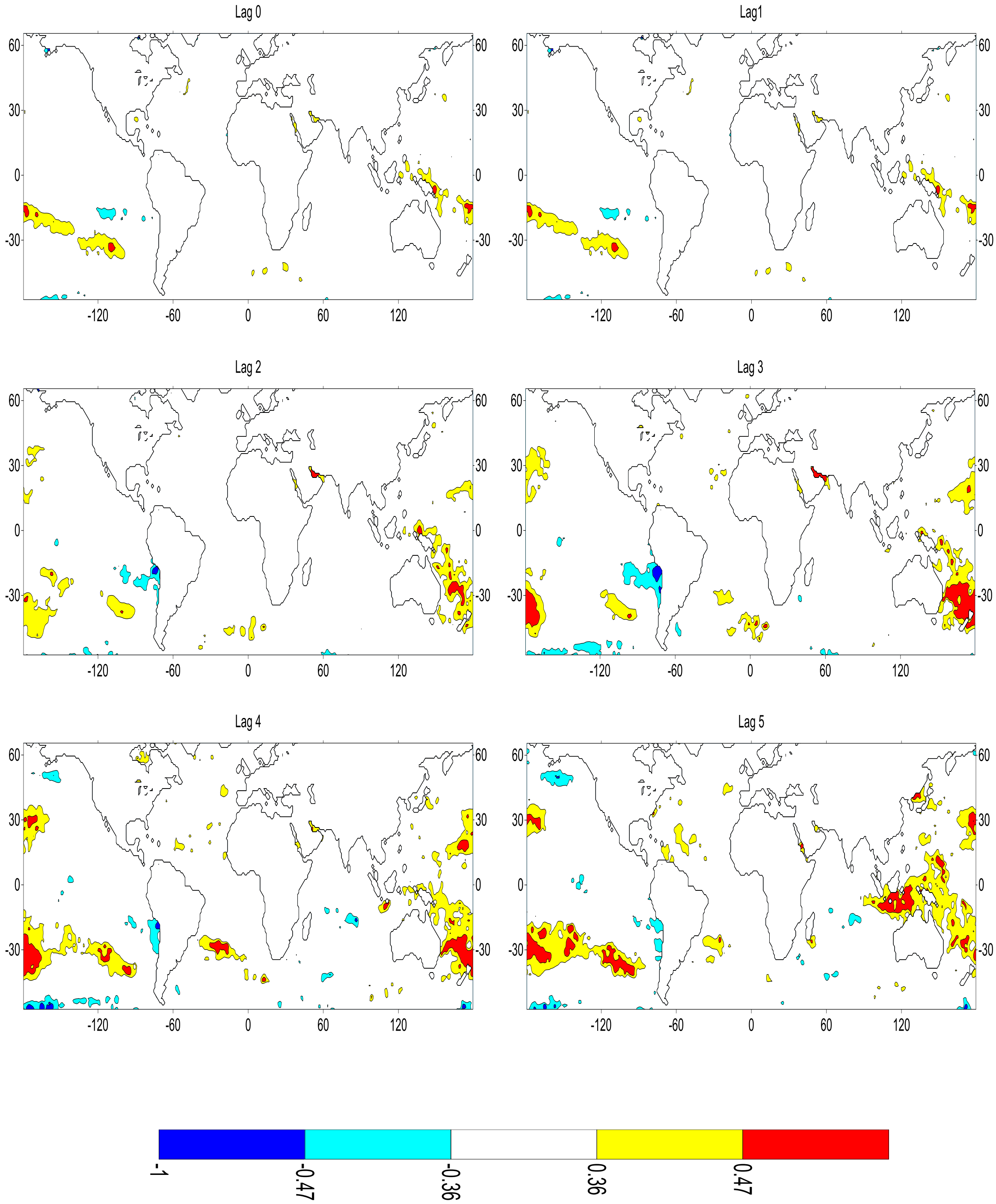


Figure 3.3 Correlation maps for *SST* and rainfall for Zone 1 at 0-5 months lag. The legend shows the scale of the correlation coefficient

At lags of 6–8 months, negative correlations were observed between Zone 1 rainfall and *SST* in the Indian Ocean, southeast of Madagascar (Figure 3.4). The correlations were more pronounced at lags of 7 and 8 months. A region of significant positive correlation was observed in the north, east and northeast of Australia in the Pacific Ocean and the area between Indonesia and Australia in the Indian Ocean at lags of 6–11 months (Figure 3.4). From lags of 8 months, the area of positive correlation moving towards the Indian subcontinent and finally reaching east Africa at Lag 11 months (Figure 3.4) in the region bounded by 30ºN–30ºS and 50–125ºE. The correlations were associated with Type I error rates (*p*) of 1–5%. Reason (2001), Behera and Yamagata (2001) in their study of subtropical Indian Ocean *SST* dipole events and southern African rainfall reported that when the *SST* is warm (cold) to the south of Madagascar and cool (warm) off Western Australia, increased (decreased) summer rains occur over large areas of southeastern Africa. This *SST* pattern leads to increased (decreased) rainfall via enhanced convergence of air with above-average moisture content over the region. These events produce above-normal rainfall over many parts in south-central Africa. Likewise, Xie and Arkin (1996) have suggested that when warm *SST* anomalies occur to the south of Madagascar and cool anomalies occur off Western Australia, summer rains over southeastern Africa are enhanced. Furthermore, these authors suggest that the impact on rainfall is related to a weakening of the maritime *ITCZ* over the Indian Ocean and enhanced moisture transport towards southeastern Africa by stronger Southeasterlies.

In the North Atlantic Ocean, a region of significant positive correlation between *SST* and rainfall in Malawi was apparent at lags of 6–8 months. The region extends from the Caribbean Sea, North America, coasts of Portugal and West Africa (Figure 3.4). Enfield and Mayer (1997) reported that the *SST* in the tropical Atlantic differed independently on an interannual basis in the zones north and south of the *ITCZ*. They further reported that these events appear to be associated with a northward shift in the latitude of the *ITCZ*, with consequent warming immediately north of the mean *ITCZ* position and weak cooling to the south. The shift in *ITCZ* northward can have an effect on rainfall amounts and distribution in Malawi as Malawi rainfall is dependent on *ITCZ*.

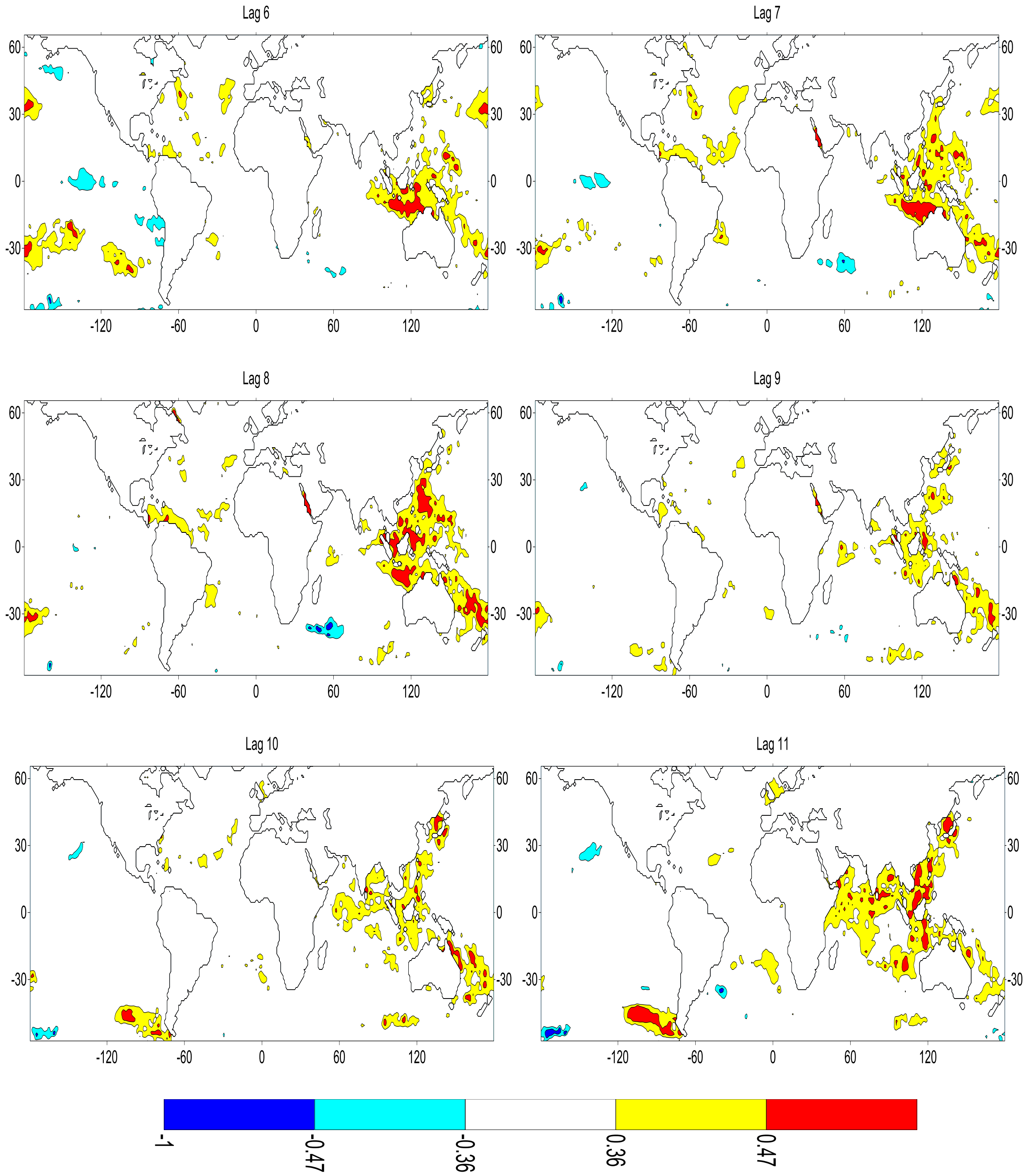


Figure 3.4 Correlation maps for *SST* and rainfall for Zone 1 at 6-11 months lag. The legend shows the scale of the correlation coefficient.

3.3.2 Correlation between SST and November to January rainfall for Zone 1(using grid data)

Figures 3.5 and 3.6 presents the results of the correlation between November to January (NDJ) rainfall and *SST*. At lag 3 to 4 months and 8 to 10 months, significant negative correlations were observed in the Indian Ocean off the coast of Somalia, southern India and Australia. At lag 11 months (figure not shown) negative correlations were observed in the Indian Ocean, south east of Madagascar. The correlation coefficients were between 0.36 and 0.52 significant at less than 0.5, 0.01 and 0.0001 respectively. Different studies have been conducted to analyse the relationship between African rainfall and the *SST* in the Indian Ocean. Nicholson (1996) reported that high rainfall in the east African short rain season (October to December rainfall) is associated with enhanced *SST* gradients in the Indian Ocean and, to a lesser extent, in the Atlantic Ocean. Goddard and Graham (1999) suggest that Indian Ocean *SST* exerts a greater influence over the east African short rains than the Pacific Ocean. Rocha and Simmonds (1997b) showed that anomalously warm Indian Ocean *SST* cause an eastward shift of the Walker circulation from the African subcontinent to central Indian Ocean. They further reported that low level circulation over southeast Africa changes with anomalously warm *SST*s over the Indian Ocean which reduces the moisture flux inland. Saji *et al*. (1999) reported that an east west dipole mode in the *SST* anomalies of the tropical Indian Ocean is coupled to the surface winds and that the *SST* dipole is significantly correlated with the rainfall variability of the two poles. The results of these studies corroborate with the findings of this study on the influence of Indian Ocean *SST* on African rainfall.

Significant negative correlations were observed in the East, South China Sea between Taiwan and Malaysia at lag 3 and 4 months (Figure 3.5). At lag 7 to 10 months (Figure 3.6), the negative correlations were observed in the East and South China Sea.

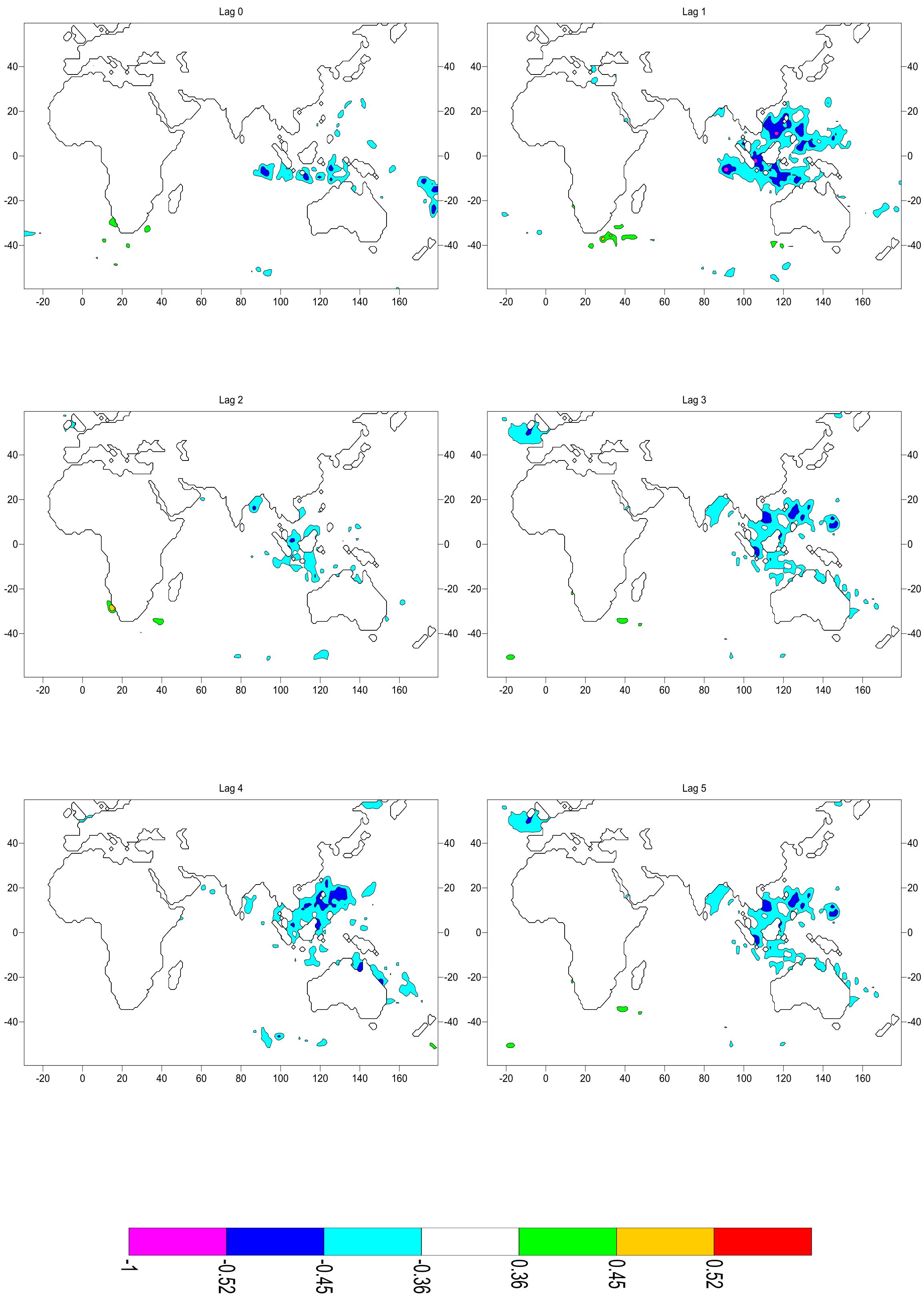


Figure 3.5 Correlation maps between November to January Zone 1 rainfall and *SST* at Lag 0 to 5 months

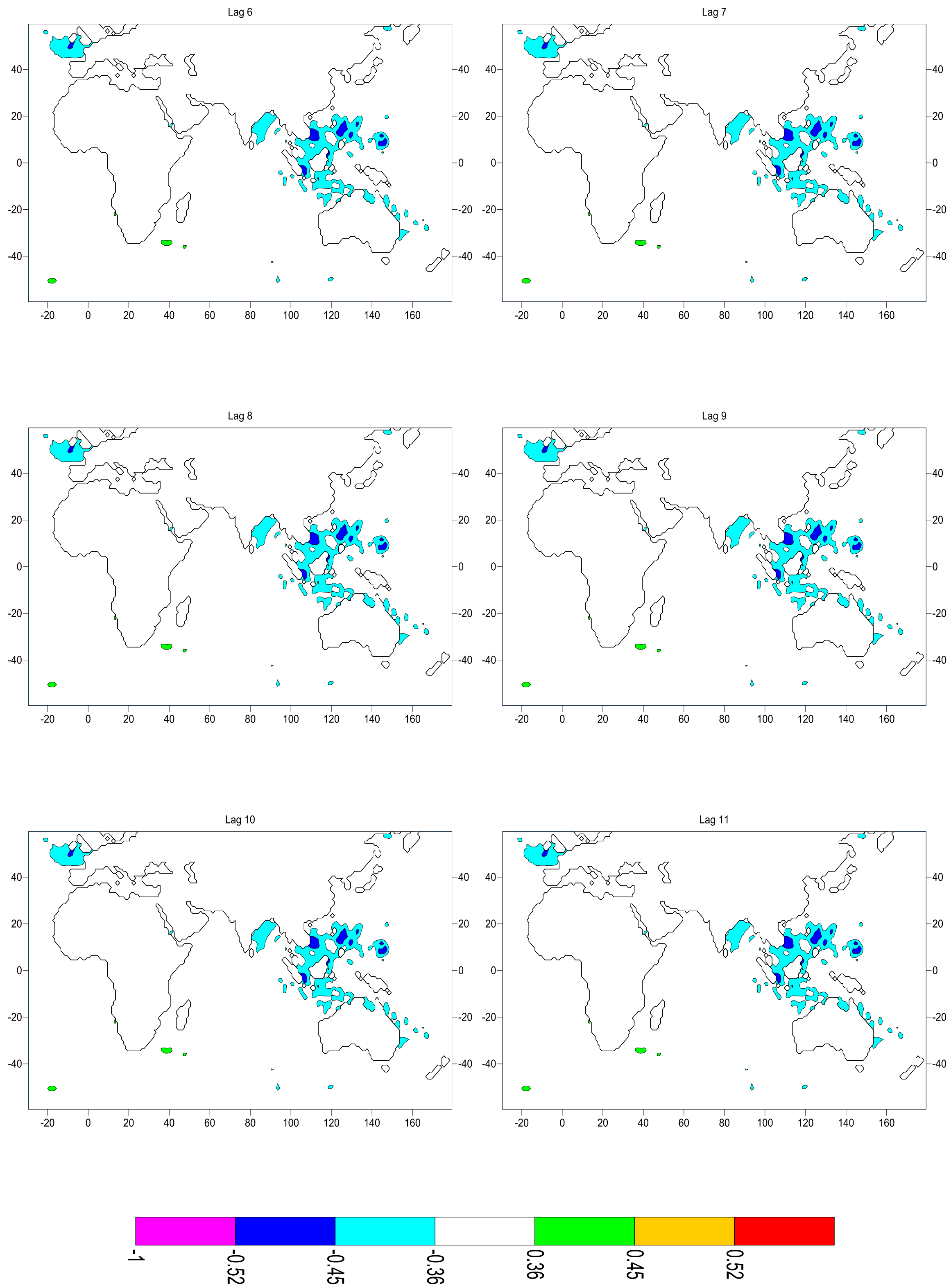


Figure 3.6 Correlation maps between November to January Zone 1 rainfall and *SST* at Lag 6 to 11 months

3.3.3 Correlation between SST and February to April rainfall for Zone 1 (using grid data)

Figure 3.7 presents the results of the correlation between February to April (FMA) rainfall and *SST*. Significant negative correlations were observed at lags 0 to 8 months in the equatorial Pacific Ocean. The correlations were significant at 99 and 99.99% level of significance. The correlations were observed within the Nino 3, Nino 3.4 and Nino 4 regions located between 5°N and 5°S and 160°E and 90°W in the equatorial pacific.

The Nino 3.4 region, which is in between Nino 4 region and Nino 3 region, is the region where the intensity of El Niño based on *SST* anomalies exceeding a pre-selected threshold in a certain region of the equatorial Pacific is classified (http://www.ncdc.noaa.gov/teleconnections/*ENSO*/indicators/*SST*.php). The most commonly used threshold is a positive *SST* departure from normal greater than or equal to +0.5°C. Mutai *et al.* (1998) found that variability in equatorial Pacific *SST*s had an influence in the prediction of east Africa short rains (October to December rains). Philips and McIntyre (2000) reported that Pacific *SST*s were positively correlated with November–December rainfall and negatively correlated with August–September rainfall in Uganda. Goddard and Graham (1999) found that anomalous *SST* over central and eastern Pacific Ocean tend to counteract the circulation and precipitation anomalies imposed by the Indian Ocean *SST* anomalies over southeastern Africa. Hastenrath *et al.* (1993) found that the causality of short rains in eastern Africa is strongly related to the southern oscillation, an atmospheric component of *ENSO*. They suggested that during high southern oscillation phase the pressure is high (low) in the western (eastern) Indian Ocean during October−November. Variations in the Pacific Ocean *SST* due to *ENSO* are known to exert a remote forcing to cause the variations of the precipitation over SA (Jury, 1996; Nicholson and Kim, 1997; Goddard and Graham, 1999; Cook, 2001). Rocha and Simmonds (1997b) reported that dry conditions over

Africa during *ENSO* years are associated with marked low level anomalous cyclonic circulations over the central Indian Ocean, which divert the moisture from the landmass and result in reduction of precipitation. These studies indicate a significant relationship between Pacific Ocean *SST* and rainfall in east and SA where Malawi is located and our results are in agreement with these results.

At lags 0 and 1 months (Figure 3.7), significant negative correlations were observed in the South Pacific Ocean off the coast of Chile. In the South Pacific Ocean off the coast of Chile, significant positive correlations were observed at lags 9 to 11 months (Figure 3.8). The correlations were significant at less than 0.01 and 0.0001 level of significance.

From lag 0 to 4 months (Figure 3.7), significant negative correlations were observed in the Indian Ocean between Malaysia and east Africa. The correlations were significant at less than 0.01 and 0.0001 level of significance. At lag 4 to 7 months (Figure 3.7 and Figure 3.8), significant positive correlations were observed in the Indian Ocean between Australia and Malaysia. The correlations were significant at less than 0.01 and 0.0001 level of significance. Mutai *et al*. (1998), Nicholson (1997), Ogallo *et al*. (1988), Cadet and Diehl (1984) have reported that short rains in eastern Africa correlate strongly with western Indian Ocean, suggesting that Indian Ocean *SST* is a major contributor to the variability of the short rains. According to Behera and Yamagata (2001), an anomalous increase in the *SST* over the southwest South Indian Ocean, south of Madagascar, during the positive phase of the subtropical Indian Ocean dipole is known to cause increase in precipitation over the SA land mass.

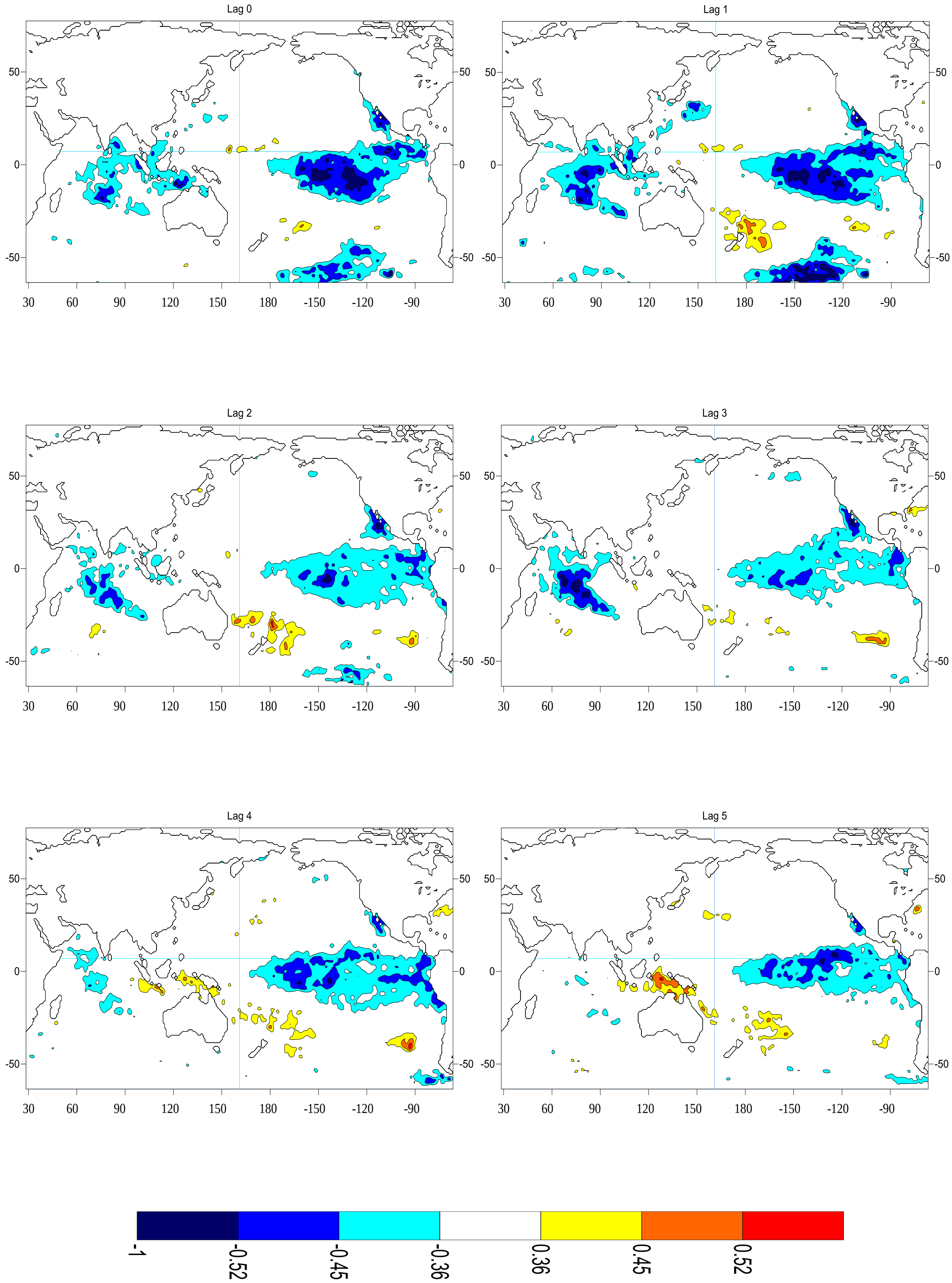


Figure 3.7 Correlation maps between February to April Zone 1 rainfall and *SST*

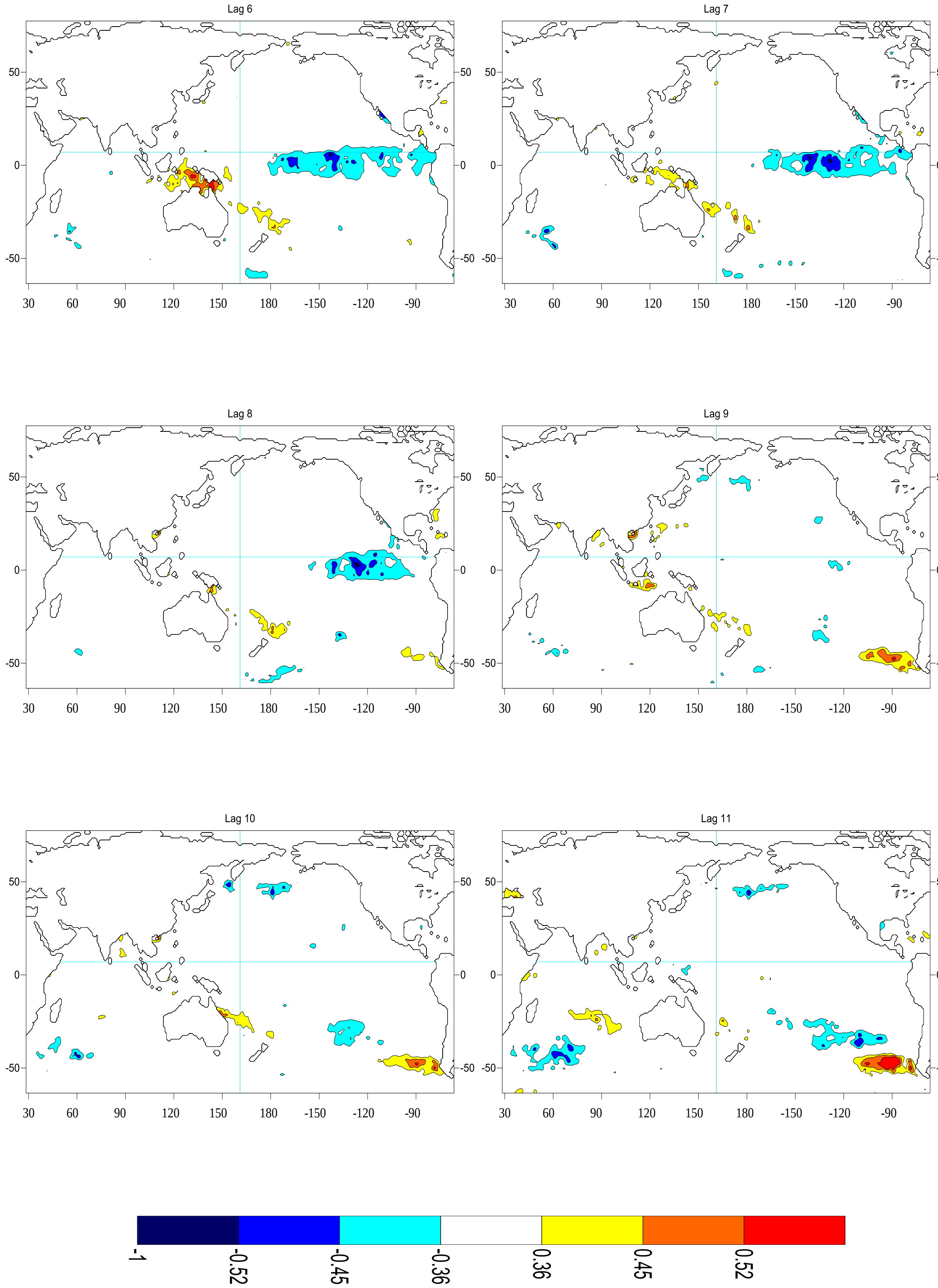


Figure 3.8 Correlation maps between February to April Zone 1 rainfall and *SST*

3.3.4 Analysis of relationship between SST and Zone 2 rainfall (using rain gauge data)

Positive correlations between the *SST* southwest and southeast of Madagascar and Zone 2 rainfall in Malawi are apparent at lags of 2–5 months (Figure 3.9). At lags of 6–11 months (Figure 3.10), significant positive correlation is apparent in the Indian Ocean, shifting from the Indonesian coast toward Australia. This region is bounded by 0–30ºS and 90–120ºE. Negative correlations between *SST* and Zone 2 rainfall in Malawi at lags of 3–4 months (Figure 3.9) are apparent in a region of the Indian Ocean bounded by 20–40ºS and 60–90ºE . The correlations in this region are associated with Type I error rates of 1–5%. According to Rocha and Simmonds (1997b), anomalously warm *SST*s in the tropical Pacific and Indian Oceans, related to *ENSO* events, produce dry conditions over much of southeastern Africa. They further stated that rainfall in southeastern Africa is greatly affected by *SST*s in the central Indian Ocean, which are partially independent of *ENSO*. Reason and Mulenga (1999) noted that there appears to be a mixed influence of El Niño and La Niña on wet and dry years and *SST* anomalies in the tropical Indian Ocean, as well as in the Pacific Ocean. This influence is reminiscent of the *ENSO* effect on dry and wet conditions over southeastern Africa. It can be deduced that the negative correlation is due to the opposite of this phenomenon. There is a significant negative correlation (p = 1–5%) between Zone 2 rainfall in Malawi and *SST* in the region bounded by 20–35ºN and 30–60ºW in the North Atlantic Ocean at lags of 5 and 6 months (Figure 3.9 and Figure 3.10). Fauchereau *et al.* (2003) revealed that in the tropical Atlantic, the influence of *SST* in the southern Atlantic overshadow the influence of *SST* and upper-air dynamics in the northern Atlantic. The study further reported that a warm South Atlantic reduces the thermal gradient with the African continent, resulting in a southward shift of the *ITCZ*.

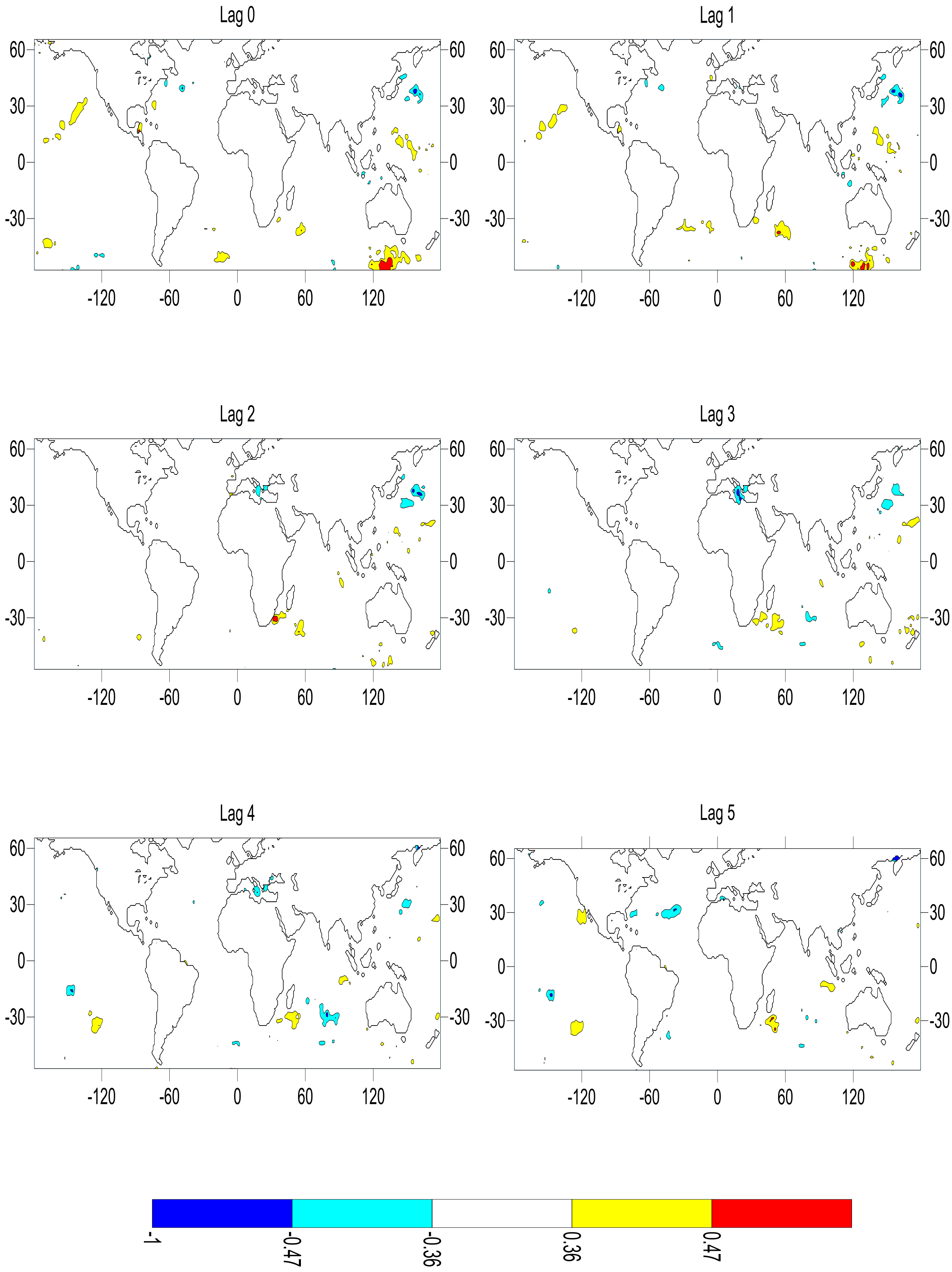


Figure 3.9 Correlation maps for *SST* and rainfall for Zone 2 at 0-5 months lags

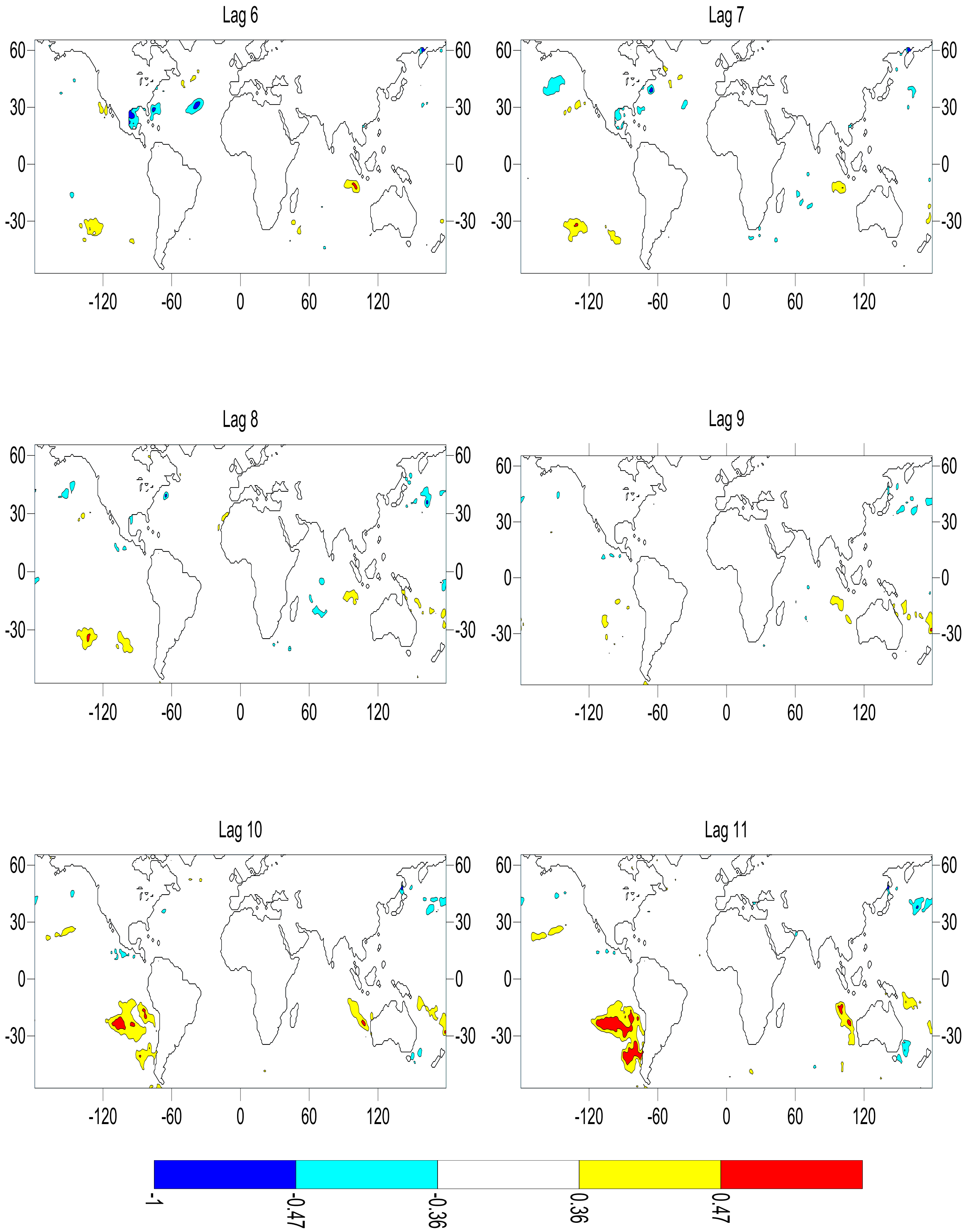


Figure 3.10 Correlation maps for *SST* and rainfall for Zone 2 at lag 6-11 months

3.3.5 Correlation between *SST* and December to February rainfall for Zone 2 (using grid data)

Figure 3.11 presents the results of the correlation between December to February (DJF) rainfall for Zone 2 and *SST*. The correlation analysis between DJF average rainfall for Zone 2 and *SST* showed significant positive correlation at lag 6 to 8 months. The correlations were observed north of Australia in Arafura Sea and east of Australia in the Coral Sea. The correlation between DJF rainfall and *SST* in the Australasian region gives an impression that the DJF rains are linked to the southern Oscillation. Stoeckenius (1981), Ropelewski and Halpert (1989), Lindesay and Vogel (1990) have reported that interannual variability in rainfall over central−east and southern Africa during the October−February season correlates strongly with the *SST* changes in the tropical Pacific associated with *ENSO* phenomenon. Nicholson and Kim (1997) found a strong connection between *ENSO* and rainfall over the African continent. They suggested a linkage through *ENSO*−induced *SST* anomalies in the Indian Ocean, which, in turn, modulate interannual variability of rainfall over Africa. Nicholson (1996) reported that *ENSO* signal in African rainfall variability is a manifestation of *ENSO*s influence on *SST*s in the Atlantic and Indian Oceans that in turn, influence rainfall. Janowiak (1988) reported that rainfall tends to be higher than normal by 10–25 percent over the equatorial eastern Africa and correspondingly lower in southeastern Africa during warm *ENSO* events. Rocha and Simmonds (1997a) found that strongest relationships are found with *SOI* when leading southeastern Africa rainfall by 3 to 6 months. Rao *et al.* (2002) reported that the Indian Ocean dipole and *ENSO* both influence the short rains in eastern Africa. They suggested that one third of positive Indian Ocean dipole events co-occur with warm *ENSO* events.

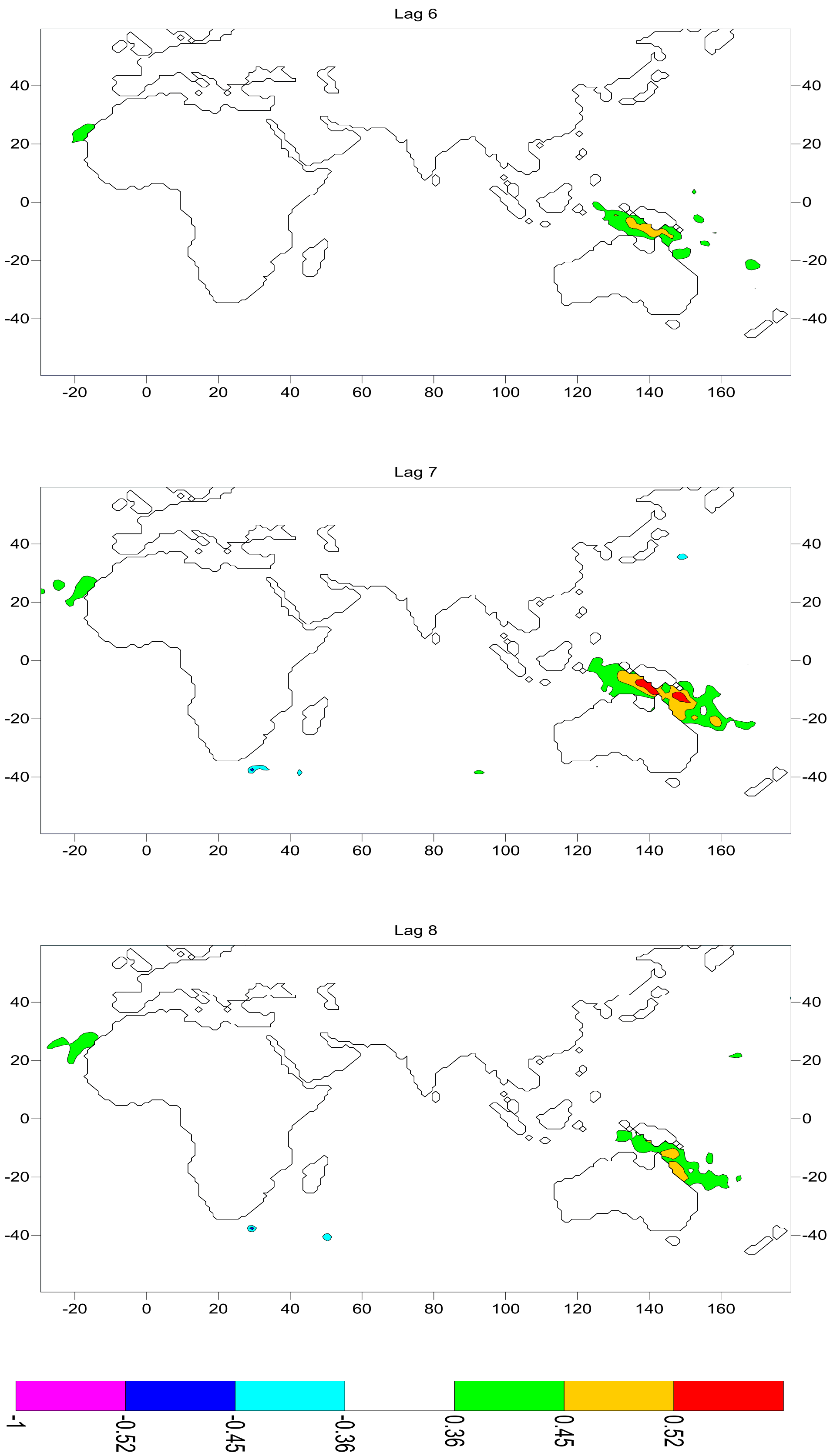


Figure 3.11 Correlation Maps between *SST* and DJF rainfall for Zone 2

3.3.6 *SST* differenced time series

At lags 5 and 6 months, significant positive and negative correlations were observed between *SST* and FMA rainfall for Zone 1 in the equatorial Pacific Ocean and north of Australia in Arafura Sea. The positive correlations were observed in the region around Darwin, Australia while the negative correlations were observed in the Nino 3.4 and Nino 3 region in equatorial Pacific Ocean (Figures 3.12 and 3.13). The correlations were at significant level of 0.001 ($r > 0.45$). According to Yasuda *et al.* (2009) taking the difference between the negative and positive *SST* time series results in a pole–dipole effect, which is the difference in *SST* temperature between these two areas, in the resulting differenced time series.

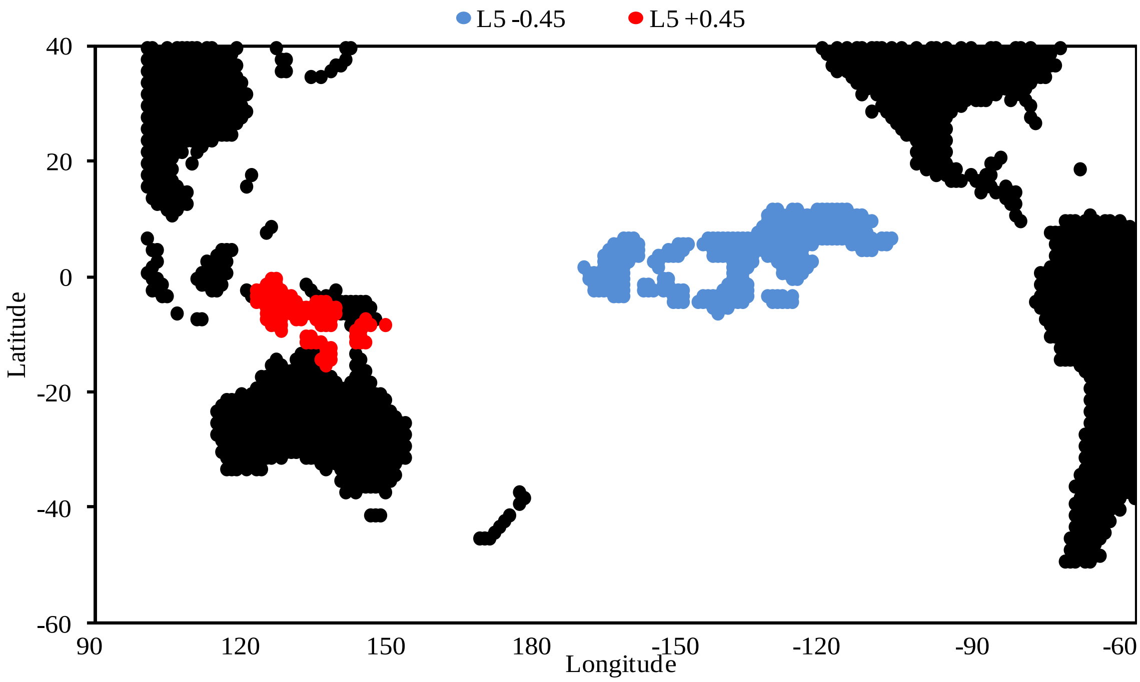


Figure 3.12 Correlation between *SST* and FMA rainfall at Lag 5 for Zone 1

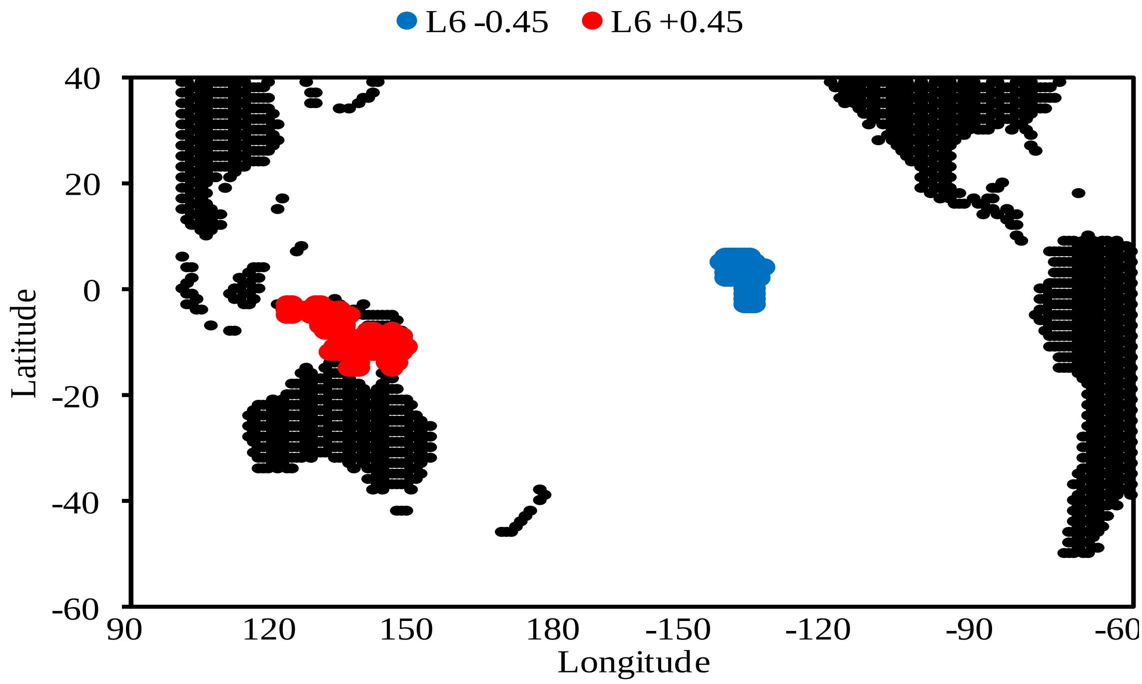


Figure 3.13 Correlation between *SST* and FMA rainfall at Lag 6 for Zone 1

We followed this procedure and used the negative and positive *SST* time series for the regions with significant correlations to calculate the differenced time series. The differenced *SST* time series were then correlated with FMA rainfall for Zone 1. There was a significant increase in the correlations between FMA rainfall for Zone 1 and *SST* differenced time series. For example, for lag 6 months, the correlation between FMA rainfall and negative *SST* time series ($r < -0.45$) was -0.506 while the correlation between FMA rainfall and positive *SST* time series ($r > 0.45$) was 0.469. However, the correlation increased to 0.562 after correlating the *SST* differenced time series and FMA rainfall. For lag 5 months, the differenced time series resulted in a correlation of 0.550, from a negative and positive correlation of -0.494 and 0.493 respectively. The correlations were significant at 0.0001 significant level. Table 3.1 shows the results of the correlation between FMA rainfall for Zone 1 and *SST* differenced time series.

Table 3.1 Correlation between FMA rainfall and differenced time series

Lag time (months)	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Negative	-0.458	-0.475	-0.468	-0.486	-0.494	-0.506
Positive	0.518	0.455	0.508	0.474	0.493	0.469
Difference	0.538	0.556	0.586	0.522	0.550	0.562

3.4 Conclusions

The study found that summer rainfall in Malawi is correlated with G*SST* from the Atlantic, Indian and Pacific Oceans. However, Malawi summer rainfall was more strongly correlated with *SST*s in the Indian Ocean compared to those in the Atlantic and Pacific Oceans. The correlation was more significant for Zone 1 (northern stations) than Zone 2 (central and southern stations). The rainfall in Zone 2 appears to be influenced more by *SST* in the subtropical Indian Ocean than by *ENSO* or the tropical Indian Ocean dipole. These findings are consistent with those from other studies, such as by Wood and Moriniere (2013). Malawi straddles both equatorial east Africa (north of 10°S) and subtropical SA (south of 15°S), and given its geographic location, these studies concluded that the northern and southern regions of Malawi are likely influenced by different climate drivers.

The NDJ rainfall for Zone 1 showed significant inverse relationship with *SST* in Indian Ocean and the East, South China Sea while the FMA rainfall for Zone 1 showed significant negative relationship with equatorial Pacific *SST* in the Nino region and significant positive correlation with *SST* in the Australasian region. We deduce that *ENSO* events in these regions play a significant role in the inverse relationship between rainfall and *SST*. Significant increase in the correlations between rainfall and differenced *SST* time series were noted in the FMA rainfall for Zone 1. DJF rainfall for Zone 2 showed significant positive correlations with *SST* in the Australasian region suggesting a linkage with *ENSO* events in the Pacific Ocean.

The correlation between Malawi rainfall and *SST* significantly increased after using the differenced time series suggesting a pole–dipole effect.

Chapter 4 Prediction of Malawi Rainfall from Global Sea surface Temperature Using a Simple Multiple Regression

4.1 Introduction

The economy of Malawi is heavily dependent on agriculture which is mostly rainfed and occupies 86 % of its workforce, and making up 38 % of its GDP and 90 % of its export earnings (World Bank, 1990). The total rainfall received determines the type of farming and which crops can be cultivated. The failure of rains for more than one month in the rainy season impacts heavily on agriculture and the economy of Malawi.

The recurrence of droughts over SA in recent years has contributed to an increased interest in research scientists to focus more attention on the study of climate variability and its predictability (Mwafulirwa, 1999). The farming community in Malawi requires an advance warning of drought/floods; however, statistical models for the prediction of seasonal rains are unverified (Jury and Mwafulirwa, 2002).

Some of the approaches used for long range forecasting of rainfall are; (a) statistical method, which uses the historical relationships between rainfall and global atmosphere parameters (Sahai *et al.*, 2003); (b) empirical method, which uses time series of past rainfall data (Iyengar and Raghukanth, 2004); and (c) dynamical method, which uses Atmospheric General Circulation Models (AGCM) and oceans to simulate rainfall (Wang *et al.*, 2005).

Malawi relies on the Southern Africa Regional Climate Outlook Forum (SARCOF), a regional grouping of climate scientists from Southern Africa Development Community (SADC) member states to develop seasonal forecasts. SARCOF meets annually before the start of the rainy season to develop seasonal forecasts for the region. The forecast covers the rainy season from October to March and is relevant to seasonal time scales and relatively large areas. The forecast is based on dynamic and statistical models that use scientifically established relationships between rainfall over SA and *SST*.

Literature on studies about rainfall forecasting in Malawi is scarce. Jury and Mwafulirwa (2002) is one notable study that was carried out to predict Malawi rainfall. The study reported that the three area *SST* index, formulated to capture *ENSO* modulated Rossby wave pattern, had the most influence in predicting Malawi rainfall, followed by air pressure over the East Indian Ocean and the stratospheric zonal wind anomaly (*QBO*). The study found skilful results with a 55% hindcast fit and two thirds of tercile categories correctly forecast in independent test.

This study therefore aims at developing a simple regression model that can be used to predict Malawi rainfall. The study will exploit relationships between Malawi rainfall and *SST* in the global oceans and use these as predictors in the models.

4.2 Methodology

Using the statistical linkage between *SST* and Malawi rainfall that was identified in the previous study, we extracted the areas of significant positive and negative correlation between *SST* and Malawi rainfall to be used in rainfall modelling. Regions with significant correlation (r>0.36 significant at 5 % error) were extracted from the maps using NOAA extracting tool available at [http:// esrl.noaa.gov/psd/data/timeseries/](http://esrl.noaa.gov/psd/data/timeseries/). These were taken as predictors of the models. Figures 4.1 and 4.2 show the correlation map showing the areas of significant positive and negative correlations for Zone 1 and 2 at Lag 7 and 11 months that were used in the rainfall modelling process

For Zone 1, significant correlations were observed in North Atlantic Ocean along the Venezuela and Colombia coast (AO_3, 15–10°N, 83–65°W); off the Island of Cape Verde (AO_2, 17–10°N, 40–25°W) among other areas. In the southern Atlantic, significant positive correlations were observed in the east of Brazil (AO_1, 20–25°S, 40–33°W). Other areas of significant correlation were; east and north east of Australia (PO_4, 10°N–20°S, 145–155°E); along Philippines and south east of Madagascar as shown in Figure 4.1.

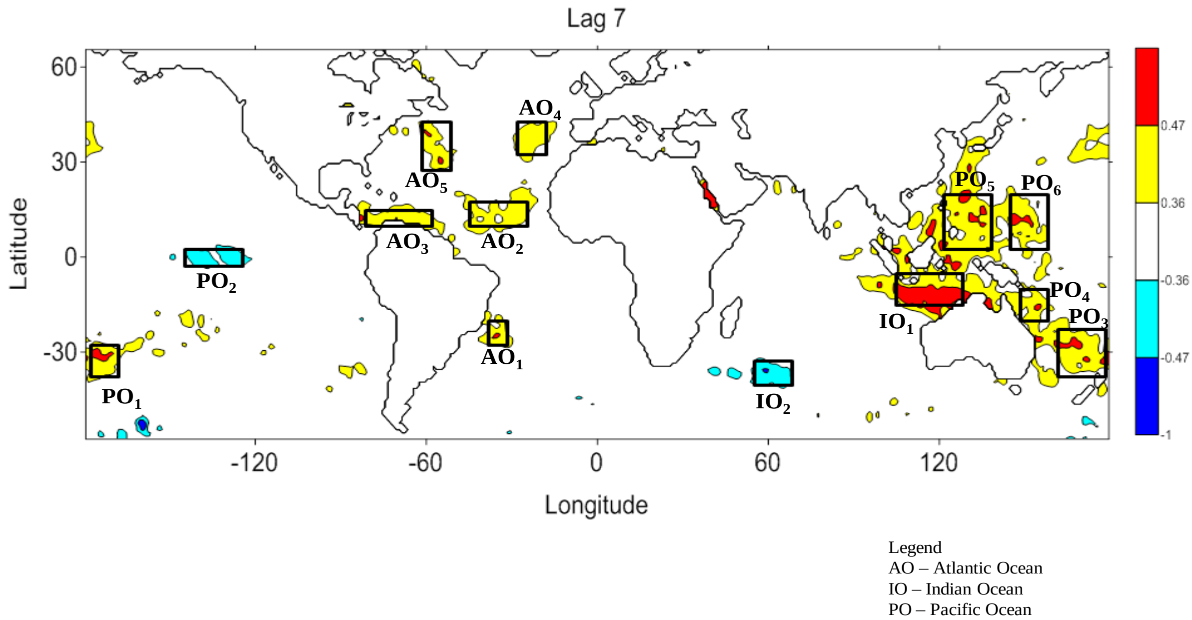


Figure 4.1 Predictors used for regression modelling for Zone 1 at Lag 7 months

For Zone 2, areas of significant correlation were observed around Australia (PO_5, 5–10°S, 155–165°E, PO_6, 35–40°S, 155–160°W, IO_1, 10–35°S, 90–110°E); off the coast of Chile in South Pacific Ocean (PO_2, 15–30°N, 80–120°W, PO_3, 35–45°S, 75–85°W) and near Hawaii Islands in North Pacific Ocean (PO_1, 26–28°N, 150-165°W) as shown in Figure 4.2. The correlation coefficients ranged from 0.36 to 0.47; these *r* values corresponded to Type I error rates (*p*) of 5% and 1%, respectively.

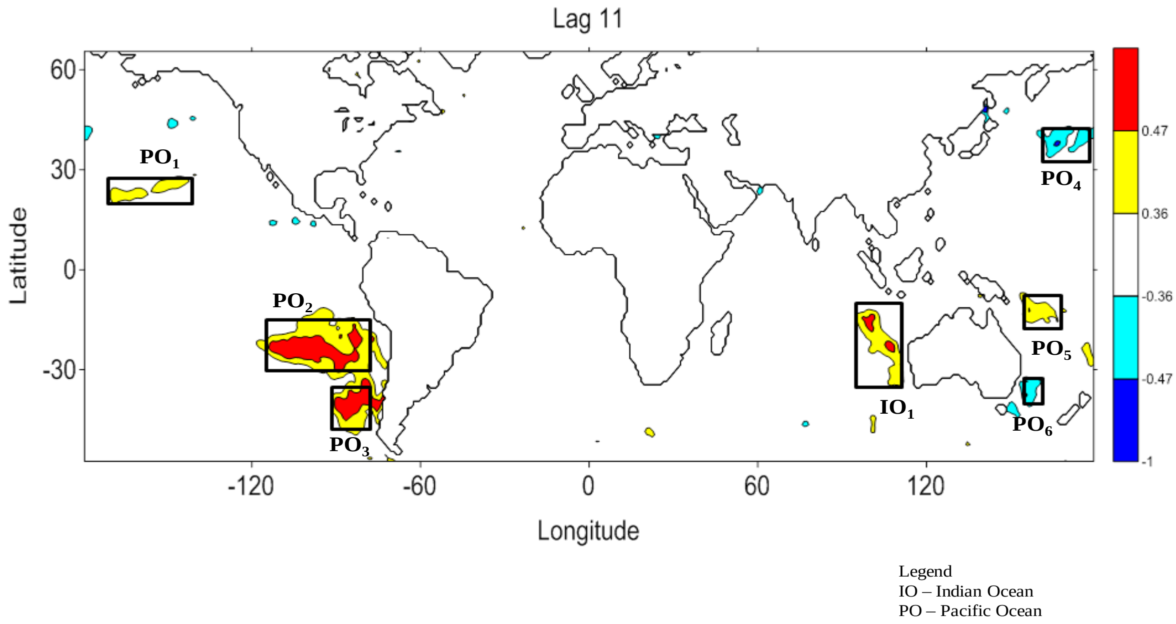


Figure 4.2 Predictors used for regression modelling for Zone 2 at Lag 11 months

Predictors had to meet the following requirements;

a) A good relationship with Malawi rainfall (correlation of r>0.36 corresponding to significant at 5 %.error)

b) A reasonable lead time (months)

c) A predictor should not have a good correlation coefficient with other predictors

Table 4.1 presents a summary of the final predictors used in development of Zones 1 and 2 models and their spatial location.

Table 4.1 Final predictors used for Zone 1 and Zone 2 summer rainfall prediction

Area	Predictors	Spatial domain	Descriptive location
Zone 1	AO_1	20–25°S,40–33°W	East of Brazil
	AO_2	17–10°N,40–25°W	Off Cape Verde Island
	AO_3	15–10°N,83–65°W	Along Venezuela and Colombia
	IO_2	30–37°S, 55–67°E	South east of Madagascar
	PO_2	3°N–3°S,45–125°W	Along the equator in Pacific Ocean
	PO_3	25–35°S,160–175°E	East of Australia
	PO_4	10°N–20°S, 145–155°E	North east of Australia
	PO_5	20–5°N,145–155°E	Off Philippines
Zone 2	PO_2	15–30°S,120–80°W	Off Chile coast
	PO_4	45–37°N,160–170°E	Off Japan coast
	PO_5	5–10°S,155–165°E	North east Australia
	PO_6	35–40°S,155–160°W	South east Australia

4.2.1 Model description

Multiple linear regression models are generally used in developing long range forecasting models. Correlations between *SST* and rainfall were performed to identify predictors to include in forecast models. The step-wise multiple regression method was used within the *R* software package (available from http://cran.r-project.org). Malawi rainfall was the target objective and the multiple linear regression model is denoted by:

$$y = \beta_0 + \beta_1 x1 + \beta_2 x2 + \dots + \beta_k xk + \varepsilon \qquad (4.1)$$

where y is the response variable

- β_0 is the intercept
- β_1 is slope coefficient for the first explanatory variable x_1
- β_2 is slope coefficient for the second explanatory variable x_2
- β_k is slope coefficient for k^{th} explanatory variable x_k
- ε is the error

The selection procedure used in step-wise multiple regression of the model was the forward and backwards procedure. It is used to control the selection of variables into the model. Variables were examined to be entered or removed with the aim of obtaining a model with a high degree of fit.

4.2.2 Model validation

The model was validated using the correlation coefficient (*r*), bias (*BIAS*) and root mean square error (*RMSE)* between observed and predicted summer rainfall. They are calculated as follows:

$$r = \frac{\Sigma\left(Y - \overline{Y}\right)\left(Y' - \overline{Y'}\right)}{\sqrt{\Sigma\left(Y - \overline{Y}\right)^2 \Sigma\left(Y' - \overline{Y'}\right)^2}} \tag{4.2}$$

$$BIAS = \frac{\Sigma\left(Y' - Y\right)}{n} \tag{4.3}$$

$$RMSE = \sqrt{\frac{\Sigma\left(Y' - Y\right)^2}{n}} \tag{4.4}$$

where; $\overline{Y}$ and $\overline{Y'}$ are the sample averages of the observed and predicted rainfall, respectively, and *n* is the number of data.

4.3 Results and Discussion

For Zone 1, significant correlations between summer rainfall and *SST* were obtained in the Atlantic, Indian and Pacific Oceans. The areas of significant correlation were extracted as indicated in Figure 4.1 and these were the predictors of the model. The predictors were modelled in *R* software using the stepwise regression methodology in the regression function and selection of final predictors was based on their significant correlation with summer rainfall, *t* value and residual standard error. The final regression model was selected based on the correlation between observed summer rainfall and predicted summer rainfall, *RMSE* and *BIAS*. Based on the criteria that predictors had to have a reasonable lead time with rainfall, regression models were developed from predictors with a lead time of 7 months lag time to 11 months lag time for both Zone 1 and Zone 2. The results for the model validation statistics for regression models for Zone 1 are presented in Table 4.2.

Table 4.2 Model validation statistics for Zone 1

Lag time (months)	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11
Model ***r*** value	0.81*	0.72*	0.48*	0.41*	0.67*
Model *RMSE*	18.7 mm	21.8 mm	27 mm	28.8 mm	23.4 mm
Model *BIAS*	0.03	0.000004	-0.03	0.03	0.001

*significant at less than 0.0001 level of significance

It can be noted from Table 4.2 above that the regression model developed at Lag 7 months gave satisfactory results as compared to the other models. The regression model at Lag 7 months was thus selected as the final model for Zone 1.

The regression equation for Zone 1 rainfall is given as:

$$MR_{Z1} = -1684.7 - 21.2AO_1 - 30.1AO_2 - 59.8AO_3 + 21.6PO_2$$
$$+68.9PO_3 - 8.3PO_4 + 102.3PO_5 + 41.3IO_2 \quad (4.5)$$

where; MR_{Z1} is Malawi rainfall for Zone 1 and .*AO*, *IO* and *PO* are predictors.

Figure 4.3 to Figure 4.7 shows the results of predicted rainfall against the observed rainfall for Zone 1 at Lag of 7 months to 11 months time. There is a general agreement between the observed and predicted values for most of the graphs (Lag 7-11 months). Notable exceptions are the period between 1982-83; 86-87 and 91-93 where the models are over predicting the values. The models are underperforming between the periods 1997-99, 2001-03 and 2008-10. The lowest correlation between observed summer rainfall and predicted summer rainfall was 0.41 at Lag 10 months (Figure 4.6) while the highest correlation was 0.81 at Lag 7 months (Figure 4.3). The correlations are significant at less 0.001 level of significance. The results of the Zone 1 models are in agreement with previous findings on the relationship between SA rainfall and *SST*. For example Nicholson (1987) reported that the *ENSO* signal in African rainfall variability is a manifestation of the influence of the *ENSO* on *SST* in the Atlantic and Indian Oceans which in turn, influences rainfall. Reason (2001) in his study of subtropical Indian Ocean *SST* dipole events and SA rainfall has noted that when the *SST* is warm(cold) to the south of Madagascar and cool (warm) off Western Australia, increased (decreased) summer rainfall occur over large areas of SA. Williams *et al.* (2008) in their study of the influence of the South Atlantic *SST* on rainfall variability and extremes over SA found that both decreasing *SST* in the central South Atlantic and increasing *SST* off the coast of southwestern Africa lead to a demonstrable increase in daily rainfall and rainfall extremes over SA.

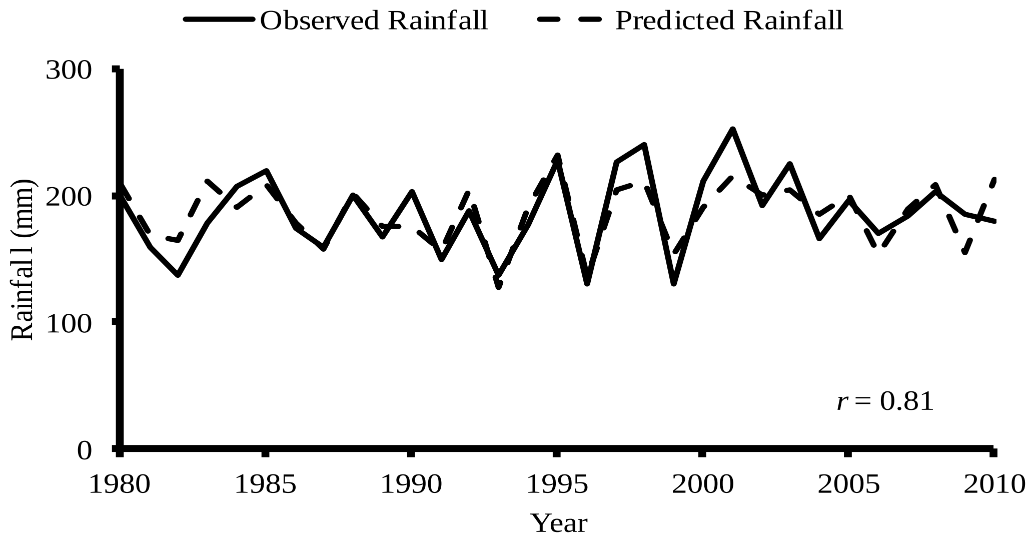


Figure 4.3 Fit of predicted and observed rainfall for Zone 1 at Lag of 7 months

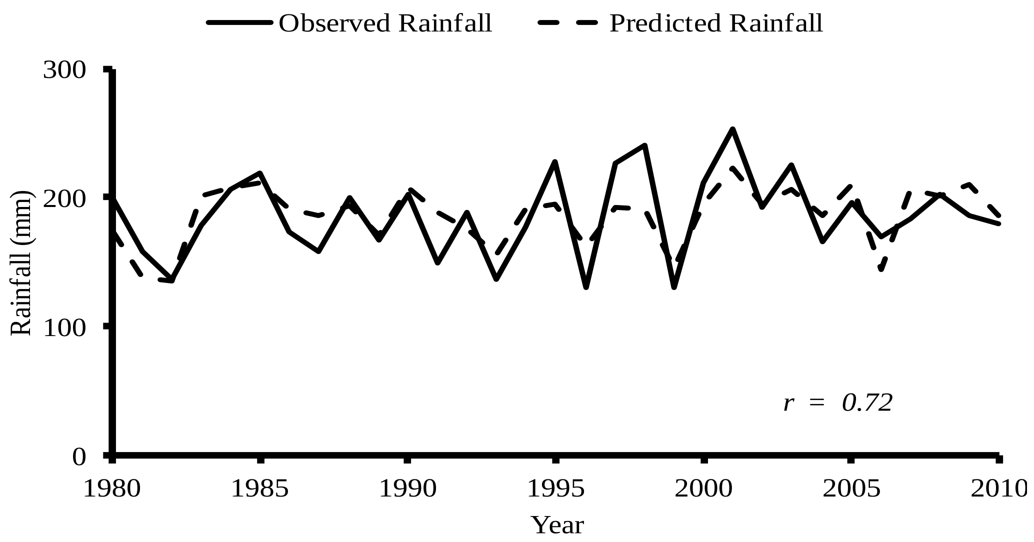


Figure 4.4 Fit of predicted and observed rainfall for Zone 1 at Lag of 8 months

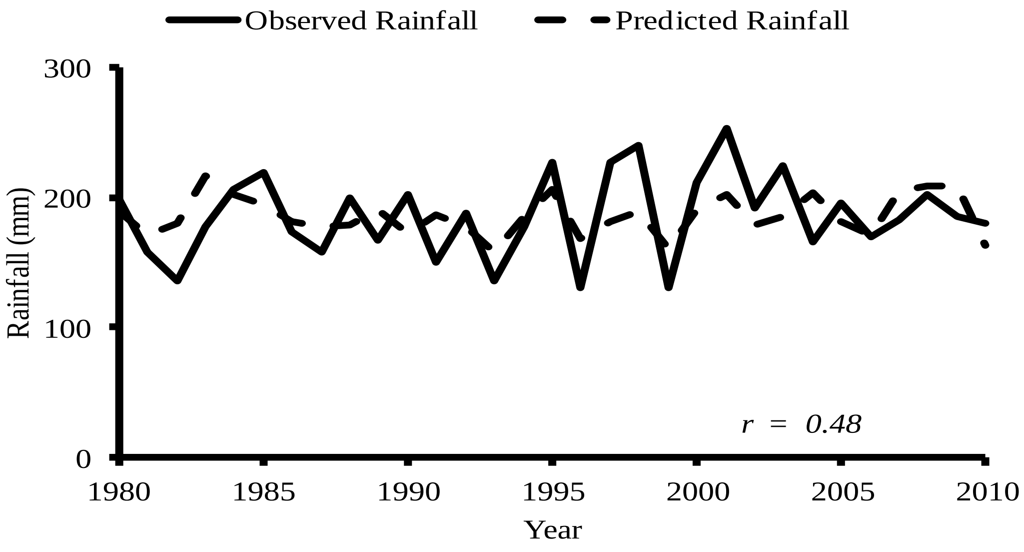


Figure 4.5 Fit of predicted and observed rainfall for Zone 1 at Lag of 9 months

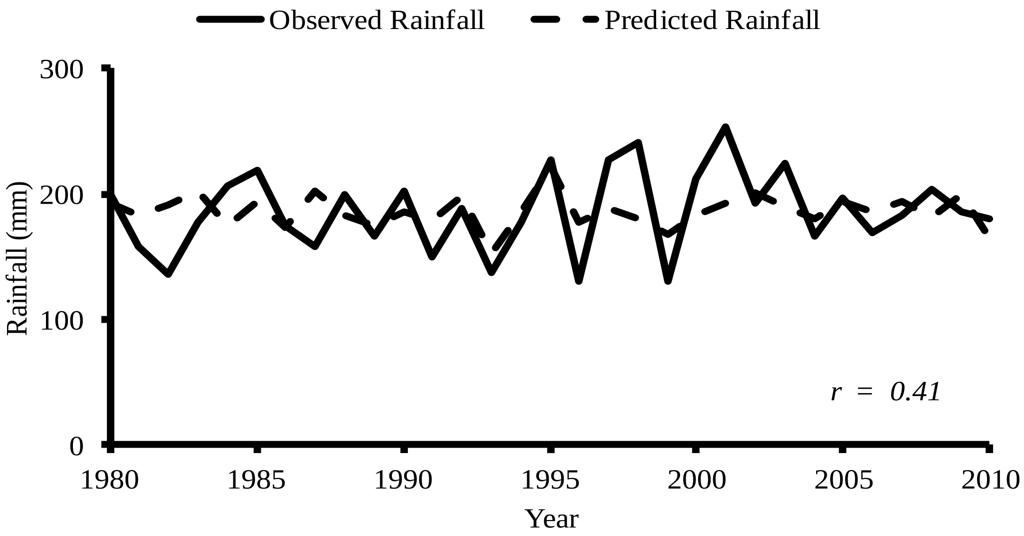


Figure 4.6 Fit of predicted and observed rainfall for Zone 1 at Lag of 10 months

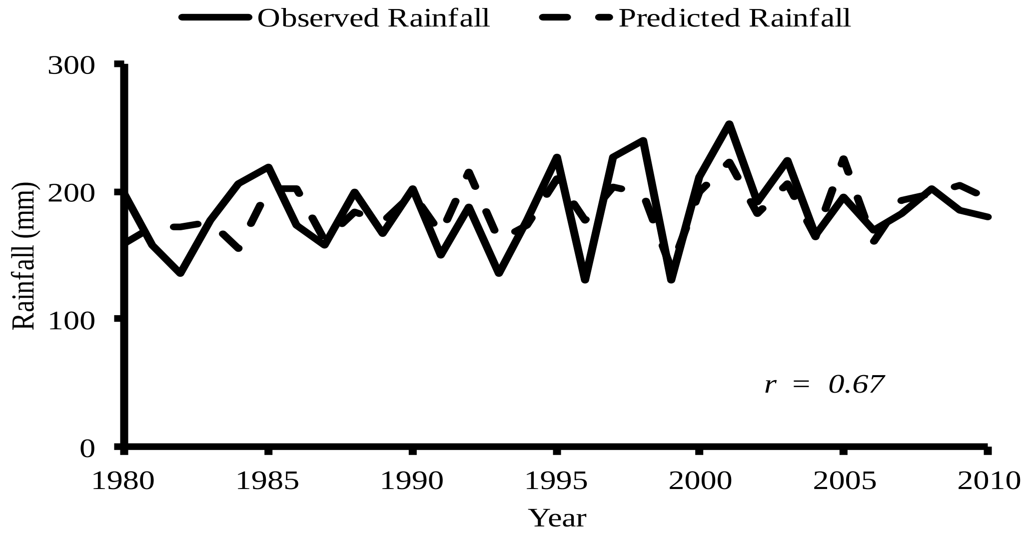


Figure 4.7 Fit of predicted and observed rainfall for Zone 1 at Lag of 11 months

For Zone 2, significant correlations between summer rainfall and *SST* were obtained at 7 to 11 months lag time. The regions of significant correlation were in Indian and Pacific Oceans. The areas of significant correlation were extracted as indicated in Figure 4.2 and these were used as predictors of the regression models. As previously explained, the predictors were modelled in *R* software using the stepwise regression methodology in the regression function and selection of final predictors was based on their significant correlation with summer rainfall, *t* value and residual standard error. The final regression model was selected based on the correlation between observed summer rainfall and predicted summer rainfall, *RMSE* and *BIAS*. The results for the model validation statistics for regression models for Zone 2 are presented in Table 4.3.

Table 4.3 Model validation statistics for Zone 2

Lag time (months)	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11
Model *r* value	0.35	0.33	0.20	0.37	0.54
Model *RMSE*	22.39 mm	22.5 mm	23.3 mm	22.20	20.0 mm
Model *BIAS*	0.02	0.02	0.02	0.05	-0.014

It can be noted from Table 4.3 above that the regression model developed at Lag 11 months gave satisfactory results as compared to the other models. The regression model at Lag 11 months was thus selected as the final model for Zone 2.

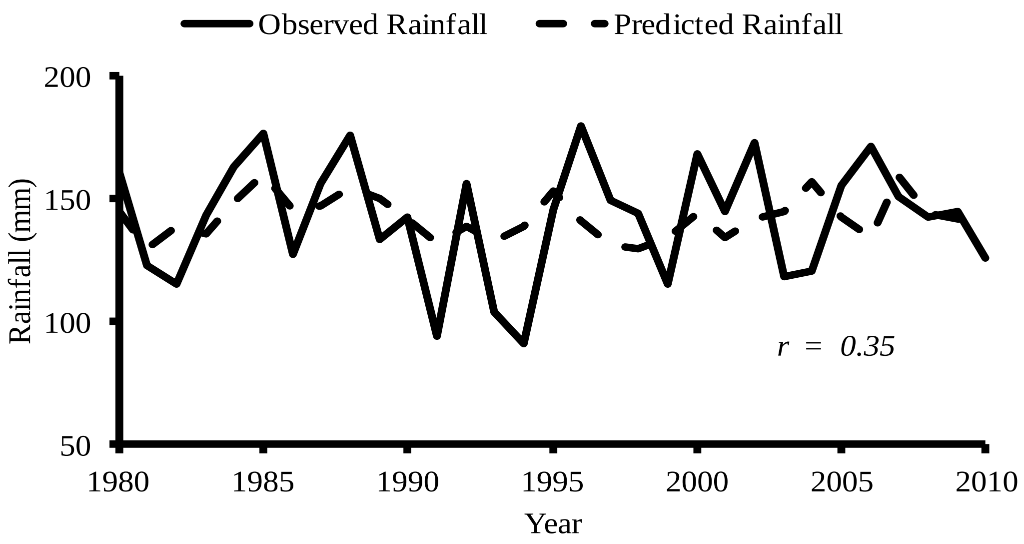
The final regression equation of the model for Zone 2 is given below:

$$MSR_{Z2} = 38.9PO_5 - 8.6PO_2 - 14.2PO_4 - 8.7PO_6 - 501.9 \qquad (4.6)$$

where; MSR_{Z2} is Malawi Rainfall for Zone 2 and *PO* are predictors from Pacific Ocean.

The observed and predicted rainfall time series for Zone 2 are shown in Figure 4.8 to Figure 4.12. It can be seen that the models have successful predictions and some series failures. The model at Lag 11 (Figure 4.12) months successfully predicted dry spells that were experienced in Malawi during 1982-83; 1992 and 2001 that were as a result of El Niño. The model overestimated values in 1981, 1991, 1994, 2003 and 2004. The model correlation coefficient (r) was 0.56, significant at 99.99% level of significance. The model *RMSE* and *BIAS* were 19.8 mm and -0.05 respectively.

It is evident that *SST* in Pacific Oceans are playing an important role in summer rainfall for Zone 2. Ratnam *et al.* (2014) have reported in their study of the remote effects of El Niño and El Niño Modoki events on austral summer precipitation of SA that the differences in the spatial distribution of precipitation over SA are seen to be related to the *SST* anomalies of the equatorial Pacific through atmospheric teleconnections. El Niño Modoki is a coupled ocean-atmosphere phenomenon in the tropical Pacific which is different from another coupled phenomenon in the tropical Pacific namely, El Niño. El Niño Modoki is associated with strong anomalous warming in the central tropical Pacific and cooling in the eastern and western tropical Pacific Conventional while El Niño is characterized by strong anomalous warming in the eastern equatorial Pacific. Associated with this distinct warming and cooling patterns the teleconnections are very different from teleconnection patterns of the conventional El Niño (www.jamstec.go.jp/frcgc/research/d1/iod/enmodoki_home_s.html.en).



.Figure 4 8 Fit of predicted and observed rainfall for Zone 2 at Lag 7 months

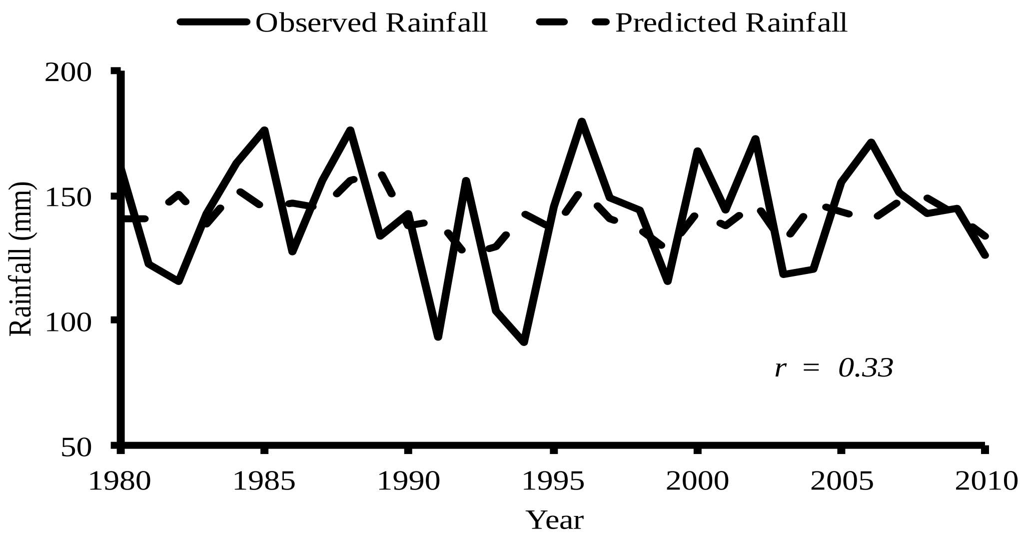


Figure 4 9 Fit of predicted and observed rainfall for Zone 2 at Lag of 8 months

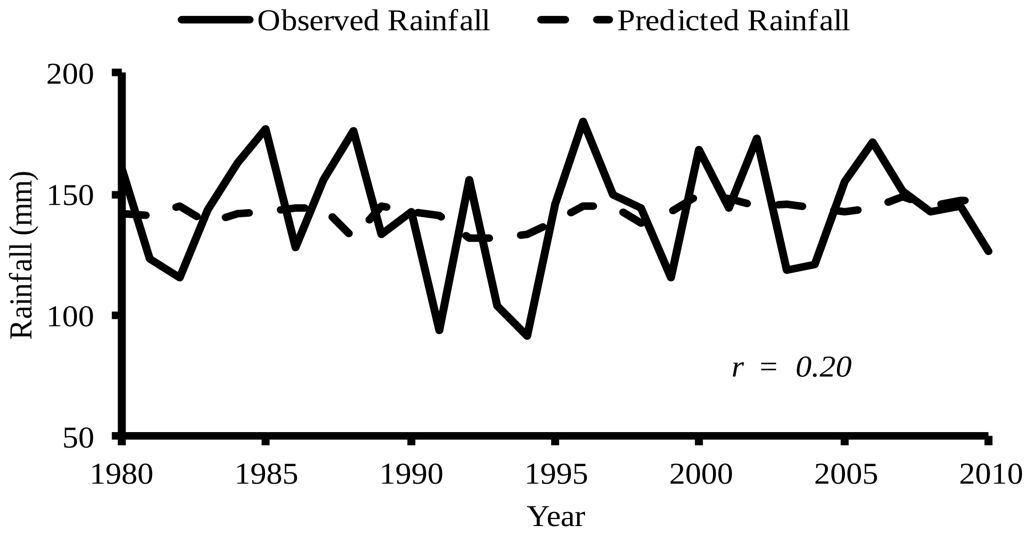


Figure 4 10 Fit of predicted and observed rainfall for Zone 2 at Lag of 9 months

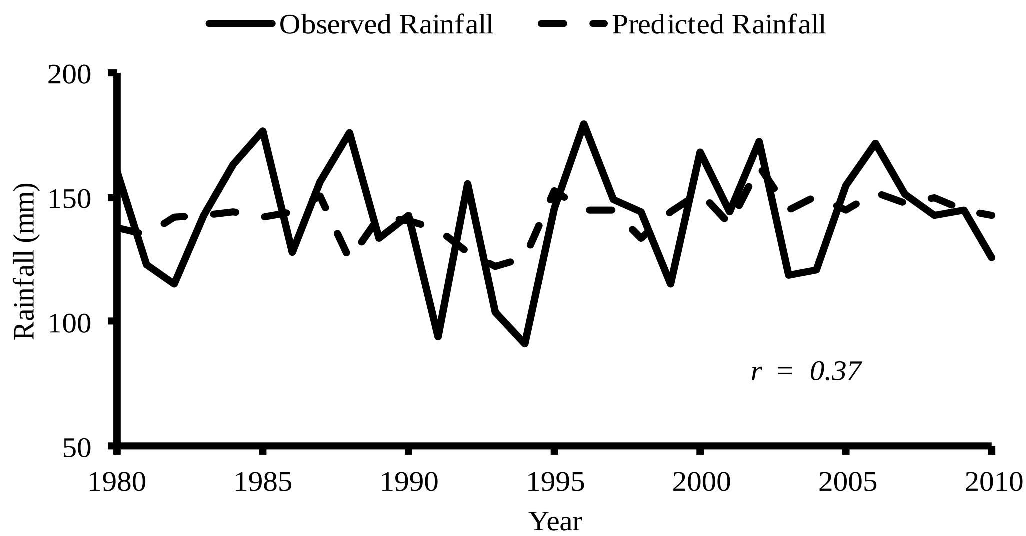


Figure 4 11 Fit of predicted and observed rainfall for Zone 2 at Lag of 10 months

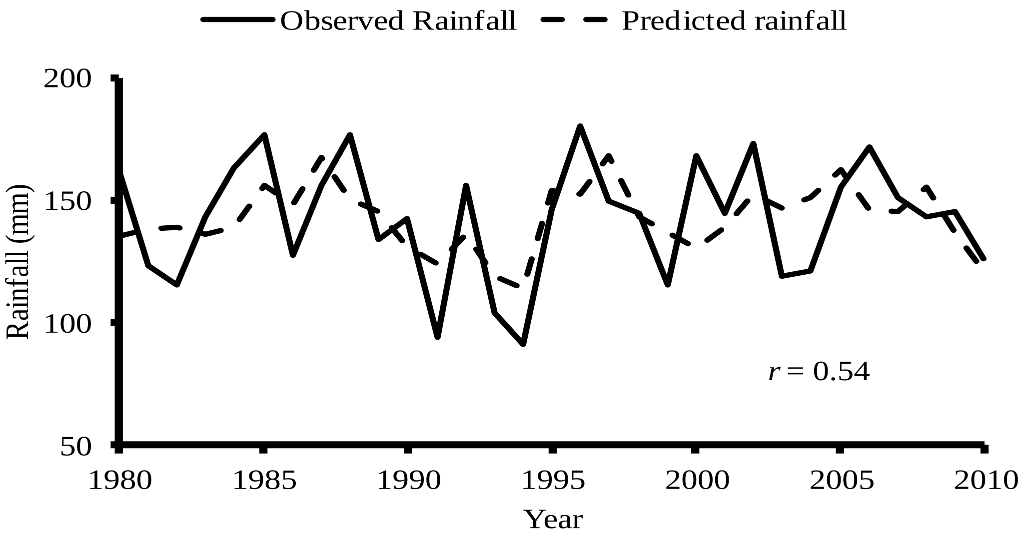


Figure 4 12 Fit of predicted and observed rainfall for Zone 2 at Lag of 11 months

4.4 Conclusions

Prediction of Malawi rainfall was done by first identifying the linkage between Malawi rainfall and G*SST* in order to determine predictors for the models. Significant correlations between rainfall and *SST* in the Atlantic, Indian and Pacific oceans were found. The correlations are significant off Australia and Madagascar in the Indian Ocean; off Brazil and Chile in the Pacific Ocean and between the equator and 20°N latitude in the Atlantic Ocean. These results are in agreement with reported previous studies. To predict Malawi rainfall, these *SST* time series were applied to a simple multiple regression model. The fit of the predicted and observed rainfall for both Zones 1 and 2 was satisfactory.

The study used rainfall data from 9 stations only out of about 40 rain gauge stations that exist in Malawi due to financial limitations on the cost of purchasing the data. There is need therefore to increase the sample size of the rain gauge stations in order to get improved results.

The study in this chapter also focused only on relationship between *SST* and Malawi rainfall. Other factors like sea level pressure and outgoing longwave radiation, if taken into consideration, can greatly improve the results of the model.

Chapter 5 Summary and Conclusions

This research work aims at understanding the causes of temporal and spatial fluctuation of rainfall in Malawi; evaluating seasonal and periodical fluctuations, analyzing the teleconnection between Malawi rainfall and global sea surface temperature(G*SST*); and developing simple regression models for predicting Malawi summer rainfall using G*SST* as predictors.

The motivation for undertaking this research work is based on the fact that Malawi has an economy that is heavily dependent on agriculture and failure of rainfall in a season or year has adverse agricultural and economic effect. The fluctuation and amount of rainfall are among the most important factors that affect agricultural production. The climate of Malawi is highly variable and has a significant influence on the amount, timing, and frequency of precipitation events and runoff patterns, which results in frequent recurrent droughts and floods. The rainfall in Malawi varies both seasonally and interannually. Floods are a major occurrence in low lying areas for example in the Lower Shire valley in southern Malawi and the lakeshore areas of Lake Malawi. Since the economy of Malawi is dependent mostly on rainfed agriculture, major floods and droughts have an impact of the performance of the economy. Undertaking to evaluation the rainfall characteristics is an important step in agricultural planning and ensuring the country's sustainable economic development. Studies on characteristics of rainfall in Malawi are scarce and hence this study attempted to fill that knowledge gap.

Most of the extreme events like floods and droughts have been linked to climatic events such as El Niño, La Niña and sea surface temperatures (*SST*) in the global oceans. The droughts of 1953/54, 1972/73, 1991/92 seasons among others were as a result of El Niño while the droughts of 1958/59, 1959/60 and 1967/68 seasons occurred when the *SST* in the eastern central equatorial Pacific Ocean were neutral. Helpert and Ropelewski (1992) reported that normal or above normal summer rainfall for southern Africa (La Niña), which includes Malawi, are experienced when below normal surface temperatures occur from June to August while above normal temperature during the same period proceed El Niño years.

The relationship between SA rainfall and G*SST* has been widely studied but studies related to Malawi are scarce. Understanding the teleconnections between Malawi rainfall and G*SST* is of paramount importance. Malawi relies heavily on rainfed agriculture and rainfall determines the type of farming and crops that can be grown. Knowledge on the linkage between Malawi rainfall and *SST* is important as it can help in the forecasting of Malawi rainfall and weather. Forecasting of rainfall can help farmers and policy makers in having an insight into how much rainfall can be received, provide early warning for droughts and floods, and plan for mitigation measures accordingly. This helps in agricultural planning and hence economic development of the country.

The study centered mainly on analyzing rainfall data from selected rain gauge stations in Malawi. Two sources of rainfall data were used in this study. Rainfall data from nine rain gauge stations selected from across Malawi were used in the study. Three rain gauge stations were selected from the three regions of Malawi. The rainfall data for the period 1980 to 2012 were used. Secondly, rainfall data from the British Atmospheric Data Center (BADC), Climate Research Unit Time Series (CRU TS) Version 3.21 of high resolution gridded data (0.5×0.5) of month by month variation were used in the analysis. The rainfall data were for the period 1961 to 2012. *GSST* and Southern Oscillation Index (*SOI*) data were obtained from the National Oceanic and Atmospheric Administration (NOAA), National Weather Service Climate Prediction Center (http://www.cpc.ncep.noaa.gov/data/). The data were for the period 1960–2012.

Overall, the research work was subdivided into three main sub studies. In Chapter 2, the interannual fluctuation of monthly rainfall over a 31 year period was studied for nine locations in Malawi. Rainfall seasonality and spectral analysis were carried out. The analysis of this time series revealed the following points:

- There was a high spatial variability of both monthly and annual rainfall. Rainfall was greatest from November to March with single peak in January, except for Karonga and Nkhatabay stations, which had dual peaks in January and March. The rainfall pattern in Malawi suggests that local factors like topography and location have a dominant role in the spatial distribution of rainfall.
- On the basis of seasonal indices, *SI* and *PCI*, rainfall time series of all stations except Nkhatabay indicated apparent seasonality (rainfall received in 3 months or less in SI, seasonal to highly seasonal rainfall concentration in *PCI*). Only Nkhatabay experienced less seasonality as it has a long rain season.
- Spectrum analysis of the rainfall time series revealed cycles at 2.15 to 40.49 years for zone 1 and 2.05 to 10.06 for zone 2. There were suggested links with the *ENSO*, *QBO* and solar cycle. These results are consistent with those found in other SA countries.
- All parts of Malawi displayed strong seasonality and interannual fluctuation in rainfall. Given the importance of rainfall to Malawi agriculture, these variations need to be applied to the planning of water resources management.

In Chapter 3, the correlation between rainfall in Malawi and *SST* were studied to elucidate the linkage between rainfall and *SST*. The study used *SST*s for the period 1979–2011 and rainfall data for 1981–2012 from nine stations, which were grouped into two zones on the basis of inter-station rainfall correlations. The Pearson correlation coefficient was used to test the hypothesis that the main influence on summer rainfall in Malawi was the Indian Ocean *SST* rather than the Pacific or Atlantic *SST*.

We found that rainfall in Malawi was more strongly correlated with *SST*s in the Indian Ocean compared to those in the Atlantic and Pacific. The correlation was more significant for Zone

1 (northern stations) than Zone 2 (central and southern stations). The rainfall in Zone 2 appears to be influenced more by *SST* in the subtropical Indian Ocean than by *ENSO* or the tropical Indian Ocean dipole. These findings are consistent with those from other studies, such as by Wood and Moriniere (2013). Malawi straddles both equatorial east Africa (north of 10°S) and subtropical southern Africa (south of 15°S), and given its geographic location. These studies concluded that the northern and southern regions of Malawi are likely influenced by different climate drivers.

The present study also revealed that the Atlantic *SST* influences summer rainfall in Malawi. The areas of influence are the southwest of SA and off the coast of Brazil, but the influence was significant for Zone 1 only. We can speculate that the Agulhas current, which flows off the southwest coast of Africa, has an influence on air-sea interactions and intensification of weather systems, including modification of regional atmospheric circulation and modulation of climate mode impacts (e.g., the Benguela Niño and the subtropical Indian Ocean dipole.

The *SST*s in the Pacific Ocean were more strongly correlated with summer rainfall in Zone 2 than Zone 1. These correlations reflect the influence of *ENSO* signals and circulation patterns, as previous studies have revealed.

The *SST*s in the Persian Gulf, Red Sea, and Mediterranean Sea were significantly and negatively correlated with summer rainfall in Malawi. Further investigations are needed to establish whether there is some atmospheric circulation anomaly that is forcing the significant correlations between *SST* and rainfall in these cases.

Chapter 4 deals with the prediction of Malawi summer rainfall from *SST* using a simple regression model. Analysis of the linkage between Malawi rainfall and *SST* was conducted in order to determine predictors for the models. Significant correlations between rainfall and *SST* in the Atlantic, Indian and Pacific Oceans were found. The correlations are significant off Australia and Madagascar in the Indian Ocean; off Brazil and Chile in the

Pacific Ocean and between the equator and 20°N latitude in the Atlantic Ocean. These results are in agreement with previous studies. To predict Malawi rainfall, these *SST* time series were applied to a simple multiple regression model. The fit of the predicted and observed rainfall for both Zones 1 and 2 were satisfactory.

The limitation to the study was that we used rainfall data from 9 stations only out of about 40 rain gauge stations that exist in Malawi due to financial limitations on the cost of purchasing the data. There is need therefore to increase the sample size of the rain gauge stations in order to get improved results. The study also focused only on relationship between *SST* and Malawi rainfall. Other factors like sea level pressure and outgoing longwave radiation, if taken into consideration, can greatly improve the results of the model.

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Summary in English

This research work focuses on three studies covering the following areas (a) Rainfall time series analysis in Malawi; (b) Linkage between Malawi rainfall and *GSST* and; (c) Prediction of Malawi rainfall from global sea surface temperature using a simple multiple regression model. The studies are summarized as follows;

The first part covers a study of rainfall seasonality and spectral analysis on the interannual fluctuation of rainfall time series in Malawi that was conducted using a 31-year time series from selected rain gauge stations with the aim of analyzing the spatial and temporal characteristics of rainfall in Malawi. The study found significant interannual fluctuation of rainfall, with topography and location playing major roles in the annual rainfall distribution. The *SI* and *PCI* showed that rainfall is highly seasonal and highly concentrated at most stations.

Cross correlations among the stations suggested two distinct zones, Zone 1 composed of Karonga and Nkhatabay and Zone 2 composed of Bolero, Kasungu, Salima, Dedza, Mangochi, Makoka and Ngabu. The two stations of Zone 1 indicates bimodal pattern on the monthly rainfall. Spectral analysis of the rainfall time series at the two zones revealed cycles at five to eight years, suggesting links with *ENSO* and double the period of *QBO*. Apart from the common cycles, the rainfall time series showed periods of 13.64 and 10.06 years, respectively, which suggests links with the solar cycle. These cycles are consistent with those found in other southern Africa countries.

Secondly, the evaluation of the linkage between Malawi rainfall and *SST* was conducted. Correlations between rainfall and *SST* were studied to elucidate the linkage between rainfall and *SST*. The study used *SST*s for the period 1979–2011 and Zone 1 and Zone 2 rainfall data from the first study. The Pearson correlation coefficient was used to test the hypothesis that the main factor influencing summer rainfall in Malawi is the Indian Ocean *SST* rather than the Pacific or Atlantic *SST*.

The study found that summer rainfall was more strongly correlated with the Indian Ocean *SST* compared to the Atlantic and Pacific Ocean *SST*s. The correlations were more significant for northern stations than for central and southern stations. These results agree with other findings, the suggestion being that different climatic drivers influence the climate of different parts of Malawi. Northern areas are strongly influenced by the *SST* Indian Ocean dipole, whereas central and southern areas are strongly linked to the *SST* in the subtropical Indian Ocean. The results reveal that *SST* in the Atlantic Ocean off South Africa also affects Malawi rainfall. The study concludes that the Indian Ocean *SST*, including in particular the *SST* dipole strongly influences Malawi rainfall.

Lastly prediction of Malawi rainfall from G*SST* using a simple multiple regression model was studied. This study deals with a way of predicting Malawi rainfall from *SST* by a simple multiple regression model using links between Malawi rainfall and *SST* found in study two above, which were evaluated and selected as predictors for the model. On the process, rainfall of Zone 1 and Zone 2 as described in study one was used. The predictors for Zone 1 model were identified from the Atlantic, Indian and Pacific oceans while those for Zone 2 were identified from the Indian and Pacific Oceans. The correlation between the fit of model predicted and observed rainfall values were satisfactory with r = 0.81 and 0.54 for Zone 1 and 2 respectively (significance level less than 0.001). The results of the models are in agreement with other findings that suggest that *SST* anomalies in the Atlantic, Indian and Pacific oceans have an influence on the rainfall patterns of Southern Africa. The study concludes that *SST* in the Atlantic, Indian and Pacific Oceans is correlated with Malawi rainfall and can be used to predict rainfall values.

Summary in Japanese

論文要旨

本研究は以下の領域を網羅する３つの解析に焦点を当てたものである。
ａ）マラウィにおける降雨時系列の変動：選択した地域の解析
ｂ）マラウィの降雨と全球海水面温度(*GSST*)とのリンク
ｃ）簡易な重回帰式を用いたG*SST*からのマラウィの降雨予測

最初の部分は、マラウィの降雨時系列の経年変動の季節特性とスペクトル特性についての論考である。解析はマラウィにおける降雨の空間的時間的特性を解析する目的で、選択された雨量観測点における３１年間の時系列を用いて実施された。この研究により、地形と位置が年降雨量分布に大きな影響を与えて、明白な経年変化があることが示された。季節指数(SI)と降雨集中指数(*PCI*)により、ほとんどの降雨観測点において、降雨は非常に季節性が強く（季節）集中的であることが示された。経年降雨分布は空間的時間的に極めて変動性が高かった。

降雨観測点間の相互相関により、別個の２つのゾーンに分けられた。ゾーン 1 は Karonga と Nkhatabay（北部）、そしてゾーン 2 は Bolero, Kasungu, Salima, Dedza, Mangochi, Makoka 及び Ngabu（中・南部)によって構成される． これら２つのゾーンにおける降雨時系列のスペクトル解析により、エルニーニョ・南方振動(*ENSO*)と成層圏準 2 年周期振動(*QBO*)とのリンクを呈する５－８年周期が検出された。

第２にマラウィの降雨と海水面温度(*SST*)のリンクの評価が行われた。降雨と *SST* のリンクを明らかにするために、両者の相関を検分した。この解析では 1979-2011 の *SST* データと上記のゾーン１，２の降雨データが用いられた。マラウィの夏季降雨の主因は太平洋・大西洋 *SST* ではなく、インド洋 *SST* であるという仮説を検定するためにピアソン相関が用いられた。

論考の結果、夏季降雨は、太平洋・大西洋 *SST* と比べてインド洋 *SST* により強く相関づけられていることがわかった。この相関は中南部の降雨観測点よりも北部において、より有意であった。これらの結果は他の報告と一致するものであり、異なった気候要因がマラウィの異なった部分の気候に影響するということを示唆している。北部にあっては、インド洋ダイポール *SST* に強く影響されているが、一方で中南部はインド洋亜熱帯 *SST* に強く結びつけられる。結果は大西洋南アフリカ沖 *SST* もまたマラウィの降雨に影響していることを明らかにしている。特にダイポール効果を含んで、インド洋 STT がマラウィの夏季降雨に強く作用していると断定される。

最後に、簡易な重回帰モデルを使った全球 *GSST* からのママラウィの降雨の予測が論じられた。この研究は、２番目の部分で明らかとなったマラウィの降雨と *SST* のリンクを評価・選定し、これを用いて簡易重回帰モデルによるマラウィの降雨の予測をしようとするものである。ゾーン１モデルの予測因子は、大西洋、インド洋及び太平洋から選定されたが、ゾーン２モデルの予測因子は、インド洋と太平洋から選定された。モデルの予測値と実測値の相関は納得できるものであり、ゾーン１及び２に対し、それぞれ r = 0.81、 0.54 であった（有意水準 0.001 以下）。モデルの結果は、南アフリカの降雨パターンに対し、大西洋、インド洋及び太平洋の *SST* 変動が影響を与えるという他の研究結果と一致している。この研究により、大西洋、インド洋及び太平洋の *SST* はマラウィの降雨と関連があり、降雨量の予測に用いられることが結論付けられる。

List of Publications

Articles published/accepted in peer reviewed Journals

Chisomo Patrick Kumbuyo, Hiroshi Yasuda, Yoshinobu Kitamura and Katsuyuki Shimizu; Fluctuation of rainfall time series in Malawi; an analysis of selected areas –*Geofizika Journal*, Vol. 31, No. 1, http://geofizika-journal.gfz.hr/vol_31/No1/31-1_Kumbuyo_et_al.pdf).

Chisomo Patrick Kumbuyo, Hiroshi Yasuda, Yoshinobu Kitamura and Katsuyuki Shimizu; Linkage between Malawi rainfall and global sea surface temperature–*Journal of Rainwater Catchment Systems*, Vol.20/No.2/pp.7–13.

Chisomo Patrick Kumbuyo, Hiroshi Yasuda, Yoshinobu Kitamura and Katsuyuki Shimizu; Prediction of Malawi summer rainfall from global sea surface temperature using a simple multiple regression model–*Journal of Rainwater Catchment Systems*, Vol.20/No.2/pp.1–6.