PROBABILISTIC FORECASTING OF DRY SPELLS IN KENYA AND AUSTRALIA

A thesis submitted in fulfilment of the requirements for the degree of

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ABSTRACT

Kenya and the Murray Darling Basin (MDB) of Australia are largely arid or semi-arid and are important agricultural areas. However, persistent dry periods and the timing of dry spells directly impact on availability of soil moisture and hence crop production in these regions. Research in these regions has not yielded desirable impacts in addressing this problem. This study aimed at examining the characteristics of dry spells and development of monthly dry spell forecasts in these regions.

Daily rainfall datasets from 30 locations in Kenya and 47 locations in the MDB were used in the analysis of monthly dry spells. The length of both monthly dry spells and dry spells going across months were separately calculated and compared. The best parametric distribution functions (pdfs) describing the empirical dry spell distribution were examined. A generalized linear model (GLM) and a generalized additive model (GAM) were used to determine the temporal and spatial trends in dry spell length and in forecasting of dry spells at 1-, 3-, and 6-month lead times.

Overall, the monthly dry spell lengths mostly followed a lognormal distribution. The mean monthly dry spell length underestimated the observed dry spell length in these regions while the monthly dry spell parameters were negatively correlated with the mean annual and monthly rainfall in Kenya and in the MDB.

Increasing dry spell trends occurred in most months and in some locations and the probability of drought risk in the cropping season reach up to 50% in Kenya and 77% in the MDB. The greatest increases were in June-September in Kenya and in autumn season in the MDB. Increasing rates in observed trends in both regions were ≥ 0.026 days/year or 1 day to 37 days increase over the entire period.

The performance of binary and continuous forecasts at 1-, 3-, and 6-month lagged SOI phases and SSTs showed modest skill (R^2) ranging from < 20% – 72% in Kenya and MDB for the total number of dry days and the maximum dry spell length in a month but better skill was indicated in Kenya than in the MDB. The challenge still remaining is to find a way to capture all the inter-intra annual variability in the dry spell series at the monthly and seasonal time frames. The current skill may be improved by including other predictors in the model such as NINO4, Pacific Ocean thermocline and tropospheric wind anomalies. The current findings can have implications for agriculture in these regions.

THESIS CERTIFICATION

I hereby certify that this thesis is my own work and to the best of my knowledge it contains no material previously submitted for any degree, except as acknowledged in the text.

Any contribution made to the research by colleagues, with whom I have worked at the University or elsewhere, is acknowledged in the thesis.

Richard Rukwaro Muita

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CHAPTER 1

GENERAL INTRODUCTION

Dry spells, generally defined as sequences of days without precipitation are used to describe dry conditions. Prolonged dry spells also known as ‘drought’ are believed to be one of the greatest challenges to farming systems in arid to semi-arid (ASALs) lands (Mupangwa et al. 2011) and often cause deleterious impacts to agriculture and the economies of many regions (Ahmed et al. 2002, IPCC 2007, Howden et al. 2010). For instance, Kenya and the Murray Darling Basin of Australia are mostly arid and drought prone and often experience agricultural losses. Drought vulnerability in these regions is probably due to the fact that agriculture is primarily dependent on rainfall which is highly variable. This suggests that examining rainfall patterns may be important in the understanding of drought characteristics in these regions.

The current study investigates the temporal and spatial characteristics of dry spell lengths (days) rather than drought. Whereas drought is broadly understood to be water shortage either; rainfall, soil moiture or ground water deficit it also has challenges particularly related to its definition and characteristics. This may at times give the wrong impression of what is the actual representation of dry conditions. In contrast, the attractiveness of considering dry spell lengths is the ease with which statistical analysis can be applied to consecutive dry days or dry spells at varied time scales. Furthermore, such analysis may improve the current understanding of drought characteristics.

In Kenya and the MDB, stochastic approaches, mainly Markov Chain models are popular in the analysis of drought (e.g. Sharma 1996, Thyer & Kuczera 2000, Barron et al. 2003, Kiem & Franks 2004). Equally, cumulative rainfall anomalies are used to represent drought (e.g. Rockström et al. 2003, Lodge & Johnson 2008). Stochastic models are criticised for inadequate representation of drought characteristics (e.g. De Groen 2002, Mul & Savenije 2013), whereas, the use of cumulative rainfall masks the actual distribution of dry days. In this light, other ways may be better to represent drought characteristics. Specifically, dry spells, normally represented by cumulative days with zero or extremely low rainfall in historical records, can reveal the variability in behaviour of dry conditions at finer and longer temporal scales which may improve considerably, the understanding of drought impacts on agriculture.

Even though numerous studies have previously examined dry spells in Kenya and the MDB (e.g. Suppiah & Hennessy 1998, Barron et al. 2003), it appears that an in depth analysis of the characteristics of dry spells lengths is less highlighted. Furthermore, whereas advances in drought forecasting in these regions are not very clear, there is little evidence of attempts to forecast dry spells lengths.

Due to the complexity of drought dynamics in ASALs as mentioned earlier, a starting point would be to identify suitable probability distribution functions that can reliably describe the observed dry spells distributions. These distributions can facilitate the fitting of appropriate models for drought forecasting. The two parameter gamma distribution for instance has been applied to describe rainfall in Australia and Eastern Africa as it suits many distribution shapes (e.g. Stern & Coe 1984, Groisman et al. 1999, Jothityangkoon et al. 2000, Husak et al. 2007).

Whilst regression based approaches remain attractive in modelling drought in Kenya and MDB, there is still a need to improve the skill of current seasonal forecasts which are relatively low in order to improve monitoring and management of agriculture against climate variability. In particular, dry spells at the monthly scale and across months can pose a great challenge to modelling drought due to the mismatch between the timescale and ability to calculate dry spells at arbitrary times. In addition, dry spells may exhibit both linear and non-linear patterns which may also add some difficulty in the analysis.

In this thesis, statistical regression methods, mainly the generalized additive model (GAM) will be used to examine the temporal and spatial characteristics of dry spells and later on to forecast intra-inter seasonal and annual dry spell length in Kenya and the MDB. The beauty of using GAM lies in their flexibility to model both linear and non-linearity in the time series. In agriculture application, the value of drought forecasts may be assessed by looking at how farming decisions are taken and as such, a farmer's survey in Kenya may provide some useful information that can be integrated in the management of climate extremes in Kenya and the Murray Darling Basin of Australia.

1.1. Motivation

This thesis presents analysis of dry spells characteristics in two different but uniquely similar regions: Kenya and the Murray Darling Basin of Australia (MDB). Kenya and the MDB are located in the eastern parts of Africa and Australia and border the western edges of the Indian and Pacific Oceans respectively. Interestingly, most of the land surface areas of these regions are dry but used for agriculture production. Agriculture happens to be the most important economic activity in both regions. However the two regions have interesting contrasts. Kenya lies in the tropics but the Murray lies in the sub-tropics. This makes their climates distinctly unique. Kenya experiences two main rainfall seasons (March-May and October-December) due to the monsoon or the double migration of the Inter-Tropical Convergence Zone (ITCZ) across the equator between the northern and southern hemispheres. In contrast, the MDB has two rainfall patterns: summer dominant (December-February) in the north and winter dominant (June-August) in the south. Both patterns are a result of the differences in synoptic weather patterns in the northern and southern hemispheres. More interesting, the rain seasons (months) in Kenya turn out to be relatively dry in the MDB and vice versa. It is not surprising therefore, that, when the El Niño Southern Oscillation (ENSO) phenomena is in the La Niña phase in the equatorial Pacific, Kenya experiences severe or extreme dry (droughts) conditions while much of the eastern MDB experience excessive rainfall or flooding.

I first learned about Australia from children story books when I was a little boy newly in school. These were picture books which illustrated numerous stories about Australia and particularly about the adventures of the Kangaroos in the fast Australian jungle. The stories were made more captivating and thrilling by our teacher who acted for us. I had no idea that my journey to Australia would be a reality more than 30 years later. Thanks to Willem Vervoort who accepted to supervise my PhD research project at the University Of Sydney. My experience during this time is a story for another day.

My research interests should focus on forecasting rainfall considering that I am a meteorologist. However, after reviewing the published literature, it seemed that it was more interesting to examine drought than rainfall in these regions. This decision was motivated by the fact that drought is less understood and a major problem for agriculture in my country which heavily depends on agriculture. As a matter of fact, drought is a serious issue not only in Kenya but also Australia which is the driest continent in the world (e.g. Webb & Reardon 1992, White & O'Meagher 1995). During my childhood days, I had some bad experiences with drought. In fact I am a die-hard survivor of the vagaries of drought. For example, I recall vividly the negative impacts of the 1981 drought in Kenya which is popularly known as “money in the pocket" because there was no food to buy from the shops although people had money. I remember how my mum fed us on pumpkins and pumpkin leaves or "mahuti ma marenge" as locally known each day, since it was the only food available after the drought dried up all the crops. In 1984, it happened again while I was in a boarding school in a pastoral region. Hunger was everywhere and we had to put and shut up on one meal per day (essentially, a small plate of boiled yellow maize or corn) via the kind generosity of the World Food Programme (WFP) of the United Nations. Today, I know that it wasn't just me who was a victim of these natural monsters but, the impacts of drought had led to death of over 70% of the livestock in pastoral areas, and thousands of people went without food (Homewood & Lewis 1987, Oba & Lusigi 1987, Fratkin & Roth 1990, Smucker & Wisner 2008). For Australia, just like in Kenya, the scars of drought (e.g. Leblanc et al. 2009) remain reminiscent of the words "lest we forget" from Rudyard Kipling's poem 'Recessional'.

Looking back, most farmers just like many of us do not see drought coming because it "creeps in slowly" (Wilhite et al. 2005) and only becomes clearer when the damage has already set in. In other words, past droughts that brought misery to farmers and the world may have sneaked in silently. This thesis may not demystify the intrigues of droughts that occurred in the past or those that will occur in future. However, it is my hope that this study can go a long way in providing some new insights and enlightenment on the science and provide some help in the management of agriculture and other sectors against drought in these regions.

1.2. Research Objectives

The main aim of this thesis is to forecast intra-inter seasonal and annual dry spell lengths in Kenya and the Murray Darling Basin of Australia. This will provide a tool that may be useful to agriculture managers and other stakeholders in Kenya and the MDB in decision making.

In order to understand the challenges related to drought, this thesis' first objective will focus on Kenya as an example to analyse farmers' perceptions on climate variability and management options they use in response to climate variability. In addition, farmers perceptions are explored by identifying the level of adoption and value of indigenous forecasts (IF) and seasonal climate forecasts (SCFs) in farm decisions, quantitative analysis of the benefits of SCFs and IF on farmers (maize) yields, and establishment of inventory of indigenous and evidence based climate forecasts to manage climate variability. Secondly, the temporal and spatial dry spells distribution in Kenya and the MDB will be investigated by establishing the best parametric distributions to describe the observed monthly dry spell lengths (DSL) and subsequently, the temporal and spatial variations in the distributions of DSL are examined. The third objective investigates the temporal and spatial trends in the DSL by looking for evidence of long term trends in the DSL at the annual scale and also the historical trends at the month and seasonal scale. The last objective is devoted to the development of dry spell length forecasts at 1, 3 and 6 months lead times.

1.3. Thesis outline

This thesis comprises of 8 chapters which outlines the research activities on forecasting of dry spell lengths in Kenya and the Murray Darling Basin of Australia.

Chapter 1 gives some background information on dry spells and drought in Kenya and the MDB.

Chapter 2 gives a review of the literature related to climate variability particularly, rainfall and drought characteristics and current climate forecasting tools in agriculture in Kenya and the MDB. Both scientific and non-scientific forecasting tools are discussed to highlight the status of agriculture management to climate variability.

Chapter 3 focuses on temporal distribution of dry spell lengths. It starts with the calculation of dry spells from daily rainfall from several locations and subsequently investigates the characteristics of dry spell parameters. In this chapter, the challenge of calculating dry spells at the monthly boundaries and across months is demonstrated when dealing with the derivation of the mean monthly dry spell lengths and forecasting of dry spells lengths.

Chapter 4 examines trends in dry spell lengths within the framework of the Generalized Linear Models (GLMs). Both temporal and spatial characteristics are analysed for the overall long-term trends as well as the monthly and seasonal trends.

Chapter 5 is dedicated to the prediction of dry spell lengths at monthly and seasonal time scales. The Generalised Additive Models (GAM) is used for logistic regression of categorical forecasts and to model numerical forecasts as a continuous variable using the Southern Oscillation Index (SOI) phases and sea surface temperatures (SST).

Chapter 6 and Chapter 7 scrutinize farmers' perceptions in Kenya in regard to climate variability and application of climate and indigenous forecasts in farm decisions respectively. Chapter 6 looks at how farmers perceive climate variability in 2 different agro-climates: a wet and high potential agriculture area and a semi-arid agricultural area both of which grow maize, the staple crop in Kenya. Chapter 7 extends on Chapter 6 but specifically focuses on how farmers use indigenous and scientific forecasts in farm decisions in the 2 regions. This reveals interesting information on how farmers' opinions and decisions differ across the 2 regions and at the farms level.

In chapter 8, a general overview of the thesis is given and the key research findings outlined. The implications in Kenya and Australia are discussed. Research limitations are pointed out and future research directions proposed before the final conclusions are given at the tail end.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

The Inter-governmental panel on climate change (IPCC) fourth assessment report indicates that the Pacific region agricultural production is expected to decline sharply by 2030 due to a rise in temperatures and severe droughts (Park et al. 2009). Similarly, negative agricultural impacts are projected in the sub-Saharan Africa region (SSA) where drought is increasingly common (Olsson et al. 2005, Sheffield & Wood 2008). Moreover, the risks of drought affecting agriculture in the past may exhibit recurrent patterns in these areas (Houghton et al. 1996, Fischer et al. 2005, Schlenker & Lobell 2010). More specifically, the recurrence of drought in semi-arid agro-pastoral regions of Kenya and Australia underline a need to strengthen the adaptive capacity of agriculture systems.

There is a considerable amount of research on drought impacts on crop yields in Australian landscapes (Heathcote 1988, Colls 1993, Horridge et al. 2005) and livestock losses in agro-pastoral areas of Kenya (Ndikumana et al. 2000, Aklilu et al. 2002, Huho et al. 2011). Despite this research it is still unclear whether those impacts have increased or declined in time and what further changes may occur in future.

Rather than drought, a number of studies that have analysed dry spells in these regions also indicate that these cause crop failures in a number of occasions (Barron et al. 2003). However, relatively very few studies provide information on the temporal and spatial characteritics of dry spells (Sharma 1996, Suppiah & Hennessy 1998). These studies however, provide some basis for further research in this area. Loukas & Vasiliades (2004), suggest that in order to understand drought better, as many features as possible that are associated with drought, such as dry spells, the number of hot days, or temperature patterns should assessed.

Whereas drought is a recurring phenomena that affects many regions, it is defined differently (Palmer 1965, Yevjevich 1967, Dracup et al. 1980, Rossi 2000, Tsakiris & Vangelis 2005). Among the varied definitions of drought, 3 categories are the most common: meteorological, hydrological and agricultural droughts (Tsakiris et al. 2007, Wong et al. 2013). Meteorological or hydrological droughts occur when precipitation or streamflow is below the longterm average for a prolonged period of time, whereas agriculture drought is indicated by a reduction in soil moisture that leads to crop failure. One of the recent definitions of drought suggests several years with less than median rainfall (Kirby et al. 2013). Studies give the impression that any one of the definitions may not be suitable for all purposes. For instance, although precipitation deficit is one of the key aspects for characterizing meteorological droughts (Palmer 1965), how is drought different if this proxy is used to characterize an agricultural or hydrological drought? When is a dry spell long enough to typify a drought class such a meterological etc.? In general, many studies define drought as a prolonged dry period or water deficit relative to normal conditions, but in view of the above question, this is ambiquous and hard to apply. In a recent study, Lloyd-Hughes (2013) concluded that as a result of numerous climatological considerations in the analysis of drought and the difficulty in quantifying the human influence, it was virtually imposible to come up with a generalized objective definition of drought. Due to these varied views on drought, this study chooses to assess dry spells which are generally successive dry days in order to improve our understanding of drought.

There has been debate on whether the frequency and severity of droughts in semi-arid SSA has increased compared to previous decades (Andresen et al. 2008, McSweeney et al. 2008, Tøttrup et al. 2012, Funk et al. 2013). In contrast, over much of Australia's agricultural regions, drought has been declared more often than the recommended 1 in 20 - 25 years which means that, the frequency of drought may have increased. Even so, recent extreme drought conditions over eastern Australia, between 1997 and 2009, compare in magnitude with other previous droughts e.g. the federation drought of the 1900s (Nicholls 2004, Murphy & Timbal 2008). However, Keating & Meinke (1998) argue that trends for the worst droughts prior to 1995 are unclear.

In Kenya, analysis of rainfall indicate no clear trends in the average annual drought patterns since the 1960s (Rowntree 1989, Andresen et al. 2008). However some case studies suggest that there has been some rainfall reduction in western and central highland areas of Kenya consistent with increasing temperatures (Mugalavai & Kipkorir 2013, Ngetich et al. 2014). Given these situations, it is necessary to investigate and have a comprehensive assessment of drought characteristics in the 2 regions.

In general, drought characteristics are relatively less predictable than rainfall patterns. Nonetheless, accurate identification and forecasting of drought conditions can benefit agricultural management and adaptation to drought (Colls 1993, Manton et al. 2001, Dessai et al. 2004). For instance, seasonal forecasts enabled the US government to save about$19 billion in benefits and an estimated $4 billion reduction in losses following the 1997/1998 El Niño Southern Oscillation events (Changnon 1999).

This review explores the characteristics of dry spells and the role of seasonal and drought forecasts in farming systems for Kenya and Australia for a better understanding of drought and its management in the regions. This includes a review of climate and drought variability in these regions and how farmers utilize indigenous and evidence based climate forecasts in dealing with dry spells risks forms part of the discussion.

2.2. Climate and Climate variability in Australia

The climate of Australia is inherently variable with over 80% of the land surface area being arid to semi-arid. The climate is tropical in the north and temperate in the south. The subtropical high pressure systems (anticyclones) off the western coast contribute to the dry and hot climate and relatively low average annual rainfall over most of Australia (BOM 2010). The continental mean annual rainfall is about 465.3 mm and the highest annual rainfall exceeds 12,000mm (Queensland).

The El Niño-Southern Oscillation (ENSO) is the largest driver of Australian climate and the main trigger of the high seasonal to inter-annual variability of rainfall (Nicholls et al. 1996, Power et al. 1998) particularly over the eastern and southern regions. Nevertheless, ENSO explains far less of the variance in rainfall over most parts and other less known factors appear to play a major role in driving the climate of the region (Klingaman et al. 2013). One recent study suggest that the Indian Ocean Dipole overrides ENSO in cooler seasons in eastern Australia (Pepler et al. 2014). In general, the Australian rainfall patterns and climates are complex and thus numerous causes or drivers have been proposed. Australia has one of the most extreme climates, as indicated by drought and bushfires, compared to other parts of the world (BOM 2010).

2.2.1. Rainfall characteristics and trends in Australia

Rainfall in Australia is widely studied (e.g. Nicholls 1983, Drosdowsky 1993, Suppiah & Hennessy 1998). Australian rainfall exhibits high seasonal and interannual variability (Drosdowsky & Williams 1991, Nicholls 1992) compared to similar climatic zones in the world (Finlayson & McMahon 1991).

Nicholls & Lavery (1992) indicate increasing trends in rainfall during summer in eastern Australia and declining trends in south-western Australia in winter. Subsequently, Hennessy et al. (1999) estimates that annual rainfall increased by 15% across New South Wales and other states due to an increase in heavy rainfall events and the number of rain days. More recently, Drost & England (2008) indicated that there is a decline in precipitation in the last half of the 20th century over eastern Australia and an increase in northern and western regions during summer and autumn. The Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the IPCC have predicted that rainfall will decline over much of Australia by 2030 (IPCC 2000, Preston & Jones 2006). In the recent decade rainfall has declined in some parts of south eastern Australia (Bradstock et al. 2013).

Analysis of the annual total rainfall across Australia (Figure 2.1) from 1900 - 2010 shows that the mean annual rainfall from 1900 – 1960 was lower (435.4 mm) relative to that from 1961 – 2010 (478mm). A step change of the annual rainfall around 1960 has been suggested by Plummer et al. (1999) and the increased mean rainfall in the latter period might have been due to an increase in high rainfall (totals) events. A linear regression fit to the rainfall indicates a significant increasing trend ($p=0.002$) in rainfall throughout the period at a rate of 0.7mm per year although most studies say this is only significant in some seasons or regions (e.g. Nicholls & Lavery 1992, Hennessy et al. 1999) in contrast to a recent study in the region (Bradstock et al. 2013).

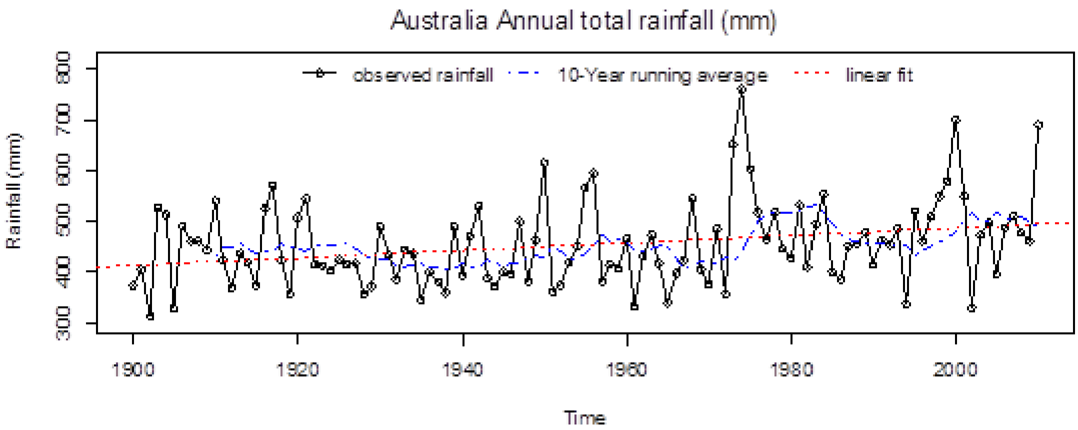


Figure 2.1: Trends in Australian annual total rainfall from 1900 – 2010. The decadal average is indicated by the dashed (blue) line that starts at 1910 while the linear fit is indicated by the dotted (red) line running from the left to the right edges of the plot. Data source: Australian Bureau of Meteorology (BOM)

2.2.2. Rainfall /drought variability for Australia in grain growing areas

The focus is on Murray Darling Basin (MDB), which is the main grain growing area located in the south-eastern part of Australia. The average annual rainfall in the MDB is about 480 mm and ranges from 1200 mm per annum (Great Dividing Range) to < 200 mm per year in the western parts (Haisman 2004). Evaporation varies from 1000 mm per year in the east to over 2000 mm in the west.

One study shows increasing trends in heavy rainfall in summer and winter in the MDB between 1910 and 1990 (Suppiah & Hennessy 1998). Some areas had drought prior to 1948 and floods in the following period (Jones et al. 2001). In the last decade alone, low rainfall or prolonged droughts occurred in 2001, 2002/2003, 2005 to 2007 and 2008/2009 with significant impacts on agriculture and water supply (Nicholls 2004, Murphy & Timbal 2008). Most of the rainfall deficits occurred in autumn. According to BOM (2008), the average seven year basin wide rainfall deficits during recent years were slightly higher compared to similar past dry periods (1937-1946, 1895-1903).

Figure 2.2, displays the rainfall deciles for Australia between 2001 and 2008 in which rainfall was well below average (decile 1) over most parts of the MDB.

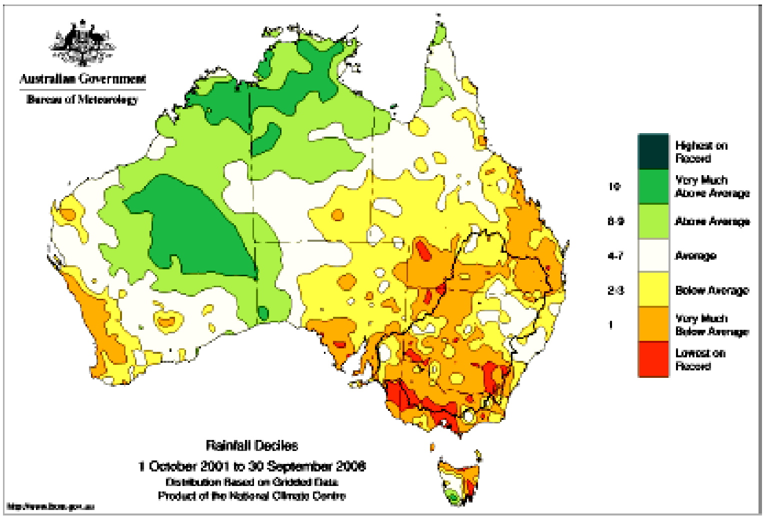
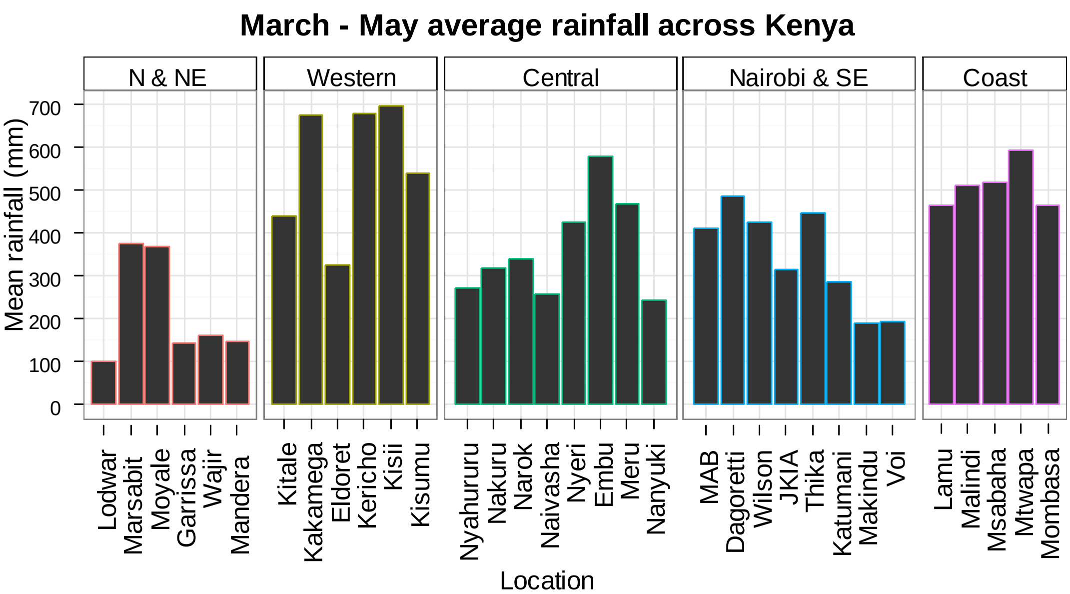


Figure 2.2: Australian rainfall deciles from October 2001 to September 2008. Map source: http://www.bom.gov.au/

2.3. Climate and Rainfall variability in Kenya

Kenya has a tropical climate and the rainfall distribution can describe its climate. The interannual rainfall variations in Kenya are closely associated with the El Niño Southern Oscillation, with more rainfall occurring during El Niño and drier conditions in La Niña years (Wolff et al. 2011). Several studies have examined the climate and rainfall variability patterns in Kenya (Bärring 1988, Ogallo 1989, Nicholson 1996, Camberlin & Wairoto 1997, Ovuka & Lindqvist 2000). The rainfall distribution across the country varies remarkably with altitude as does the temperature range which varies substantially from about 15°C in central highland regions to 29°C at the coastal areas. Temperatures are slightly higher in ASAL regions in the north (McSweeney et al. 2008). Note that most of the country is either arid or semi-arid (ASAL) (Sombroek & Braun 1980).

Figure 2.3, shows an evaluation of the average total rainfall based on the 1961 - 2009 period during MAM and OND seasons for different regions in Kenya. Clearly, the western and coastal regions indicate more rainfall in MAM season compared to the other regions. In contrast, during the OND season rainfall seems to be roughly similar in western, central and Nairobi (SE) regions. These patterns of rainfall highlight important information with regards to management of food production in Kenya. From a practical context, however, the average or cumulative rainfall anomalies commonly used to indicate drought occurrence in this region, should be regarded cautiously as it may not be representative of the actual drought characteristics (distribution, duration, severity etc.).



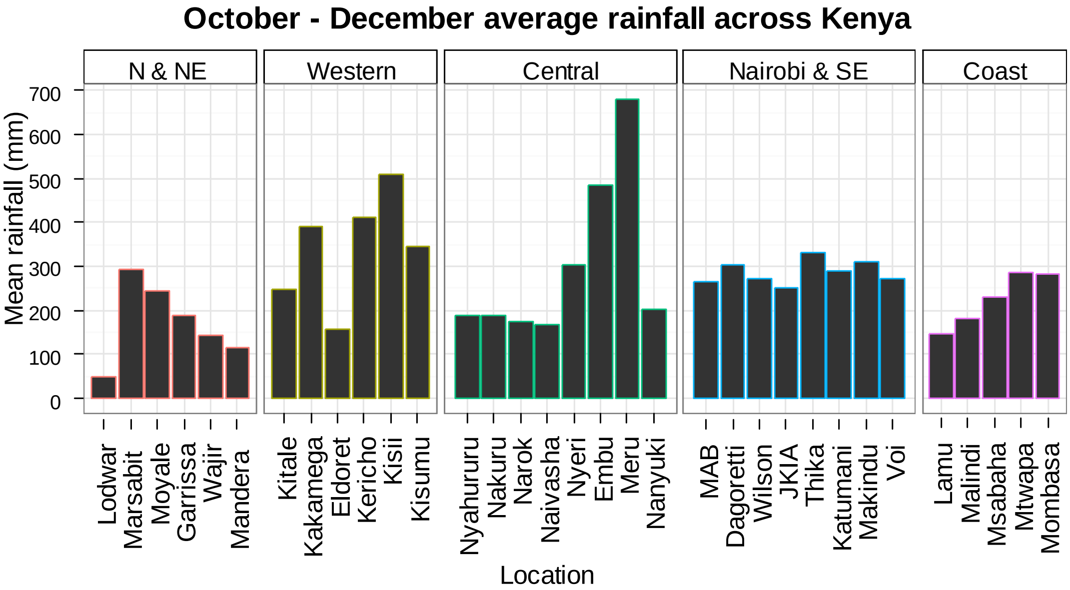


Figure 2.3: Seasonal average rainfall for long (MAM) and short (OND) (bottom) rain seasons across selected stations over Kenya from 1961 to 2009 based on 30 year climatology

2.3.1. Temporal - spatial rainfall characteristics and trends in Kenya

In most parts of Kenya there is no statistically significant trend in rainfall since 1960 (Ogallo 1993, McSweeney et al. 2008). As an example, rainfall analysis of a few locations in the ASAL of Kenya suggests some declining trends in the MAM season since 1950 (Figure 2.4). At Moyale for instance, the trend in rainfall was statistically significant (p=0.01) and declined by 2.4 mm per year over the entire period.

However, rainfall, shows diverse temporal-spatial characteristics over Kenya (Ogallo et al. 1988, Beltrando 1990, Camberlin 1995) and particularly indicates greater variability in the rainfall amounts (Ovuka & Lindqvist 2000) in the short rain season (OND) than in the long rain season (MAM) (Conway et al. 2005). Rainfall variability is larger over high altitude areas in eastern and western Rift Valley compared to low land areas (Ogallo 1989) although the day to day variability is more marked due to heavy precipitation events compared to seasonal or inter-annual variations (McSweeney et al. 2008). One question however, is whether the temporal and spatial rainfall patterns reflect the nature and magnitude of drought in Kenya. For example, a recent study by Shisanya et al. (2011) revealed that most locations in semi-arid areas of Kenya had below average rainfall in most of the MAM and OND seasons in both the El Niño and La Niña years from 1960 – 2003. This can be interpreted to mean that drought or drier conditions persisted in these years which appear to contradict the above results. What this suggests is that, a clear link between rainfall and drought or dry spells with climatic drivers e.g. ENSO needs to be investigated in order to understand the current characteristics of climatic variability in Kenya.

Given this, the temporal and spatial uncertainty in the rainfall patterns may pose a challenge in quantifying and predicting drought characteristics in Kenya. Nevertheless, it might be possible that the indication of declining rains reflect increasing trends in drought conditions and vice versa in Kenya.

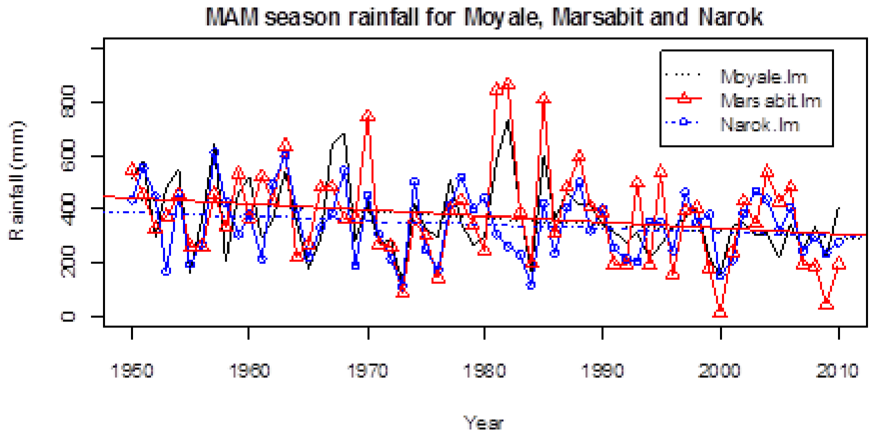


Figure 2.4: Total rainfall over Moyale, Marsabit and Narok in the MAM season from 1950-2010. Linear regression trends are indicated by the dotted (Moyale.lm, adj.R^2 = 0.1, p-value=0.01), solid (Marsabit.lm, adj.R^2 = 0.03, p-value= 0.08) and dashed (Narok.lm, adj.R^2 = 0.02, p-value=0.1) lines.

2.4. Climate extremes and relevance in agriculture

Climate extremes such as prolonged dry spells cause damage to agricultural production (Sivakumar 1992, Battisti & Naylor 2009). For example, the 1998-2000 La Niña related droughts in Kenya cost about 14% of the GDP, most of which is linked to reduced agricultural production and water resources degradation (Davis et al. 2006). It is therefore useful for any study on drought to consider analysis of impacts.

From Table 2.1, it can be seen that between 1991 and 2005 droughts accounted for 8% of all natural disasters globally (EM-DAT 2005). Climate related disasters alone constituted > 70% of the total global (EM-DAT 2005). For example, in Africa, the 1983 Ethiopian drought alone caused 300,000 deaths, whereas the drought of 1994/1995 drought resulted in about 50% decrease in agriculture production in Australia (ABARE 1995).

Shorter climate extreme events have also been known to have severe impacts on agriculture. For example, the 1997/1998 ENSO related floods and drought of 2000 over eastern Africa, led to huge agriculture losses and millions of people affected equivalent to what would be expected from normally longer drought events (Collette 2000). In other words, droughts often lead to food crises in Kenya (Campbell 1999). Clearly, drought can cause major damage to agriculture and other human activities. Due to most of the agriculture dependence on rainfall in this region, it is important to assess drought.

Table 2.1: Comparison between climate and non-climate related disasters globally from 1991-2005.

Type of extreme event	Percentage distribution
Wildfire	3.4
Extreme temperature	3.5
Drought	7.8
Windstorms	26.6
Floods	30.7
Tsunamis	0.2
Insect infestation	1.0
Volcano	1.7
Land/mud slides	5.1
Earthquakes	8.9
Epidemics	11.2

2.4.1. What is drought?

Three main drought types are recognized globally: meteorological, hydrological and agricultural droughts. The drought types relate to periods of below normal long term rainfall (Palmer 1965), deficient surface and subsurface water (Palmer 1965), and deficient soil moisture that leads to crop failure (FAO 1983) respectively. Economists have also related drought to a period of low water supply which erodes society's production and consumption needs (Dracup et al. 1980). Some of the fundamental aspects of drought studies include the identification and estimation of its occurrence, duration, severity and spatial scale (Pelletier & Turcotte 1997, Agnew & Chappell 1999, Rojas et al. 2011).

Drought definitions have continued to be modified and multiplied. For example, a review by Wilhite & Glantz (1985) identified more than 5 categories of droughts. It is possibly due to the varied definitions that the quantification and characterisation of drought continues to be a problem. This may be an obstacle to developing efficient drought monitoring systems (Wilhite & Glantz 1985). Some general aspects related to drought definitions and dry periods are discussed in Byun & Wilhite (1999) and the studies therein. Some of these concepts include; consideration of consecutive dry days with no precipitation or little rainfall over a specified period of time. A range of daily precipitation thresholds (amounts) such as; <0.1mm, <1mm, <5mm, have been used to quantify drought (Dracup et al. 1980, Moon et al. 1994, Wauben 2006). Byun & Wilhite (1999) argue that concepts like dry days and precipitation thresholds, quantify drought intuitively rather than objectively. A number of studies also feature the concept of "severity" in defining drought. (e.g. Byun & Wilhite 1999).

Alternatively, other studies distinguish between what is assumed "drought" and what it is not. For instance, Tsakiris & Vangelis (2005) distinguish between aridity and drought, terming aridity to be "a more or less permanent dry climatic condition" whereas drought is a temporary condition. In this case, aridity can mean desert like conditions (Maliva & Missimer 2012). In this regard, aridity indices have been used as proxies for quantifying the magnitude and severity of drought in many regions (Arora 2002, Ntale & Gan 2003, Croitoru et al. 2013). An aridity index expresses the ratio of potential evaporation to precipitation, which indicates the level of dryness over a climatological region. One of the weaknesses of using aridity index to represent drought is the usage of monthly period (precipitation, evaporation and time) which is not represenative of the actual natural cycle of drought occurrence.

Whereas drought is a time period of water deficit, definitions can change from one place to another and across time due to the close link between local rainfall patterns and the atmospheric and synoptic features of an area (Rossi et al. 1992, Tsakiris & Vangelis 2004, Mishra et al. 2009). This makes that the understanding of drought differs with place and situation. The Australian Bureau of Meteorology (BOM) categorizes drought in terms of rainfall as either "lowest on record", "serious" or "severe" rainfall deficiency whereas Kenya upholds the meteorological definition of a period of below normal rainfall to identify drought.

In contrast to a meteorological context, it has been argued that drought should be assessed not only based on precipitation but also on other environmental and social factors (Tsakiris & Vangelis 2005). Tsakiris & Vangelis (2005) suggests that drought conditions are a function of interactions between atmospheric processes, physical, social, environmental and economic factors. This includes factors such as precipitation amounts, evapo-transpiration and soil and vegetation characteristics. However, quantifying or modelling some of the parameters in order to represent drought is difficult. Moreover, most of these datasets are difficult to find in many regions.

In conclusion for the identity of drought, it is clear that opinions on drought are divided. Even so, it can be seen that most of the definitions are of meteorological nature and generally attempt to characterize the magnitude and coverage of drought. While, drought definitions are constantly being updated to suit the needs of a particular sector, region or situation, pursuit of a better way to represent drought is still required. Following this, the current study opts to focus on dry periods rather than defining drought in order to characterize dry conditions in Kenya and Australia. Taking up dry spells is motivated by the fact that they are more objective, quantifiable using daily rainfall and can easily be applied in any region where historical rainfall records are available. Furthermore, for agriculture drought/applications, opting for dry spells is more appropriate since crop growth is highly dependent on short-term moisture conditions, and crops maybe more sensitive to dry conditions during critical growth stages.

2.4.2. Drought indices

Drought indices (DI) are the most popular tools for drought monitoring (Tsakiris et al. 2002). DI can be used to quantify the moisture condition of a region and hence determine the risk of drought (Sivakumar et al. 2010). Several DI exist and are used across many regions including US (e.g. Wehner et al. 2011); Asia (Smakhtin 2004, Patel et al. 2007, Cai et al. 2011), Africa (Ntale & Gan 2003, Touchan et al. 2011), and Australia (Stephens 1998, Mpelasoka et al. 2008). Review by Heim (2002) for example identified 13 major DI applied in the United states in the 20th century alone, while Niemeyer (2008) identifies more than 100 DI. Table 2.2 summarizes some of the major drought indices that are used in the analysis of drought.

The Palmer's Drought Severity Index (PDSI) is the most extensively used DI globally and is suggested to give effective estimates of drought (Oladipo 1985, Kari et al. 1987, Heim 2002). The PDSI is derived using a soil moisture/water balance algorithm which is based on daily air temperature, precipitation and soil moisture data. The PDSI has been used in Europe to assess trends in drought in the 20th century and in the US to determine when to provide drought assistance (Briffa et al. 1994, Quiring & Papakryiakou 2003). When compared with the Standardised Precipitation Index, droughts over Europe were found to exhibit insignificant extreme and moderate trends (Lloyd-Hughes & Saunders 2002). Recently and in sub Saharan Africa, PDSI was used to assess drought between 1945 and 2005 and findings showed that increasing drought trends increased incidences of water and fertile land conflicts by 45% (Couttenier & Soubeyran 2011).

Several articles however fault PDSI and other DI [see for example: Heddinghaus & Sabol (1991); Byun and Wilhite (1999); Heim (2002); Mishra & Singh (2010)]. Some of the weaknesses of PDSI include: reliance on climatological mean although drought strongly correlates to specific times, durations and consecutive occurrences of precipitation deficits (Byun & Wilhite 1999), complexity in interpretation (Guttman 1998) and also the use of other factors other than rainfall masks the reliability of detecting meteorological droughts. PDSI has also been accused of giving unrealistic drought estimates in the tropical and other regions (Bhalme & Mooley 1979, Oladipo 1985).

The SPI has been suggested to give better drought estimates compared to PDSI due to its direct link with precipitation (Guttman 1998, Livada & Assimakopoulos 2007). The SPI which is based on probability density function and derived from standardized precipitation can be calculated for any location with long-term precipitation records. However SPI dependency on rain alone may cause initial data value changes when other climatological factors predominate (Tsakiris et al. 2002) and inaccuracies may occur due to rainfall measurements and availability of gauging stations (Zargar et al. 2011). The SPI and PDSI did not exhibit the same spatial variation across regions with the later indicating much differences (Alley 1984, Guttman 1998, Heim 2002). Few studies however have analysed the spatial stability of SPI (e.g. Vicente-Serrano 2006). A number of papers indicate that the SPI can be used to identify different types of drought (agricultural, hydrological etc.) (e.g. Hayes et al. 1999), is generally simple to interpret, time flexible compared to PDSI and can be calculated for a number of time scales (Komuscu 1999, Patel et al. 2007).

The BMDI proposed by Bhalme & Mooley (1980) is simple compared to PDSI and although it utilizes similar principles as PDSI, it is based on rainfall only whereby the moisture index in PDSI has been substituted with a simple rainfall index (Oladipo 1986). Generally, it has been observed that patterns of drought duration also vary among the different indices (e.g. Soulé 1992).

Although drought indices enable the detection of onset and other attributes of drought across many regions, the Normalized Difference Vegetation Index (NDVI), Crop Moisture Index (CMI) and Vegetation Condition Index (VCI) cannot be good tools for monitoring the long-term impacts of drought due to their short time scales although they may be better for short term events such as agricultural drought. The vegetation based indices are based on the presumption that as drought evolves the NDVI decreases, surface reflectivity and temperature increases and soil moisture depletes (Ghulam et al. 2007). Liu & Kogan (1996) for example found that images of VCI gave better indication of drought severity at the regional level over Brazil compared to NDVI and suggested that better temporal and spatial estimates of agriculture production could be obtained using VCI. The NDVI index also suffers from other ailments ranging from soil to atmospheric and vegetation effects (Huete 1988, Ji & Peters 2003).

Table 2.2: Examples of major drought indices used in the monitoring of drought around the world

Drought Index and source	Time scale	Concept
Palmer's Drought Severity Index (PDSI) and Moisture Anomaly Index (Z-Index), (Palmer 1965)	Monthly - 2weeks	Based on precipitation and temperature inputs using a water and soil balance model. Considers both meteorological and hydrological droughts.
Standardized Precipitation Index (McKee et al. 1993, Chambers & Gillespie 2000)	3-48 months	Takes droughts and wet spells at multiple time scales based on precipitation deficit. The index utilizes the gamma distribution to fit precipitation totals.
Crop Moisture Index (CMI) (Palmer 1968)	Weekly	Focuses on agricultural drought drawn from weekly mean temperature and total precipitation. CMI values are obtained using evapo-transpiration and wetness anomalies
Normalized Difference Vegetation Index (NDVI) (Strommen et al. 1980, Tucker & Choudhury 1987)	Monthly/ Year	Calculated from AVHRR data from NOAA and is based on the differential reflectivity of green vegetation
Vegetation Condition Index (VCI) (Kogan 1995)	Weekly - (3month)	Based on Satellite AVHRR percentage of NDVI to the maximum amplitude and measures duration, onset and intensity of drought on vegetation.
Deciles (Gibbs & Maher 1967)	Monthly	Based on distribution of long term rainfall and drought is classified according to ranks of rainfall totals being in the lowest below 10 % (decile 1) of recorded rainfall. Its mainly used to monitor drought in Australia
Bhalme and Mooley Drought Index (BMDI) (Bhalme & Mooley 1980)	Monthly/Year	Based on precipitation and calculated as the percentage deviation of rainfall from the long term mean.
Percent of normal precipitation [Operationally used in many meteorological centres globally]	Month - Years	Generally used as a meteorological drought index based on rainfall departure from the average (normal) - 30 years is the climatological base period used.

Deciles on the other hand give fairly accurate statistical estimates of drought although require consistent long precipitation records which are hard to find in many regions. For further detailed description of drought indices, readers are referred to Heim (2002); Niemeyer (2008); Zargar et al. (2011).

In conclusion for DI, they can be useful tools for assessment of drought but none of the studies used a common definition of DI. Similar to drought definitions, DI have also been changing or modified to suit different situations, which may suggest uncertainty in their ability to accurately detect and represent drought conditions.

2.4.3. Can forecasting drought benefit agriculture?

Reliable climate forecasts can arguably enable decision-makers to examine a wide range of management strategies for climate extremes in agriculture (e.g. Meinke & Hochman 2000). However, the predictability of climate extremes is not easy (Katz & Brown 1992). Although sparse spatial coverage and limited long term data sets, particularly in ASAL regions, are a major limitation to prediction of extreme events (Easterling et al. 2000), the rare nature and variability of extreme events also complicates forecasting (Frei et al. 2000).

If drought can be forecasted accurately and in advance, it can be easier to define crop management strategies such as sowing time and selection of crop to plant. This can minimize losses or maximize benefits linked to climate extremes (Nelson et al. 2002). Forecasts have been found to reduce crop damage in extreme drought years in Latin America regions, such as Peru and Brazil (Charvériat 2000), enhance identification of crop benefits in Australia (Meinke & Hochman 2000, Kokic et al. 2007) and facilitate improvement of crop simulations in Kenya (Hansen & Indeje 2004).

Previous efforts to forecast drought and other extremes have resulted in higher or lower probabilities of occurrence of extreme events compared to actual observations (e.g. Sharma 1996, Ebert & McBride 2000, Ash et al. 2007). The challenge is to develop more robust ways of predicting drought particularly now that climate change may increase the uncertainty of forecasting drought.

2.4.4. Impacts of dry spells and droughts on agriculture

Studies on impacts of climate extremes on agriculture have been rising steadily in recent years (e.g. Kane et al. 1992, Frich et al. 2002, Morton 2007, Piao et al. 2010).

A search on “impacts of climate extremes on agriculture” in the Web of Science for instance indicates that, publications increased by 16% in the last 10 years (Figure 2.5) with over 800 citations in the overall period.

Even if prolonged dry spells severely affect agriculture, their impacts on agriculture raises questions such as; what is “extreme” for agriculture; what “extremes” are relevant to agriculture and how long is “extreme” for agriculture and so on. Addressing these questions is challenging and proving difficult, particularly due to climate change (Steffen et al. 2011).

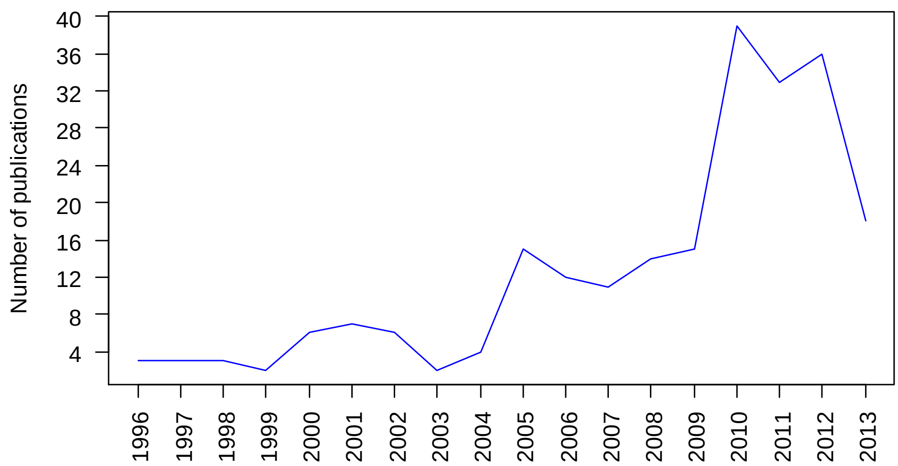


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Figure 2.5: Number of publications on “impacts of extreme climate on agriculture” since 1996. Source: Web of Science

2.4.5. Impacts of dry spells and drought on Australian Agriculture

Growing seasons in Australia are crop specific and depend on rainfall patterns (e.g. Collins et al. 2000). Drought is a significant factor affecting rainfall patterns in Australia (Nicholls 2005). Many studies show that, at the inter-annual scale, the El Niño Southern Oscillation has a major impact on rainfall patterns and droughts across Australia and particularly eastern Australia (Nicholls 1992, 2004, Pudmenzky et al. 2011, Broich et al. 2013). The 6-month total rainfall (June-November) for the 12 strongest El Niño years between 1905 and 1998, for instance, were "below average" (decile 2 or 3) across much of eastern Australia (http://www.bom.gov.au/climate/ahead/soicomp.shtml). Dry (more wet) conditions in eastern Australia are often linked to the El Niño phase (La Niña phase).

A “serious” drought from one or 2 dry years can become “severe” and more detrimental to agriculture if it is followed by a long period of below-average rainfall such as the “Federation drought" and the 1991-1995 drought over Australia (http://www.bom.gov.au). However, quantifying drought characteristics on the basis of severity and other attributes can be tricky due to problems related to objectivity (Vicente-Serrano et al. 2011). For instance, rainfall that gave a bumper wheat yield in the 1880's in Australia can be categorized as drought in the 1980's. In agricultural terms, this may suggest that coping mechanisms for wheat under similar conditions in the 2 periods has changed. In the latter period, it seems that the same rainfall could not sustain a wheat crop. Nevertheless, focus of wheat improvement has been more on maximizing production given plentiful input (Richards 1991, Eagles et al. 2001), although in recent times focus seems to shift to wheat improvement against "drought resistance" (e.g. Passioura 2006, Biswas et al. 2010, Zheng et al. 2012).

Shorter droughts of 1 or 2 years can also have a major effect on crops. For example, 1982-1983 was one of the severest droughts over Australia in 20 years and caused widespread wheat crop failure in eastern regions (Colls 1993). Howden et al. (2010) argues that small incremental changes to farming systems could prolong production, but more severe climates can cause crops to fail.

Drought can also impact large spatial areas. According to BOM, 97% of Australia had below median rainfall in the 2002 drought, again leading to large scale crop and pasture loss nationwide. Such impacts may be explained by other factors, like high evaporative demands and hydrological processes, rather than only rainfall (Verdon-Kidd & Kiem 2010, Gallant et al. 2013).

The frequency of drought over Australia has increased, and drought has been declared in most agricultural areas in more than 5% of the years since 1900 (e.g. Hennessy et al. 2008). These situations necessitated a drought declaration criterion change from 1 in 20-25 years to more than 1 drought in 20-25 years (Smith & McKeon 1998).

While focus has mainly been on drought impacts, no study as yet has explored whether dry spells (which are normally shorter) have similar or different impacts on agriculture in this region. For example, is the impact of a one month long dry spell on a particular crop different from a 3 months long drought? Or when is a dry spell long enough to be considered a threat? Nonetheless, increasing dry spells/days or exceptionally dry years should translate to increasingly dry climate (Hennessy 2008).

2.4.6. Impacts of dry spells and drought on Agriculture in Kenya

Several studies have examined the impacts of low rainfall in Kenya (e.g. Nicholson 1989, Verschuren et al. 2000). In the recent past, dry conditions persisted in consecutive seasons over Kenya (Figure 2.6). It is the occurrence of inadequate rainfall, rather than rainfall failure, which causes crop losses. Rojas et al. (2011), suggests that the probability of drought occurrence in Kenya is higher in the shorter (OND) rain season than in the longer (MAM) rain season. However, as yet, there seems to be no study that has examined the variability of drought in the two seasons.

Prolonged droughts such as 1999 - 2001 and 2007 - 2009 were both highly intense and extensive (> 2 years) and marked with extremely low rainfall in all seasons. The 1999 - 2001 droughts specifically affected both marginal and high-potential agricultural areas leaving 4 million livestock dead and 3 million agro-pastoralists affected (Aklilu et al. 2002). The losses due to floods and droughts in Kenya are estimated at Kshs 16 billion (approx. 215M AUD) per year (Mogaka et al. 2006). A summary of past droughts in Kenya is given in table 2.3. It appears that droughts in Kenya re-occur every 1 to 2 years.

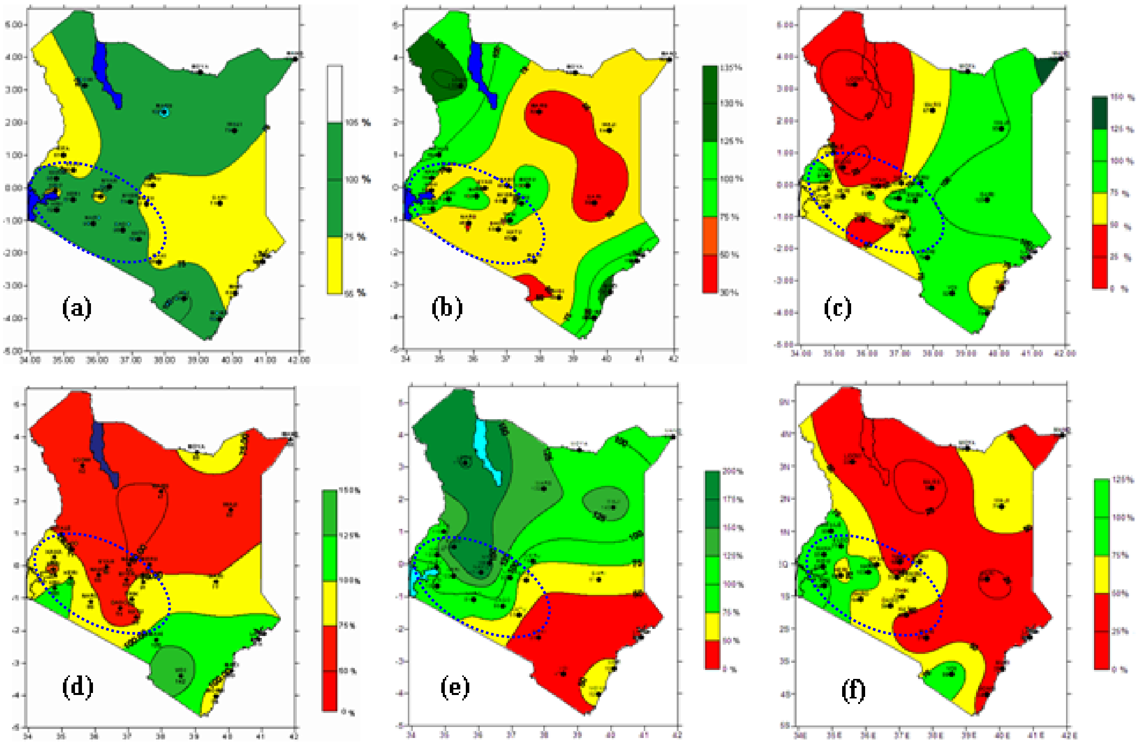


Figure 2.6: Percentage total seasonal rainfall over Kenya for (a) MAM 2006 (b) MAM 2007 (c) OND 2007 (d) MAM 2008 (e) OND 2008 (f) MAM 2009. Main agriculture areas are ringed in blue dots.

Table 2.3: Agricultural impacts of some selected droughts in Kenya

Drought Period	Impacts	Spatial coverage and reference
1983/1984	Over 50 - 75% of livestock lost in ASAL / pastoral areas	Pastoral areas most affected (Sperling 1987)
1995/1997		Marginal/pastoral areas affected (Kandji 2006)
1999-2001	3 million people affected. 4million livestock lost. Food aid distributed worth US$ 200 million. Loss of pasture	Country wide and mostly pastoral areas except the coastal region (Aklilu et al. 2002, Anyamba et al. 2002)
2000	4million people in need of emergency food. Power generation losses ~ US $20 million. Decline in GDP ~0.3%	Most of the country (Duran 2005, Kandji 2006)
2004/2005	Failure of long rains (March–June). Total crop failure and 2.3 million people in need of assistance. Drought declared as a "national catastrophe"	Most of the country (Kandji 2006)
2007-2009	10 million facing hunger. The Kenya Red Cross Society distributed a total of 200 MT of seeds to 20,000 farming households. More than 70% of livestock numbers lost.	Most parts of the country (IFRC 2010, Wangai et al. 2013)
2011	3.7million people affected and massive crop failure.	Most agro-pastoral areas (Janzen & Carter 2013)
Other previous droughts		
1914-19, 1928, 1931-34, 1939-40, 1943-1944, 1948, 1954, 1960-1961,1964-1965,1970-1971, 1973 1974, 1979-1980		(Jackson 1976, Nyamwange 1995)

Indirectly, drought is related to pests' infestation on crops in Kenya (Rose et al. 1988, Musebe et al. 2011, Tefera et al. 2011). Mostly, locusts and army worms attack during crop seasons, whereas weevils invade during postharvest and storage (e.g. Hoskinson 1997). Additionally, wind storms during dry conditions can cause severe damages to crops in semi-arid areas such as Laikipia as well as in other areas (Oteng'i et al. 2000, Stigter et al. 2002). In general, there is less information about the extent of impacts associated with the last 2 factors.

In conclusion, for drought impacts in Kenya and Australia, it seems there is very little exact quantification of the damage of agriculture due to drought events. For instance, no studies show how much rainfall in millimetres increase translates to x or y crop damage increase or number of livestock losses. An increase of drought by a certain number of days e.g. 5 days equating to crop damages of z magnitude would be a better quantification scheme of the impacts of extreme climates than current cumulative estimates. This might probably be because drought characteristics are not fully understood in the 2 regions.

2.5. Managing drought risks for agriculture in Kenya and Australia: Role of Seasonal forecasts

In recent years, there has been increased interest in conditioning agriculture to climate variability (e.g. Campbell 1999, Mendelsohn & Dinar 1999, Jones et al. 2007, Niggli et al. 2009, Meinke 2010). One of the main motivations has been the increase in severity and frequency of drought occurrence and other climate risks (Le Houérou 1996, Hobbs 2007).

Generally, managing risks of drought on agriculture largely depends on individuals rather than collective actions (Risbey et al. 1999, Pannell 2010). It is of benefit to manage drought because agriculture is a very important economic activity in Kenya and accounts for 30% GDP and 70% of employment in the rural areas (GOK 2010). Similarly, Murray Darling Basin (MDB) agriculture contributes to over $8 billion annually or 1/3 of the whole agricultural output (Crabb & Milligan 1997). Whereas, it is of interest to clearly understand the role of seasonal forecasts in the management of drought risk for agriculture, it is important to examine both indigenous (personal experiences and knowledge) and evidence based climate forecasts. This is because farmers in these regions use both at one time or the other. However, the critical question also is: what to forecast?

2.5.1. What is managing drought in Agriculture?

In agriculture, managing drought risks might be taken to mean a process of maintaining various farming goals such as yield and sustainability (Risbey et al. 1999) or actual farmer behaviour response, such as early or delayed planting and harvest dates, use of fertiliser, and crop choice (Mendelsohn 2000) which is expected to ensure success or limiting of crop yield losses. It also includes policy decisions to manage climate risks (e.g. Salinger et al. 2005, Howden et al. 2007, Jones et al. 2007). Policy, in this context means actions taken by state governments, such as legislation and regulations which facilitate changes that may lead to a reduction in vulnerability to climate change and variability (Burton et al. 2002, Pielke Jr & Conant 2003).

More importantly, managing drought risks in agriculture should involve examining of how uptake of climate forecasts (indigenous and science (evidence) based) influence agronomic decisions. Studies suggest that climate information can improve farmers adaptive capacity to climate risks (Marshall et al. 2010). Such assessments may be used to form a basis for formulations or implementation of agricultural policies or potential coping options.

2.5.2. Problem in contextualising agriculture management of drought

A major problem in designing an agriculture management system for drought is that the future is unknown. One key question would then be: how do we measure or quantify a successful system? As yet, no universal way has been proposed. Previous assessments focus on key impacts of climate on agriculture and not drought in particular, whereas the potential or actual benefits of managing drought impacts on agriculture have received little attention (e.g. Callaway 2004, Tubiello & Fischer 2007). Most common approaches evaluate agricultural gross outputs based on given climate scenarios (for example, Reilly 1995) and this has been criticised to ignore the short term impacts of managing drought (e.g. Maddison 2007).

One obstacle towards contextualising an agricultural drought management system is that a long time is required to build more effective and sustainable systems (Cash et al. 2003) which is practically not possible. In other words, if we consider the use of climate forecasts there might be uncertainty in quantifying the quality of such as system or choice and how this will work in practice (Neil Adger et al. 2005).

Nevertheless, no perfect system can exist in practice and therefore it is worth testing and improving on the existing options in order to experience whatever benefits may be achieved.

2.5.3. Nature and context of agriculture management of drought in Kenya

Drought and famine are well documented features of Kenyan ASALs (e.g. Oba et al. 1987, Rowntree 1989, Holmgren & Öberg 2006). Studies in Kenya, show that, farmers and pastoralist have numerous agronomical and livestock production practices that facilitate them in the management of drought (Porter 1965, Kabubo-Mariara 2008). For example, due to drought, pastoralists in Kenya have derived some characteristic watering mechanisms and grazing habits. Camels and goats are more browsers than cattle and sheep (Campbell 1999), whereas indigenous dominated or mixed species ensure disease and drought resilient herds during dry periods (e.g. Western 2003, Huho et al. 2011).

Diversification into crop farming by herders (Campbell 1999) and also mixed cropping and drought tolerant crops are important features characterising resilience to drought in Kenya. Small scale on-farm water harvesting systems (RWH) have been tested not only in boosting maize production in ASALs but also to deal with drought (Rockström et al. 2003). However, RWH may have the challenge of a lack of sufficient space considering that most farms in Kenya are small.

In general, indigenous based drought management options are an important aspect of all the agricultural practices in Kenya (Luseno & Winnie 2003). Although, the use of scientific forecasts (SCF) by farmers has been low, it seems there is some interest since the last decade (e.g. Luseno et al. 2003, Lybbert et al. 2007). Overall, the above studies suggest that IK is useful in the agriculture management of drought risks in Kenya.

2.5.4. Nature and context of agriculture management of drought in the Murray Darling Basin

Management of drought in Australia in general, is driven by modern agricultural innovations including: farm choices, choice of planting dates, moisture conservation and soil nutrient inputs (e.g. Gomez-Macpherson & Richards 1995, Robertson & Holland 2004). These are supplemented by Decision support systems such as Yield Prophet (D'Souza et al. 1993), simulation models (Jochinke et al. 2007) and seasonal forecasts (Hochman et al. 2009). Tillage practices in the MDB such as retention of crop residues improve the humus content of the soil, reduce soil erosion, and improve yields (Freebairn 1992, Lawrence & Vanclay 1994). While crop varieties combined with other coping mechanisms are common in the MDB, their use is driven by the growing season rather than climate variability (Finlay & Wilkinson 1963, Meinke & Stone 2005). These practices increase the ability to manage drought risks on farming enterprises (Rounsevell et al. 1999).

Even though irrigation is one of the key agricultural strategies in Australia, its sustainability continues to attract debate (Adamson et al. 2007). Whereas some irrigation types such as micro-irrigation techniques yield very high return per unit of water used (Quiggin 2001), it is argued that all irrigation schemes in Australia cannot be justified on economic grounds, because they increase rather than reduce the effects of severe drought (Hart 2004, Anderies et al. 2006).

Table 2.4 gives a summary of ways of managing drought risks and other climatic threats in Australia as discussed in the reviewed literature. In general, it appears that most of the strategies are aimed at boosting agriculture productivity and driven by profitability rather than risk evasion.

Table 2.4: Agricultural management strategies in Australia

Adaptation type	Category & Aim	Location	Resultant impact
1. Diversification of farm /crop businesses (e.g. Risbey et al. 1999, Kokic et al. 2007)	Short term / To provide higher returns and crop insurance.	Australia	Most farms increased productivity under different climate conditions
2.Access to innovations, such as agribusiness services (Risbey et al. 1999, Kingwell 2006)	Long term / Increased ability to respond to climate impacts	S.W. Australia and most other parts of Australia	Maintenance of profitability for farmers from 1995 to 2002 despite drier conditions.
3. Farm deposits of 1999/2000 and Exceptional Relief Payment (Martin et al. 2005)	Short term / To build cash reserves for farmers as a cushion for drought	Broad acre and dairy farms in Australia	Farmers obtained tax benefits if the deposits were held for a minimum of twelve months.
4. Agronomic improvements e.g. early and delayed sowing (Loss et al. 1998, Turner 2004)	Short term / Long term. Delayed sowing to control black spot disease	South-western and southern Australia	Improved management of faba beans under low rainfall.
5. Use of seasonal forecasts in crop management (Risbey et al. 1999, Keogh et al. 2004)	Short term / Long term / To improve farm decisions	NE. Australia and NSW	Provide support system such as Whopper cropper and crop diversification.
6. Government related drought policies (Nelson et al. 2002)	Short /Long term strengthen farmers' ability to manage risk	NSW and Queensland	Enhancement of self-reliance to farmers to respond to Climate risks

7. Conservation measures e.g. planting of trees, (Lawrence & Vanclay 1994, Turner 2004)	Long term / Increase agriculture production	NSW and S. Australia	Implementation of on-going government policies on ways to improve conservation
8. Investments in crop insurance and research (Quiggin & Chambers 2006)	Short term / To make tactical and strategic agricultural decisions	Australia	Benefited farmers from drought and flood related losses
9. Adoption of crop varieties (McCallum et al. 2001)	Short & Long-term / improved seed yield under a range of seasons.	South western Australia	Prior to 1997
10. Application of fertilizer, and pesticides (SiddiqueABD et al. 1999, Howden et al. 2003)	Short-term/Long-term/ Control pest peak seasons and boost soil quality.	Southern Australia	Increase in crop production
11. Irrigation (Haisman 2004)	Since early 1900	MDB	Currently contributes to 3% GDP

2.5.5. Indigenous based knowledge on climate for Agriculture management of drought

In recent times, indigenous knowledge (IK) has become important in climate change management (e.g. Duerden 2004, Morton 2007, Adger et al. 2009). So far, one major obstacle in using IK is how to integrate it with science (e.g. Dennis 1998, Newton et al. 2005, Chalmers & Fabricius 2007). Whereas the science view of IK is biased such that it is accused of not factual and unquantifiable (Johannes 1993), Moss (1976) argues that scientific decisions can also be wrong in making the differences between observation and interpretation clear.

2.5.6. How indigenous based knowledge is understood and defined

Generally, understanding IK is difficult (McKinley 2007). Berkes and Folke (2002) differentiate IK from local knowledge (LK). They say, LK is part of IK but a generic term that refers to knowledge accumulated from observations of the local environment and by a specific group of people but in contrast, IK refers to LK held by indigenous people. This however, shows no clear cut difference between the two arguments. Green (2008), discusses Horsthemke's (2008) article's criticism of IK. Horsthemke see IK as an incomplete and questionable form of knowledge and adapts a universal view that knowledge is not relative to a particular culture or social context. Green argues that, while this can be correct in some aspects, diverse knowledge should be evaluated on the basis of its ability to advance understanding.

Aikenhead and Ogawa (2007) see IK as diverse cultural ways of understanding nature. This gives a multi-faceted meaning to IK comprising of indigenous, western-scientific view and a mix of the two. This assertion does not demystify the meaning of IK. Warren et al. (1995) modifies this view and distinguishes LK from that of the international education system. More elaborately, Berkes et al. (2000) define IK as a cumulative body of knowledge, practice, and belief, evolving by adaptive processes and handed down through generations and relates to living things and environment. This corroborates Agrawal (1995) assertion that IK is contextual, specific to a community, and passed from one generation to another.

The Oxford English Dictionary as cited in Dove (2006) defines indigenous as: 1). Born or produced naturally in a land or region; native or belonging naturally to (the soil, etc.) and (2). Of pertaining to, or intended for the "natives". In application, LK is understood to be new and different data from the typical scientific data that may have been available but never used because its usage was not known or was discredited (Mackinson & Nottestad 1998).

In Australia, IK has generally been understood to refer to knowledge related to the Aborigine people and LK as informal knowledge of communities in the rural areas (e.g. Grenier 1998, Chambers & Gillespie 2000). In Brazil, knowledge of local fishermen is classified as LK (Gerhardinger et al. 2009) but in the Solomon island, both IK and LK mean the same thing (Aswani & Lauer 2006) as is elsewhere (e.g. Chalmers & Fabricius 2007, Leach et al. 2007, Raymond et al. 2010). In Kenya, McCorkle (1989) refer to LK as IK to show its role and significance in framing successful agricultural research, development, and extension.

As highlighted, it is clear that the understanding of IK and its difference with other forms of knowledge remains problematic. Subsequently, the interactions between IK and scientific knowledge may be crucial towards understanding quantifications of benefits to farmers from management of climate risks. As an example, a study in Kenya is used to evaluate how indigenous and evidence (scientific) based climate forecasts benefit agriculture in the management of climate risks.

2.5.7. Indigenous Knowledge use in agriculture management of drought in Kenya

In Kenya, IK is used more by agro-pastoralists than other farmers in the management of drought (Western 2003). One of the earliest uses of IK is documented by Hollis (1909), in which a traditional doctor proclaimed magical measures to stop calamities such as severe droughts and pests infestations.

Rainmaking is a popular practice in some parts of Kenya and other regions globally (e.g. Davis 1972, Taube 1995, Wade 1997). In eastern and western Kenya, some communities use traditional experts to diagnose causes of drought, or too much rainfall, and to reverse the situation (Akong'a 1987). This information helps the farmers decide on the best time to prepare their farms and plant. Rainmakers use changes in natural features as indicators of weather (DMC 2004).

Some of the traditional ways of managing drought by pastoralists in Kenya include grazing early in the morning and migration to other areas during bad years. Use of local cultivars such as Katumani, burning of weeds and crop residues and use of ash as a pesticide to control some pests during the growing period are other agricultural mechanisms used by farmers to deal with climate variability in ASALs. These approaches are tactical. For example, grazing livestock early in the morning ensures palatability of a dew laden pasture as well as reducing the rate at which stocks require water (Huho et al. 2011), while maintaining multiple traditional varieties of crops, such as sorghum and tuber crops, provides drought resistance compared to modern cultivars (Conelly & Chaiken 2000).

Some communities use traditional conservation agriculture or “agro-forestry”, popularly known as the “shamba system” where crops are grown together with trees in high potential areas of Kenya (Oduol 1986). This also doubled as a government plan to encourage conservation of traditional species and to boost food security for small scale farmers. However, this system has since led to encroachment and wanton destruction of forest land (Baldyga et al. 2008). During famine periods, traditional indigenous plant species such as wild fruits and leafy vegetables (Maundu 1997) become useful sources of food in the ASAL regions.

2.5.8. Indigenous Knowledge use in agriculture management of drought in the Murray Darling Basin

The earliest forms of IK practices in the MDB are reviewed in Allen (1974). The indigenous people in the basin exploited aquatic food and cereals along the riverbanks and migrated away from the rivers only during rainfall seasons. In contrast, during dry seasons they dug out roots of water-storing plants and during winter, acacia seeds, fruits and tubers became alternative sources of food. Collection of seeds has been an arid land coping strategy in northern and eastern parts of the basin. In modern Australia, many native acacia species continue to be used in sand dune stabilisation plantings in dry environments and provide fodder and green manure (Thomson 1987). Similar to Kenya, indigenous people across Australia use some 10,000 native plant species for food (Twarog & Kapoor 2004).

The, in1988 established, MDB commission, which brings together state and special interest groups such as indigenous people and farmers (MDBC 2011), appears to be an informal basis for inclusion of IK in resource management. The commission's structure for instance, recognises the generation and access of all forms of knowledge including research (Haisman 2004) and the involvement of indigenous people in decision making (MDBM 2001).

Numerous studies (e.g. Martin & Lockie 1993, Millar & Curtis 1999, Crase et al. 2005) underscore the importance of IK in management practices in MDB. Millar & Curtis (1999) show that farmers' knowledge was useful in the establishment of native and added perennial grasses in the upland pasture areas of MDB. Inclusion of land-holders can provide more information on agricultural management (Robertson et al. 2000). Incidentally, some practices in the MDB such as collection of seeds and construction of fences to control stock access into creeks (Curtis et al. 1998) are traditional by nature and date back to practices by early farming communities in Australia. The formation of LandCare groups is a strategy similar to the group alliances in traditional systems in the pastoral areas of Kenya (e.g. Huho et al. 2011) different only in terms of their formal context.

Comparing Kenya and MDB, migration in search of pasture is the most common drought evasion mechanism by pastoralists in Eastern Africa (Campbell 1999) which is similar to farmers' in the MDB temporarily excluding stocks from flood plain grasslands and allowing regeneration before resuming grazing (Roberts & Marston 2000). In other words, the traditional pastoralism in Kenya resembles the commercial pastoralism across some parts of Australia rangelands (Cook et al. 2010) and is based on ideas borrowed from Africa (Ampt 2013). Similar to Kenya, it seems from these studies that, there isn't any effort to formally transform or integrate these practices into a scientific framework in the MDB.

2.6. Using seasonal climate forecasts in management of drought

Seasonal climate forecasts (SCF) can be used in managing drought risks and SCFs have been found to influence agricultural activities (e.g. Agrawala et al. 2001, Willows & Connell 2003). As an example, mitigation efforts by the US, based on the

1997/1998 climate predictions, returned benefits estimated at $19 billion and reduced losses to $4 billion (Changnon 1999). Likewise, the World Food and Agriculture Organisation (FAO) made climate data more available, to enable monitoring of weather and agriculture in Africa following the 1997/98 El Niño related events (Blench & Marriage 1998). These examples underscore the potential of SCFs in management of climate risks.

However, one of the current challenges of understanding the potential of SCF in the management of drought is the lack of a solid framework to analyse and evaluate potential management strategies. This means that research should focus on how climate forecasts can be used to adapt agriculture to drought and other climate extremes.

2.6.1. Application of SCF in management of drought for agriculture in Kenya

Application of seasonal forecasts for epidemic outbreaks rather than other climate risk sensitive sectors is perhaps one of the most studied examples in Kenya (e.g. Linthicum et al. 1999, Thomson et al. 2000, Hay et al. 2001, Checchi et al. 2006, Indeje et al. 2006). Linthicum et al. (1999), showed that, the Rift Valley Fever (RVF), which is linked with widespread livestock losses in pastoral areas of Kenya, can be predicted 5 months in advance.

Climate forecasts in the Kenyan context require inclusion of local or indigenous forecasts (IF) because they are the mostly used (Onduru & Du Preez 2008, Ogallo 2010). As an example, one study shows that only 20% of the agro-pastoralists in Kenya and Ethiopia choose SCF compared to those in favour of, or having more confidence in, indigenous forecasts (IF) (Barrett 2001). In general, indigenous forecasts (IF) are related to the use of bio-physical and natural features and farmers'experiences to indicate the local weather patterns. While pastoralists use IF in response to drought (e.g. Oba & Lusigi 1987), it is not well understood how farmers implement climate information in management decisions.

Increased variability in climate patterns and the frequency of droughts in recent years is making it more difficult, even for pastoralists, to rely on traditional (IF) forecasts only (Kaitho et al. 2010). This means that skillful SCFs may provide a better tool for farmers in the management of extreme risks in Kenya. One challenge is that availability of forecasts may not necessarily lead to better risk preparedness if a prediction of the 1997-1998 ENSO in Kenya is anything to go by. Despite timely predictions, big losses in agriculture and other sectors still occurred (Magadza 2000).

In general, climate forecasts in Kenya are not specifically developed for drought monitoring but rather for rainfall evaluation. By looking at the seasonal forecasts from the Kenya Meteorological Department (e.g. http://meteo-kenya.net/Wx/seasonal.pdf) one common feature is that they show the expected rainfall probabilities for various regions which are used to give advise on various sectoral impacts. Drought /dry conditions are normally highlighted in terms of ‘depressed’ or below normal rainfall. In recent years, a drought modeling experiment for Africa based on remote sensing and in-situ hydrological information was launched (http://drought.icpac.net/Resources/ADM_Background.pdf). However, the performance of the drought system, its operational use and accessibility to farmers and other stakeholders is unclear.

While SCFs can be of benefit to farming in Kenya, farmers show more interest in forecasts when depressed rainfall/drought or other extremes are predicted. Barrett (2001) for example, show that, farmers are more likely to respond to predictions of above or below-normal rainfall, than normal rainfall. This means that a drought forecast may be a better indicator of risk compared to a rainfall probability forecast. This may however be challenged by the lack of technical adaptation capacity and often erratic rainfall patterns, although farmers may still voluntarily increase the use of drought forecasts alongside other coping mechanisms to boost their resilience. In a practical sense, there is little success (e.g. Frenken et al. 1993, Hansen & Indeje 2004, Nyangweso et al. 2010) in linking seasonal climate forecasts with crop predictions in Kenya, which suggests that new and better ways may be required to achieve this.

Drought forecasts need to be accurate and reliable if they have to be accepted by farmers in Kenya. Few studies have tried to improve the skill of seasonal forecasts in Kenya. Hansen and Indeje (2004) used statistical methods while Stigter et al. (2002) assigned an economic value to SCF. Hansen and Indeje (2004) predicted 36% and 54% of the variance of total precipitation and rainfall frequency, respectively, in the OND rain season which suggests low reliability for crop predictability. Hansen et al. (2009) further used GCM based forecasts which indicated that SSTs offered insignificant skill in 2 semi-arid locations in Kenya with relatively low crop predictions. More recently, Masinde & Bagula (2010), in an ongoing project, are testing the integration of indigenous and/or farmer innovations or non-climatic data outputs to seasonal forecasts using mobile phones and wireless sensors techniques.

From the above studies, the gaps in the application of SCF in Kenya are the lack of downscaled localised forecasts and difficulty in interpretation. However, recent decentralisation of meteorological services in Kenya, may boost the interest for localised forecasts. Ndegwa et al. (2010) suggests that it may be possible to assess the quality of localised SCF in farm management through participatory approaches involving farmers and the scientific community. Again, there appears to be no clear information on the quality of climate forecasts or more so the skill of drought forecasts in Kenya. This may be due to a lack of any major quantitative assessments of forecasts across sectors.

2.6.2. Application of SCF in management of drought for agriculture in the Murray Darling Basin

In the MDB, there are various examples of how SCFs have been applied in adapting agriculture to climate change (e.g. Meinke & Stone 2005, Predo et al. 2007, Rebgetz et al. 2007, Marshall et al. 2010). Most of these studies are based on agricultural farming systems and more specifically assess the value of climate forecasts (Hammer et al. 1996, Podbury et al. 1998, Ritchie et al. 2004, Wang et al. 2009).

In the MDB, two-thirds of the farmers were found to apply SCFs in their farm decisions (Keogh et al. 2004). These maybe determining planting areas and making other cropping decisions (e.g. Ritchie et al. 2004). Previously, wheat farmers in northern New South Wales had shunned SCFs in their activities (Hayman & Alston 1999). Meinke and Stone (2005) and the studies there in, indicate that the use of SCFs in Australia need 3 main attributes: consistency, skill, and value, for them to be applied in the management of climate risks.

The SOI based forecasts have been useful predictors of spring and summer rainfall in the Basin and most farmers use them in farm-decisions (Keogh et al. 2004). For wheat farmers, it has been suggested that, the forecasts lead to higher wheat returns (Abawi et al. 1995). In another example cotton farmers in Queensland have used cycles of MJO to realise crop benefits, although only 20% expressed high confidence in the use of SCF (Keogh et al. 2004). Nonetheless, while most farmers use SCFs in the MDB, most farmers had low confidence in the SCFs. Although this was based on irrigation farmers, the results suggests that there may be other issues which may need addressing in order to improve forecast use. Hayman et al. (2007) says that, integrating SCFs in Australian agriculture decisions is a bigger challenge than previously thought. The low confidence in forecasts may be because some farmers prefer old farming methods which are largely driven by financial stability and wellbeing (Hogan et al. 2010).

Others argue that explicitly providing skilful seasonal forecasts may improve use of forecasts and possibly lead to better management decisions (e.g. Hammer et al. 1996, Challinor 2009). However this is in contrast to studies that suggest that the skill of SCFs has improved over the last few decades (e.g. McIntosh et al. 2005, Saha et al. 2006, Smith et al. 2007). While this may be expected to translate in better decisions, there is still a need for deeper understanding of whether skill alone is sufficient for improving acceptability of SCFs in decision making. Issues such as capital base (Byron et al. 2004), and whether SCF translate to farm profitability (e.g. Scoccimarro et al. 1994, Hammer et al. 1996, Meza et al. 2008) affect farmers' ability to use forecasts. Apart from accuracy, there should be improvements in the relevance, reliability, stakeholder engagements and so on.

The above studies reveal that farmers in the MDB utilize climate forecasts in farm decisions. However, similar to Kenya, it appears that the use of climate forecasts in the MDB is not specifically for drought management.

2.6.3. Analysis and characterization of dry spells

As mentioned before, drought is generally a prolonged dry period. However, the temporal patterns of dry spells can be important indices of drought in a region. Dry spells can be derived using the number of consecutive days without rain. In other words, the sum of successive dry days defines the length of a dry spell. The analysis of dry spells for several locations in a region can identify temporal and spatial behaviour of dry spells lengths. Several methods for single sites or regional analysis have been proposed. In most cases, they attempt to identify homogeneous areas, select some suitable probability distributions and finally approximate precise parameters to describe the observed distribution.

Stochastic models are the most commonly used tools in the analysis of dry and wet spells (Gabriel & Neumann 1962, Gregory et al. 1993, Sharma 1996, Ochola & Kerkides 2003). Markov Chain Models (MCMs) which assumes that the chance of current day rain is governed by the state of rain or no rain in the preceding days

(Miall 1973) are the most popular. They are preferred for their easy application (Mishra & Desai 2005) particularly in obtaining transition probabilities rather than direct theoretical calculations (Nobilis 1986). They also allow for estimation of extremes and future expected values (Logofet & Lesnaya 2000) as well as accounting for uncertainty surrounding variable relationships (Pfeifer & Carraway 2000). They have been applied in Greece (Anagnostopoulou et al. 2003), semi-arid regions of Kenya and Australia (Sharma 1996, Barron et al. 2003) and many other places (e.g. Gabriel & Neumann 1962, Stern et al. 1981, Berger & Goossens 1983, Woo 1992, Smith et al. 1997, Ochola & Kerkides 2003, Tesfaye & Walker 2004, Tolika & Maheras 2005, Lennartsson et al. 2008, Frei & Schär 2010), generally to generate and fit dry spells of different durations from daily rainfall.

However, MCMs estimate parameters poorly (Sharma & Lall 1999). They tend to create problems for small samples and heavy tailed distributions (e.g. Gregory et al. 1993, Kyselý 2008) and over or under-estimate short or longer dry spells (e.g. Cancelliere & Salas 2004, Paulo et al. 2005). Several studies cited in de Groen (2002) indicate that MCMs represent the variability in monthly rain days poorly. Moreover, MCMs are limited to the exponential distribution, but climatic data may not necessarily be exponential in nature (Fuqua 2003). Again, MCMs are unsuitable for short term records as they require longer daily weather records to estimate the model parameters more accurately (Geng et al. 1986).

Alternatively, numerous probability distribution models have been used to estimate dry and wet spell distributions. Most of these are based on transformations of the normal distributions for rainfall analysis and aim at satisfying assumptions for normality and constant variance in the errors. The disadvantage of these, however, is that different transformations may be required for different periods of the year and the presence of zero value data for dry days invalidates the constant error variance (e.g. Stern et al. 1982a, Fletcher et al. 2005).

Distributions such as the truncated negative binomial distribution did not give solutions for likelihood equations for 10 periods for Kansas City rainfall records resulting in unacceptable values and poor estimates for data records <30 years (Roldan & Woolhiser 1982). However, some distribution extensions such as the generalized extreme value (GEV) and generalized Pareto distributions from the Gumbel distribution (Lana et al. 2006, Su et al. 2009) give good estimates of annual extreme dry and wet spells such as in the case of Spain and China but again the return of one extreme value per year may have less significance for the timing of agriculture activities such as planting time or cropping.

As it may not be possible to identify a suitable distribution to describe observed dry spells from the existing large number of probability functions, it is much easier to assume that such distributions may come from the commonly used distribution functions in climate analysis. Specifically, the two parameter gamma distribution (e.g. Mooley 1973, Stern & Coe 1982, Husak et al. 2007) represents the skewness of precipitation in many places. The gamma distribution has the capability to represent different distribution shapes and has only positive values. However, the estimation of the shape and scale parameters is difficult (Gupta & Kundu 2001).

Direct methods can be described as those that obtain the sequences of days with rain/no rain from daily rainfall by summing successive days of observations for arbitrary periods such as 30 days and other statistics such as the onset of rains. According to Stern et al. (1982a) a direct method is one that estimates the unconditional probability of a dry period, assuming that it can start at any point before the period of interest and continue in or beyond the period. Direct methods are mainly useful for being conventional and simple to apply and require little assumptions made on the distribution of rainfall amounts/days as in other methods. By specifying the temporal scale of interest (e.g. monthly) at any location, one can obtain useful agronomical information such as significant trends, periods or areas already under drought. In contrast, indirect methods (e.g. stochastic models) generally give probabilities of rain conditioned on an initial rainy day and allows for calculation of the probability that a dry spell lasts exactly n days e.g. n=14 or 30 days (Wilks 1995) which may not necessarily be true. Furthermore, it is more difficult to allow re-parameterisation of future projected statistics from such models (Srikanthan & McMahon 2001). Stern et al. (1982a) suggests that conditional probabilities are more suitable for analysing probability of planting following a rainy day which may not be feasible when it comes to having no rain on the initial day.

Numerous studies suggest that direct methods for dry/wet spells identification can yield acceptable results (Cheng 1978, Douguedroit 1987, Serra et al. 2006, Tammets 2010). For instance, Cheng (1978), found that dry spells in southern China from 1884 -1970 exhibited 3 distinct dry periods in a year with nearly same time year to year occurrences. Furthermore subsequent studies, e.g. Zhai et al. (2005) and Bai et al. (2007) and Wang et al. (2010), show that there have been changes in the seasonal trends over China since 1951 with the longest wet spells decreasing from the southeast to the northwest regions.

As indicated earlier, one common criteria in the analysis of dryspells is the use of rainfall amounts to define a dry day or a dry spell. On other occassions, some studies use fixed periods of time to characterize a dryspell. For example, analysis over Estonia used a moving average of daily rainfall totals to investigate the months with extreme dry or wet days (Tammets 2007). An extreme dry spell was defined as a period of 20 successive dry days with no rain and an extreme wet spell as a period of 10 successive wet days with ≥10mm rainfall. Although the study by Suppiah et al. (Suppiah & Hennessy 1998), found trends in dry days between 1910 and 1990 (a dry day was defined as a day with rain ≤ 0.1mm) over Australia there was no attempt to examine the trends in dry spell lengths (cumulative dry days). Subsequent studies have similarly indicated increased number of dry days and rainfall decline (Murphy & Timbal 2008, Potter & Chiew 2011).

Similarly, drought is invariably a major constraint to food security in Kenya and relatively few studies have assessed dry spells in relation to agriculture, e.g. Barron, Rockström et al. (2003). To the best of our knowledge, published evidence of assessment of the spatial characteristics in dry spells in Kenya and the Murray Darling Basin are limited.

2.6.4. Analysis of trends in dry spells

Analysis of trends in dry spells may provide new information that may be important in the prediction, monitoring and management of agriculture to drought impacts. Increasing spatial and temporal trends can be good indicators of the periods and regions that have higher drought risks while declining trends may suggest areas with improved precipitation patterns. This information can be used in planning and decision making.

Generally, spatial trend patterns are often used to map drought and other extreme events (e.g. Vicente-Serrano 2006) and can give a better picture of where and how different dry spell characteristics are distributed. In using dry spell characteristics we are more likely to capture a more detailed picture of the drought situation at a location than using the commonly used drought metrics such as cumulative rainfall anomalies or indices. For example, a good comparison between the observed dry spell lengths and the estimated probability distribution may be used to accurately predict the risk of drought.

This analysis is important because studies in Kenya and the MDB suggest that drought will increase in these regions. Therefore, there is great interest in determining trends in drought in order to mitigate associated risks. The few studies that specifically analysed trends in dry spells in Kenya and the MDB focused on fairly limited timescale and scope which may may not give a comprehensive picture of drought risk in these regions (Suppiah & Hennessy 1998, Timbal 2004, Alexander et al. 2007, Alexander & Arblaster 2009, Gitau et al. 2013). Curiously, all the studies consistently used the monthly time stamp (calender dates: 1 - 30 etc) in their analysis without providing any justification. Does a dry spell or drought start on the first day of the month and end before or at the end of that month? Moreover, do crops or ecosystems sense the environment as “month”? Again, is there agreement between trends in the dry spells (length) analysed using the monthly time stamp and when this is not taken into account?

Furthermore, there seems to be uncertainty between different GCM models suggesting different trends directions in future, at least for MDB (CSIRO 2001a, Hughes 2003), and therefore examining the climate of these regions may contribute some knowledge towards improving our understanding of future drought patterns in the 2 regions.

Relationships between dry spells and climatic factors are important in the understanding of bio-physical processes of drought and how this may impact on agriculture adaptation to climatic risks. Spatial analysis in the MDB for instance indicates significant relationships between drought and crop yields (e.g. Stephens 1998, Robinson et al. 2009) and between rainfall and ENSO (Potgieter et al. 2005, Liu et al. 2007).

Although rainfall is one of the most important climatic factor, it is less significant in explaining the spatial distribution of surface water availability compared to other predictors in southern MDB (Brown et al. 2012). Dry spells would be expected to exhibit strong correlation with rainfall. For example, Keating et al. (2002) suggests that the annual average rainfall across the MDB exhibits an east - west effect around latitude 33^0S and varies from 300 to 850 mm while a second effect shows a north - south pattern with rainfall estimated at 600 mm while the average annual rainfall in winter indicated an increasing pattern southwards. It is possible that dry spells may follow a similar pattern which is likely the variation in winter (frontal system) dominated and summer (convective system) dominated rainfall in the region.

2.6.5. ‘What to forecast?’ – Forecasting or Predicting dry spell lengths

There is much overlap between prediction and forecasting and most times researchers use them interchangeably. However, predictions can be viewed as an interface between weather forecasting and climate forecasting and are sensitive to initial (the starting conditions of the lower atmosphere’s boundaries) conditions when used for modelling climate/weather (Palmer & Anderson 1994). Forecasting on the other hand implies integration of a weather-prediction model and improving on the length and dynamically coupling with the lower boundaries and most importantly the Oceans (Shukla 1998).

In climate forecasting, only certain climate information may practically be useful in the management of climate risks (Kiem & Verdon-Kidd 2011). This means that, to identify and address climatic needs satisfactorily, the right climate information must be provided. In general, three ways can used to forecast drought:

1) Probabilistic forecasts which are based on historical climate data in which some probability distribution functions are used to establish the likelihood of an event of a given magnitude occurring (e.g. rainfall amount, drought duration, severity etc).

2) Statistical forecasts, which can incorporate lagged relationships between climatic data such as monthly rainfall and SSTs.

3) Deterministic forecasts , which model climate systems.

In spite of these choices and as earlier mentioned, understanding and forecasting of drought is difficult. But, addressing the question; ‘what to forecast?’ may be a good start towards achieving what is possibly relevant and useful to forecast. Opting to forecast dry spell lengths may be one option which may be useful but challenging. For instance, a skilful forecast of a dry spell or number of dry days maybe more useful for cropping during the critical flowering period (Patt & Gwata 2002) compared to a probabilistic rainfall forecast since crops are highly sensitive to shorter extreme climatic variations such as mid-season dry spells or extreme high or low temperatures. One of the challenges would be how to deal with the mismatch between start and end of dry spells and the time stamp for potential predictors like SSTs which are normally recorded at a monthly time scale. Secondly, a good relationship must exist between dry spells and potential climatic predictors so as to achieve some skilful forecast.

Generally, climate modellers assume stationarity in historical observations in order to forecast the future which can be interpreted as a drought event in one year is more likely to be similar to that of another year and in the future. This reasoning may not be realistic considering that several temporal/spatial variations (seasonal, multi-year, decadal etc.) and physical mechanisms and processes may exist in the climate system and trigger different patterns in drought. For example, rainfall and temperature in the MDB has been shown to be non-stationary (Kamruzzaman et al. 2011).

To be able to have some predictability between potential predictors and the observed dry spell data, one possibility is to consider forecasting the number of dry days or the maximum dry spell length in a month. Still, dry spells extending across monthly boundaries may complicate the analysis and hence the predictability of this relationship may be lost. It is likely that this issue of the temporal differences between observations and potential predictors will remain. There are a number of examples that suggest studies disregard this aspect (e.g. Farmer 1988, Barros & Bowden 2008, Hansen et al. 2009, Wittwer & Griffith 2011, Charles et al. 2013).

Different modelling methods have been used to forecast rainfall/drought in Kenya and the MDB of Australia. Multiple linear regression (MLR) models are the dominant seasonal forecasting systems used in Kenya (Owen & Ward 1989), whereas, the coupled general circulation models (CGCM) are common in Australia (Power et al. 1998). In recent years the Australian Bureau of Meteorology (BOM) have developed a dynamical model (POAMA) (Elliot et al. 2005). Few studies however, have attempted to evaluate the skill of drought forecasts in these 2 regions. As indicated earlier, the skill of seasonal models in East Africa and Australia is relatively low (~60%) but reasonably better in summer (December - February-DJF) (e.g. Palmer et al. 2008). The latter being due to the fact that summer rainfall is strongly correlated with the ENSO (Nicholls 1992). In Australia, this relationship has been used in the SOI-phase forecasting system of Stone & Auliciems (1992). The skill of the MLR based forecasts in Kenya is poorly known as there has been limited verification of the forecasts (Ogallo et al. 2008) but the skill of the CGCM based forecasts are low (~50%) (Hunt 1991, Hansen & Indeje 2004).

In view of the above, there is clearly a need to improve the quality of drought forecasts in Kenya and the MDB. Moreover, while modest advances have been achieved in climate forecasting in the 2 regions, clearly these have literary been more on “rainfall” estimates and less on “drought”. Towards improving the skill of climate forecasts, some recent studies such as; Barros & Bowden (2008), Hwang & Carbone (2009), and Wong (2010) indicate that still, only little improvement (<70%) on the skill of drought forecasts has been achieved.

Coming from these studies, the use of rainfall probabilities to analyse drought rather than the raw data itself e.g. dry days may be one of the reasons for the low performance of drought forecasts in the 2 regions. Secondly, the models used to forecasts drought are not precise enough in indicating the onset and end of drought periods. Lastly, similar to rainfall forecasts in these regions, drought forecasts may be less useful in monitoring drought because they are based on a monthly exception which may also be a factor linked to the low skill. Whether this is or is not be the case, the current study will attempt to forecast dry spell lengths and number of dry days with the hope that this will improve the current performance of drought forecast in the 2 regions.

2.7. Conclusions

From this review, extreme events, and mainly drought, in Kenya and Australia have significant impacts on agricultural production. In order to develop a useful drought forecast for the two regions, a clear understanding of the effects of drought on agriculture and management of negative impacts is important. Both indigenous and scientific forecasts are shown to be useful, particularly to compliment other agronomic and technological strategies, but the actual benefits from the use of forecasts in farm decisions remain unclear.

Modelling drought is problematic in these regions and whereas statistical approaches continue to be used to forecast drought, the skill of current climate forecasts remains relatively low. Examining the characteristics and forecasting of dry spells may be a potential tool for improving our understanding and management of drought in these regions.

Whilst, dry spell forecasts are expected to provide improved management of climate change and variability impacts on agriculture in Kenya and the MDB, robust ways to relate dry spells length to the key climate drivers in this regions, such as the Southern Oscillation Index and sea surface temperatures, will be the main challenge.

CHAPTER 3

CHARACTERISING MONTHLY DRY SPELL DISTRIBUTIONS IN KENYA AND THE MURRAY DARLING BASIN, AUSTRALIA (PART 1)

Abstract

Understanding the temporal and spatial distribution of dry spells can benefit rain-fed agriculture production in (semi) arid lands (ASAL). This study examines how parametric distributions can describe monthly and annual dry spells, as well as the temporal and spatial variations in these distributions in Kenya and the Murray Darling Basin (MDB) in Australia based on 50 year daily rainfall records from 30 locations in Kenya and 47 locations in the MDB.

Log normal distributions best described the distributions of dry spell lengths at both locations. The parameters (shape and scale) of the fitted distributions are mostly linearly correlated with annual mean rainfall, but relationships with mean monthly rainfall were also non-linear. This reflects that the spatial variation in observed dry spell lengths is strongly related to total rainfall. The spatial analysis suggests slightly stronger trends in dry spells with latitude than with longitude in both Kenya and the MDB. The temporal variations in dry spells in these regions are most likely sea surface temperature related.

To demonstrate that the derived dry spell distributions can be applied as an indicator of the degree of dryness, the probability of exceeding 5, 10 or 15 dry days in a growing season was calculated. It varied between 1% to ~ 60% in the growing seasons in Kenya but reached more than 70% in the MDB. Using estimated dry spell probabilities based on annual rainfall or spatial coordinates show potential to make predictions in ungauged locations. This information can be useful for crop management in Kenya and the MDB.

3.1. Introduction

In semi-arid and arid lands (ASALs), rainfall amounts and distributions vary sharply in time and water deficiency becomes a key constraint to agricultural production (Smith 2000). The ASALs cover over 1/3 of the global surface area, 80% of which is agricultural land (Reynolds et al. 2000). Agriculture in these areas is rain-dependent and returns low yields (Rockström et al. 2003) and drought is a critical factor (Webb & Reardon 1992, Horridge et al. 2005, Dinar et al. 2012).

In East Africa, the frequency and severity of drought appears to be increasing (Wakabi 2006, Huho & Mugalavai 2010) leading to food shortages (Benson & Clay 1998, Goston 2011). For instance, over the last 3 decades, serious droughts have occurred in Kenya at least 10 times (Huho 2011, Mwangi 2013) and the frequency has increased from 20 years 3 - 5 decades ago to about a year at the present time (Kalungu et al. 2013). In parallel with the trends in Kenya, severe droughts, at least since the mid 1990's, have dominated in the Murray Darling Basin (MDB) of Australia (Erskine & Warner 1998, Horridge et al. 2005, Tan & Rhodes 2008, Ummenhofer et al. 2009) with serious effects for agriculture and other sectors (Kirkup et al. 1998, Kiem & Franks 2004, Bond et al. 2008). According to Gallant et al. (2013) the frequency of drought events has declined over western and eastern areas of the MDB from 1960 - 2009 although the length of droughts have increased compared to the previous decades. In view of a growing global population and increasing food demand (Schneider et al. 2011), the above studies raises fundamental questions about the impact of changes in drought on agricultural production in ASALs.

Research on drought in Kenya and the MDB has mostly focused on its impacts and adaptation to agriculture (e.g. Akong'a et al. 1988, Downing et al. 1989, Keating & Meinke 1998, Baethgen et al. 2003, Howden et al. 2007). Mostly, global circulation models (GCMs) (e.g. Howden et al. 1999), have been used to simulate crop scenarios or to make climate predictions (e.g. Ringius et al. 2009) and study potential adaptations such as drought-resistant crops (e.g. Gregory et al. 2002, Luo et al. 2009).

Whereas most studies highlight drought in relation to agriculture, the term "drought", generally defined as a prolonged dry period, is not appropriate to describe the occurrence of short dry periods or dry spells. Dry spells are known to induce crop failures. For instance, dry spells of 10 or more days during the growing season are a major cause of crop failures in rain-fed agriculture systems in semi-arid areas (e.g. Kassie et al. 2013). Crop simulations in Brazil show that up to 65% of yield reductions can occur if dry spells occur in the flowering phases (Sousa & Frizzone 1997), whereas, Traore et al. (2013) indicated that a one day increase in dry days during the growing period in West Africa led to yield losses of 41kg/hectare. In

Kenya and other similar semi-arid environments, dry spells occur in almost all the planting seasons (Barron et al. 2003) and have the severest impacts on crops if the growing season is shorter due to delay in the onset or early cessation of the rains (Sivakumar et al. 2005). This underscores the critical role of the occurrence of dry spells in the growing season in rain-fed agriculture systems over ASALs.

According to Leclerc et al. (2013), “Drought is an ambiguous concept because climatology, hydrology, or agronomy can define it differently”. In this light concentrating on dry spells which generally refer to a number of consecutive days without appreciable rainfall (Ngetich et al. 2014), may be more important in the context of farmers.

One of the important aspects in characterizing dry spells is the definition of a dry day. A daily rainfall threshold below a certain amount is normally used to denote a dry day whereas consecutive dry days are used to define a dry spell. A threshold of 0.1 mm per day is often used for rain gauge precision (e.g. Wauben 2006) and in several studies it defines a rain/dry-day (e.g. Adedoyin 1989, Traore et al. 2013). It is argued that a daily rainfall amount not exceeding 0.1 mm is of no significant impact on dry spell characteristic. Nevertheless, several other authors have used different rainfall thresholds and typification of dry spells (e.g. Huth et al. 2000, Frich et al. 2002, Porto de Carvalho et al. 2013). For example, Huth (2000) define a dry spell as a period of 10 consecutive days with precipitation not exceeding 1mm but Porto de Carvalho et al. (2013) defines a dry spell as 10 successive days without any rainfall. Interestingly, Frich et al (2002) uses 1 mm threshold to define the maximum or longest dry period. Clearly, the definition of a dry day varies and is generally taken to be either a day without or not exceeding some rainfall threshold and a dry spell as a sequence of dry days.

Parametric distributions have been used extensively to characterise the properties of dry spells (Douguedroit 1987, Lana & Burgueno 1998, Dobi-Wantuch et al. 2000, Vicente-Serrano & Beguería-Portugués 2003, Lana et al. 2006, 2008, Deni & Jemain 2009, Sushama et al. 2010, Vargas et al. 2011). For example, Lana et al. (2006) used the Generalized Extreme Value (GEV) and Generalized Pareto distribution (GPD) distributions (Table 3.1) to calculate the annual maximum dry spell lengths (AM) and shorter dry spells for the Iberian Peninsula using daily rainfall thresholds of 0.1mm, 1.0mm and 5.0mm. They found that the GEV gave a better fit between the empirical and theoretical distributions of dry spells compared to the GP and the spatial distribution of the statistical dry spells parameters tended to show a north to south orientation. In contrast, Sushama (2010) had applied the GEV and GPD to AM and other extreme dry spells over Canada and found that the distributions underestimated the mean number of dry days and return periods of the dry spells. It appears that the GEV has mainly been used for 'extreme' values and might be less appropriate to characterise the full distribution. In the recent past, Modarres (2010) analysed the AM over Iran and found that while the AM exhibited a homogenous pattern over the region using the L-moment method, the frequency distribution followed the generalized logistic distribution (GLOG), with the cluster analysis depicting a west and east regimes consistent with the GLOG and Pearson Type III distributions in each of the 2 regimes. In addition and as can be seen from Table 3.1, there are several other parametric distributions that have been used to describe the empirical distributions of dry spells in specific regions.

Table 3.1: Example of dry spell distributions from selected studies in different regions

Region (no. of locations)		**Dry spell type**	**Parametric distribution**	**Reference**
Austria	(81)	≥monthly	truncated negative binomial	(Nobilis 1986)
Catalona-Spain	(69)	>20 days	Poisson	(Lana & Burgueno 1998)
Hungary	(20	monthly	Mixed geometric	(Dobi- et al. 2000)
Iberian-Spain	(43)	Annual	generalized extreme value	(Lana et al. 2006)
Malaysia(north)	(10)	All dry spells	truncate negative binomial	(Deni et al. 2008)
Isfahan	(31)	Annual/maximum	generalized logistic	(Modarres 2010)
Malaysia -south	(17)	all dry spells	weibull	(Yusof & Hui-M 2012)
Botswana	(13)	Seasonal/Annual	generalized logistic	(Kenabatho et al. 2012)

Despite the importance of the above studies, some pertinent issues can be identified. Firstly, it is unclear as to when a dry spell should be considered to be a drought and often the two terms are used interchangeably. Secondly, variations in rainfall thresholds used to define a dry day or dry spell suggests that dry spells remain inadequately understood and therefore there is a need to further characterise dry spells such as the temporal distribution, occurrence and duration. Thirdly, very few of the studies evaluated the variation in the spatial patterns of parameters that relate the distributions to local factors such as rainfall and latitude and other climatic factors. This may assist in understanding the spatial variability in the dry spell length and relationship with other climatic drivers such as the El Niño Southern Oscillation (ENSO).

Because dry days can cross monthly boundaries, it is of great interest to understand how probability distributions of such dry spells behave at monthly and across monthly boundaries. The question is whether a distribution of dry spells lengths calculated within monthly boundaries (e.g. Gitau et al. 2013) is similar to a distribution of the dry spell lengths when calculated from the actual starting or end time (at a different month)?

This study builds on previous work in the 2 regions (e.g. Suppiah & Hennessy 1998, Ochola & Kerkides 2003), and current work on drought at the seasonal scale (Gallant et al. 2013, Mwangi et al. 2013). The study answers 2 main questions: (1.) What is the best parametric distribution to describe monthly and annual dry spells in Kenya and the MDB; and (2.) What is the temporal and spatial pattern in parameters describing these distributions. Additionally, the probabilities of exceeding dry spells at selected critical thresholds in the growing seasons (growth stages) for maize in Kenya and wheat crop in the MDB are examined.

3.2. Methods

In the following, a dry spell is defined as the number of successive dry days within a month. However, in some cases, there are more successive dry days than the number of days in the month. This is dealt with separately. We chose to focus on case study areas in Kenya and the MDB, Australia as these two areas are ASALs, but with different climate characteristics.

3.2.1. Data and study areas description

Kenya is located between latitudes 5^0 N - 5^0 S and longitudes 34^0 E - 42^0 E while the MDB, Australia is between latitudes 24^0 S - 38^0 S and longitudes 136^0 E- 153^0 E (Figure 3.1).

Much of Kenya has 2 main rainfall seasons (March-May and October-December) complemented by a third season (June-September) in the western highlands (Davies et al. 1985). The average annual rainfall ranges from about 2000 mm in the western and central highlands to < 300 mm in the northern and south eastern regions (Kabubo-Mariara 2008).

The northern MDB has summer dominated rainfall, while rainfall in the southern MDB is winter dominant (Chiew et al. 2008). Average annual rainfall ranges from 0 - 400 mm in the western areas to 600 – more than 1000 mm in the southern and eastern parts of the MDB (MacDonald & Young 2000). Up to 80 % of both regions are classified as semi-arid or arid with annual potential evaporation ranging from more than 1700 mm in the north to 1000 mm in the south.

Daily rainfall data for 1961 - 2010 was obtained from the Kenya Meteorological Department and the Australian Bureau of Meteorology and used to analyse monthly dry spells in both regions. The rainfall data for 30 locations in Kenya (Figure 3.1a) and 47 locations in the MDB (Figure 3.1b) were selected based on data record consistency, allowing < 4% of data missing, and a climatic range in locations from north to south. Selected locations in the MDB had < 1% missing data and the Kenyan locations 0.2 – 3% missing. The missing data was filled with the 30 year daily averages if less than 2 weeks of data was missing; otherwise it was interpolated or filled with data of the same period from nearby stations and with similar climatological characteristics.

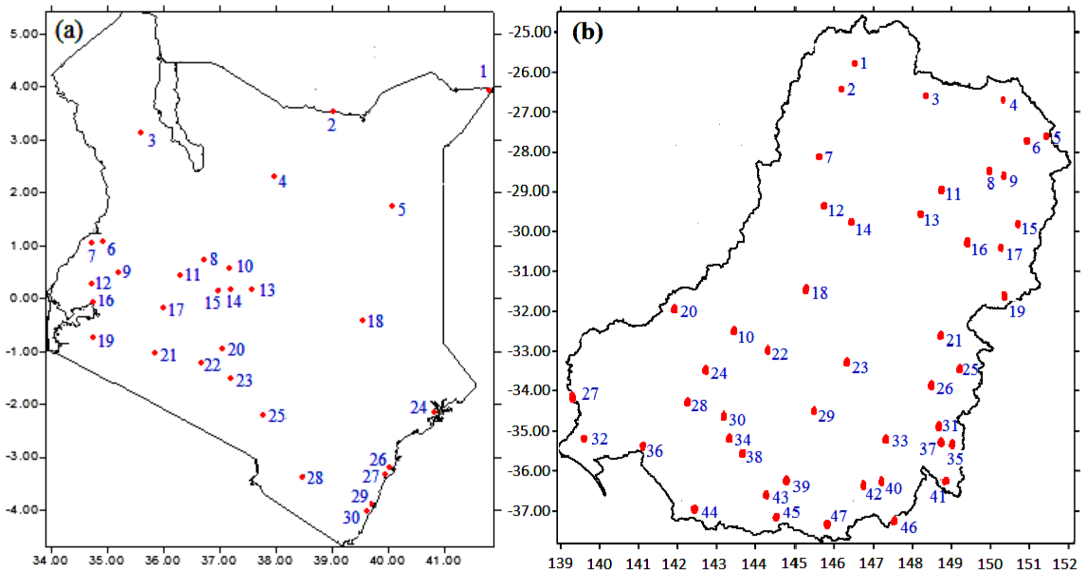


Figure 3.1: The study locations (1-30) in (a) Kenya (latitudes 5^0 N - 5^0 S and longitudes 34^0 E - 42^0 E) and (1-47) (b) Murray Darling Basin of Australia (latitudes 24^0 S - 38^0 S and longitudes 136^0 E- 153^0 E). The mean annual rainfall for all the locations in the 2 regions is given in Appendix A1 & A2 respectively.

3.2.2. Calculation of the monthly dry spell length

A threshold of $q \leq 0.1$mm daily rainfall denotes a dry day, and i=1, 2..., is the day of the month. The length of a dry or wet spell is the sum of consecutive days below or above the threshold. The daily rainfall data is converted into a binary vector (X_i):

$$X_i = \begin{cases} 0, & if \quad rain_i > q, \quad wet\ day \\ 1, & if \quad rain_i \leq q, \quad dry\ day \end{cases} \qquad [3.1]$$

Where, $rain_i$ is the daily rainfall amount for any particular day (i).

To calculate the length of the dry spells in a month, the vector X_i was summed over consecutive days after sub-setting the overall time series by month.

$$D_0 = 0,$$

$$D_i = \begin{cases} D_{i-1} + 1 & if \quad X_i = 1 \\ 0 & if \quad X_i = 0 \end{cases} \qquad [3.2]$$

Where, D_0 is the initial dry spell length count, set to 0 for each month and D_i the dry spell length at day i.

3.2.3. Calculating the dry spell length incorporating 'Long' dry spell into the next month

The previous analysis results in a maximum dry spell length between 28 and 31 days for a completely dry month. This might underestimate the "true" dry spell length as sometimes dry spells might be longer than 1 month (i.e. 'Long' into the next month), or dry spells start half way the month and continue into the next. Hence forth we call this dry spells, 'Long' since they are generally longer than the monthly dry spells. Such 'Long' dry spells would have important implications for crop production. In this second case, the continuing dry days were incorporated in the subsequent month. This resolves part of the problem but makes the term "monthly" questionable. Incorporating the 'Long' into the next month in the calculation of the dry spell length using equation [3.2] involves dividing by month after equation [3.2], rather than after equation [3.1].

3.2.4. Deriving the mean and maximum dry spell length

The vector P calculates the dry spells similarly for spells within each month and beyond the month ('Long').

$$P_i = \begin{cases} D_i & if \quad D_{i-1} < D_i > D_{i+1} \\ NA & Otherwise \end{cases} \qquad [3.3]$$

In both cases P_i is assigned to the day/month where the dry spell ends. NA's will be returned in cases where dry spells do not end in a particular month but only in a subsequent month. The vector P is subsequently subset by month for the 'Long' method. Mean and maximum dry spell length were calculated using different methods.

- For method 1, the mean monthly dry spell length equals the number of dry days divided by the number of dry spells in a month.
- For method 2, the mean monthly dry spell length including 'Long', is again the sum of the dry days divided by the number of dry spells in a month. This means dry spells crossing into the next month are included in the calculation of the mean monthly dry spell length for the month in which the dry spell ends.
- For method 3, the mean monthly dry spell length including 'Long' was calculated from dry spells within a month as well as dry spells starting in the month, but ending in the subsequent next month. This method calculates some dry spells lengths twice.
- The maximum monthly dry spell length was calculated as the longest dry spell within a month (Max method 1). If no dry spell is recorded in a month, "NA" is returned.
- As an alternative, the maximum dry spell length (Max method 2) was calculated as the longest dry spell in the month or the longest (cumulative) dry spell crossing into the next month(s). Compared to Max method 1, NA's are returned if there is no dry spell starting and ending in a month and some maximum dry spells will be duplicated (because they are counted in both the month they start and the months they end).

3.2.5. Annual dry spell length

Annual dry spells are simply the number of consecutive dry days in a year. The mean annual dry spell length was calculated as the total length of dry spells divided by the number of dry spells in a year and the annual maximum dry spell length is the longest dry spell in a year. No dry spells were assumed to cross annual boundaries.

3.2.6. Probability distribution functions (pdfs) of the dry spells

Empirical dry spell distributions were fitted to parametric distribution functions using the **fitdist** function in the fitdistrplus package in R (Delignette-Muller et al. 2010) which estimates parameters using a maximum likelihood method (Chambers & Hastie 1992). More specifically, the lognormal, weibull and gamma distributions were fitted to the dry spell data series using the minimum Akaike Information Criterion (AIC) (Akaike 1974). In addition to the above analysis, parameters of the best fitting distribution were correlated with mean annual and monthly rainfall, for both regions.

3.2.7. Spatial analysis of the distribution function parameters

A generalized additive model (GAM) was used to investigate the spatial distributions of the dry spell distribution parameters. GAMs are non-parametric extensions of the Generalized Linear Models (GLMs) (McCullagh & Nelder 1989) whereby the predictors are defined in terms of a sum of smooth functions of the covariates (Buja et al. 1989, Maindonald 2010). A GAM model differs from the Generalized Linear Model (GLM) in that a flexible smooth predictor can replace the linear predictors. GAMs have the general form:

$$g(\mu) = \alpha + \beta_i \sum_{i=1}^{n} f_i(X_i) \qquad [3.4]$$

Where $\boldsymbol{g}$ **(.)** is a link function of the mean $\boldsymbol{\mu}$ and each of the $\boldsymbol{f_i}$ **( )** is a function that smoothes the $\boldsymbol{i^{th}}$ component of the predictor ***X.***

GAMs were fitted to the lognormal distribution parameters of the ‘Long’ dry spells using latitude and longitude as covariates (***X***). A GAM model was first fitted with independent covariates using smoothing splines (Wood & Augustin 2002). The performance of the model was checked using the model error residual plots and estimated convergence information. Subsequently, the interaction between the covariates was modelled, as dry spell parameters would most likely be correlated to an interaction of latitude and longitude representing locations in space. Generally the GAM model residuals were better described by a gamma distribution.

3.2.8. Probabilities of exceeding of a dry spell length during the growing season

The probability of exceeding 5, 10 and 15 dry spell days during the growing stages for maize in Kenya and wheat in the MDB are considered. The 3 thresholds are based on the literature and experimental studies (e.g. Jackson et al. 1983, Rockström et al. 2002, Fox et al. 2005, Mkhabela et al. 2010, Semenov & Shewry 2011). The most critical periods for maize crop occur around tasseling, flowering and grain filling or from >60 to 100 days after sowing and after anthesis and during flowering and grain filling (stages) for wheat or from 100 - 120 days after sowing. Dry spells ≥ 10 days at flowering and grain filling stages are considered to be critical and can lead to crop failure.

In Kenya the assumed sowing date is at the start of March (long rain season) and maturity in August/September. In the MDB sowing date varies between the northern and the southern regions and ranges from 5th May – 16th August in the North and from April – 15th September in the southern regions, while 'big differences in flowering time can occur in winter wheats and varieties" from late August to October (GRDC (a) & (b) 2011) depending on early or late planting (Stapper & Lilley 2001). Maturity may occur in November or later (http://www.dpi.vic.gov.au). In this study, August is used as an example for the optimal flowering time assuming early planting in the MDB. The entire growing season (all cropping stages) and the flowering/grain filling stages are examined separately. The lengths of the stages for maize are 30, 50, 60 and 40 days (n=180) while the lengths for wheat stages are 30, 140, 40 and 30 days (n=240) respectively (FAO 1998). The datasets for the months of the growing seasons is subset from the entire dry spell series for each location.

From these data sets, the probabilities of exceedances (*PE*) for each dry spell threshold (*i=5, 10, and 15*) are generated from the empirical cumulative function of the 'Long' dry spell lengths using:

$$PE = 1 - ds_i \qquad [3.5]$$

Where ***ds*** is the $\boldsymbol{i}^{th}$ value of the observed cumulative probabilities

3.3. Results

3.3.1. Overall distributions of the monthly and 'Long' dry spells in Kenya and MDB

Figure 3.2 gives the overall distributions of the monthly and 'Long' dry spells lengths for all locations in Kenya and the MDB. In Kenya, the monthly dry spell lengths vary between a day to a full month across all the months and the median is highest in January and February (~5 days) (Figure 3.2a). Similarly, in the MDB, monthly dry spells range from 1 day to a full month across all months, and the median is highest in February and March and lowest in July (Figure 3.2b). In Kenya and the MDB, there is less variation in the monthly dry spells across the months. In contrast, the overall distribution in the 'Long' dry spells in Kenya and MDB indicates a more variable pattern. Dry spells increase from January - April and from May - December in Kenya with the lowest values occurring in May in the main monsoon season. Similar to the monthly dry spells, the highest median dry spell is indicated in January and February. The 'Long' dry spells lengths in the MDB seem to increase from January - May but, at the scale of the figure (d), the overall distribution is roughly even across all the months. This is mainly due to the very high variation in the dry spells across the months. The highest median dry spell is indicated in March and April (~6 days) and the lowest in July-September.

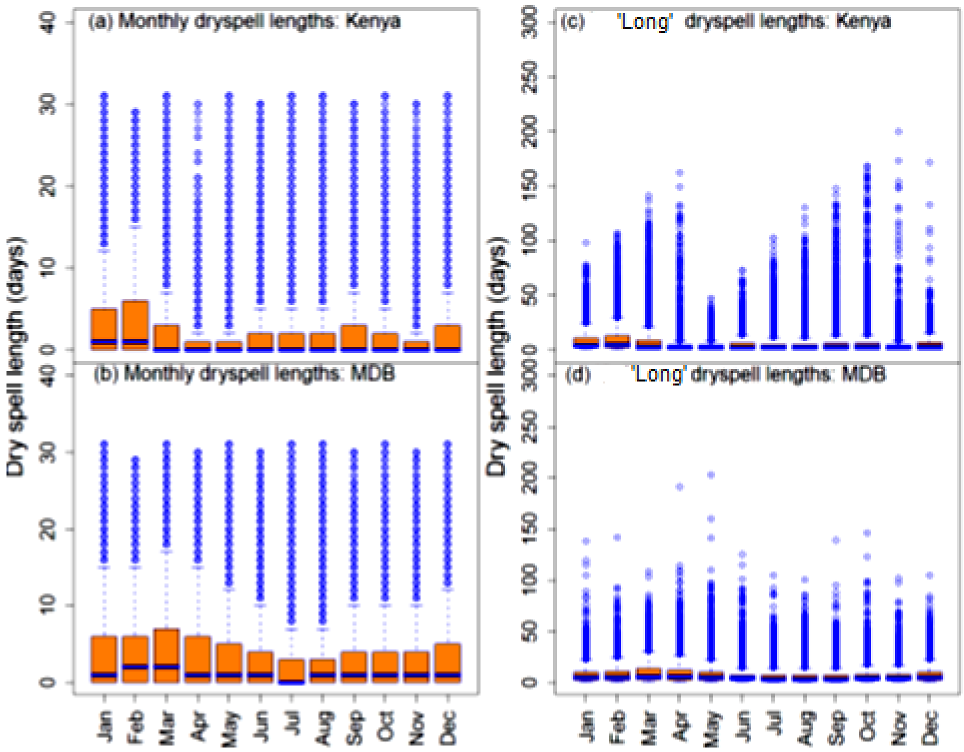


Figure 3.2: Box plots for the overall monthly (left panel) and 'Long' (right panel) dry spell length in (a) and (b) Kenya and (c) and (d) MDB.

Overall, the median dry spell length for both the monthly and 'Long' dry spells is longer in the MDB compared to Kenya (Table 3.2).

Table 3.2: Median dry spell lengths for Kenya and the MDB for the monthly and 'Long' dry spell lengths

	Kenya		MDB	
	Monthly	'Long'	Monthly	'Long'
January	5	4	4	5
February	5	5	5	5
March	3	3	5	6
April	2	2	5	6
May	2	2	4	5
June	2	2	4	4
July	2	2	3	3
August	2	2	3	3
September	3	3	3	3
October	2	3	4	4
November	2	2	4	4
December	3	3	4	5

Although the median is relatively low for both types of dry spell lengths, there is some difference across locations and regions. In Kenya, the median monthly dry spell length is highest in locations in north eastern and south eastern regions and varies from 1 to 24 days and is far lower in the wetter regions of the central, western and coastal regions areas (1 - 3 days). The inclusion of dry spells for wet regions in the calculation of the overall median dry spell lengths may be the cause of the low overall median values observed. In the MDB, higher median dry spell lengths are indicated in northern (~4 - 12 days) and central locations (~4 - 10 days) and the shortest in the southern locations (2 - 8 days). Overall, the longest median dry spell length in the northern (and central) locations is around July and August while this is around January - March in the southern locations. This agrees with the seasonal variation in rainfall in the MDB.

3.3.2. Distributions in overall dry spell lengths (lumped by all months)

Figure 3.3 shows typical distributions of the mean monthly, monthly and 'Long' dry spell and a clearly right skewed distribution for the monthly dry spells lengths. The majority of the drier locations indicate bimodal distributions for the mean monthly dry spell length. This is logical as those locations would have several dry spells longer than one month ('Long') (Figure 3.3c) and these are lumped at the end of the month in the mean monthly dry spell calculation. Figure 3.3 further indicates that there are no mean monthly dry spells between 15 – 27 days which is not visible in the underlying monthly dry spells (Figure 3.3b). This is probably due to the monsoon effect as, on the average, dry spells either cover the whole month in the dry season or are much shorter in the monsoon period. The latter case is probably why humid areas do not show strong bimodal behaviour. The bimodal distributions also do not show up for the 'Long' calculations, as longer dry spells can now be included (Figure 3.3c).

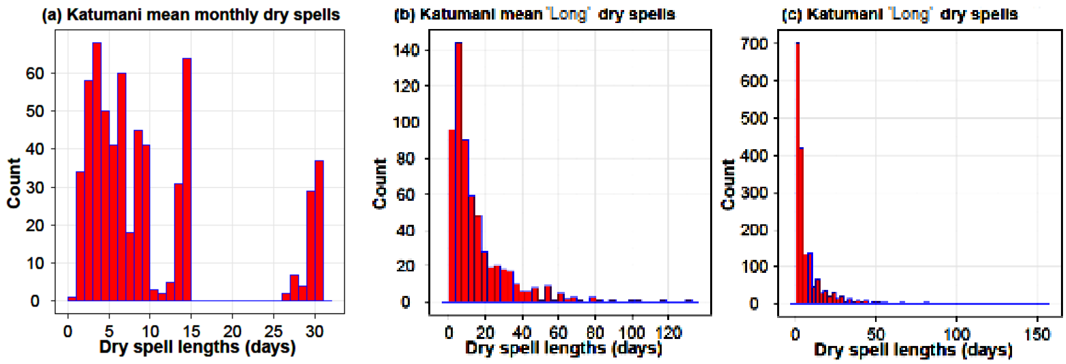


Figure 3.3. Histograms for (a) mean monthly, (b) mean 'Long' and (c) 'Long' dry spells for Katumani in Kenya

However it is important to highlight the differences in the calculation methods of the different dry spells. The mean dry spell length at the monthly scale resulted in a truncated distribution which underestimates the actual dry spell lengths within the monthly boundaries. The analysis for monthly dry spells also resulted in a maximum dry spell length equal to the month length for a completely dry month, which is biased if dry spells continue into the next month. Therefore considering dry days in the following month(s) ('Long') might achieve a better estimate of the true distribution of dry spell lengths. The parametric distribution fitting concentrates on the underlying empirical distributions of dry spell length.

The analysis of the cumulative distribution functions (CDF) fitted to the monthly and 'Long' dry spells suggest that the gamma and lognormal distributions fit most of the points of the empirical data better than the weibull distribution (at $p \leq 0.05$). For example, based on the AIC values, the monthly and 'Long' dry spells distributions for Katumani are best described by the lognormal distribution (Table 3.3).

Table 3.3: Comparisons between the 3 distribution functions fitted to the empirical dry spell length data for Katumani in Kenya.

Dry spell type		Gamma (**AIC value**)	Weibull (**AIC value**)	Lognormal (**AIC value**)
Maximum	(Method 1)	4634.2	4637.6	4627.4
	(Method 2)	4934.5	4960.7	4908.8
Monthly		12424.1	12421.3	12063.2
'Long'		10789.3	10695.1	10236.0
Mean Annual		201	206	201.2

However, in all cases for Kenya and the MDB the differences between the fits of the distributions were found to be small (Figure 3.4). Given that the lognormal distribution gives a slightly better fit, the rest of this study only uses this parametric distribution

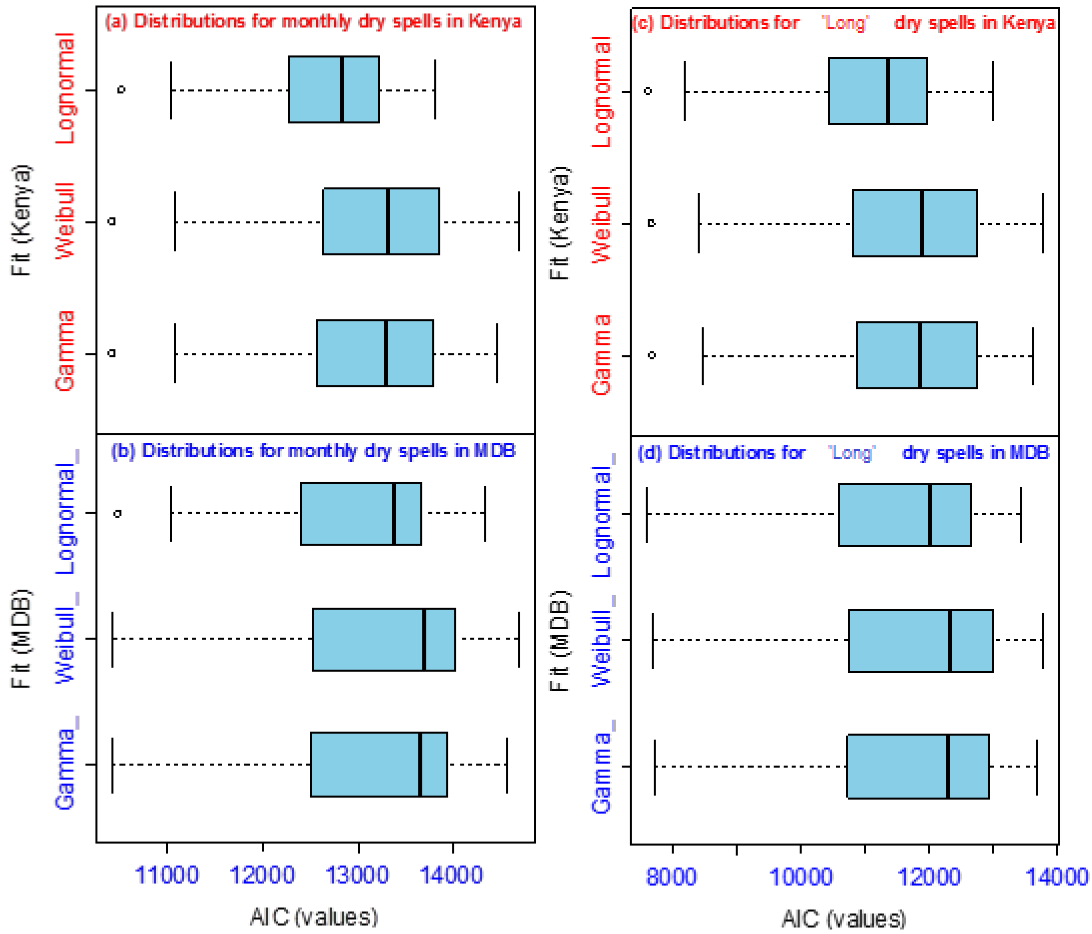


Figure 3.4: Box plots of AIC values for the gamma, weibull and lognormal distributions for monthly (left panel) and 'Long' (right panel) dry spells in Kenya and MDB

3.3.3. Correlations for the dry spell length distribution parameters with rainfall

The log normal distribution is characterised by two parameters: the shape parameter (mu), representing the mean of the log transformed data, and the scale parameter (sigma), representing the variance of the log transformed data. The scatter plots in Figure 3.5a correlate the parameters of the lognormal distributions for monthly dry spells with mean annual rainfall at locations in Kenya. In all cases, the linear correlations are strong ($p < 0.01$). Negative correlations between the shape ($r = -0.9$) and scale ($r = -0.84$) parameters and rainfall indicate that both the mean (shape) and the variance of the dry spell length increases with decreasing rainfall. In contrast, all the correlations for parameters of the overall 'Long' dry spells lengths with rainfall are lower (r < 0.4) and do not show strong patterns (Figure 3.5b). However, the negative linear relationships with rainfall are significant ($p < 0.05$) for both the shape and scale parameters of the log normal distributions.

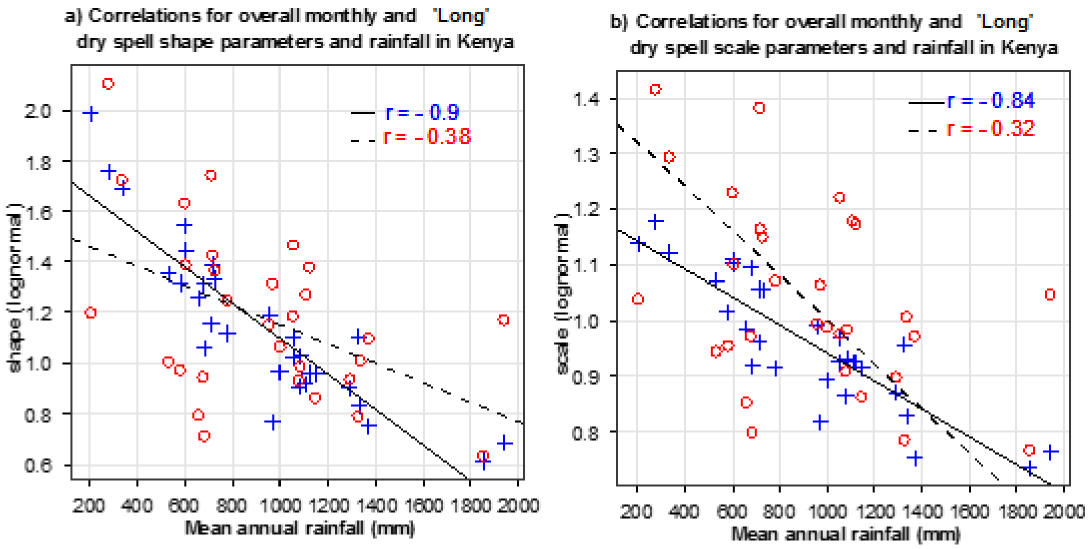


Figure 3.5: Scatter plots for the overall monthly and 'Long' dry spell lognormal parameters and rainfall in Kenya fitted with a linear regression (solid=monthly and dashed='Long') trend line.

In the Murray Darling Basin, the parameters fitted to the distributions of the overall monthly dry spells lengths have less strong relationships with mean annual rainfall, ranging from r = -0.46 to r = -0.54 (Figure 3.6) and similar to Kenya, show declining trends ($p < 0.01$) and negative correlations between the lognormal parameters and rainfall. Note that the scatter in the data in the figure represents the spatial variability of the parameters. In contrast, the correlations between the 'Long' monthly dry spells parameters and mean annual rainfall in the Murray Darling Basin are insignificant (NS) and do not indicate any clear trend.

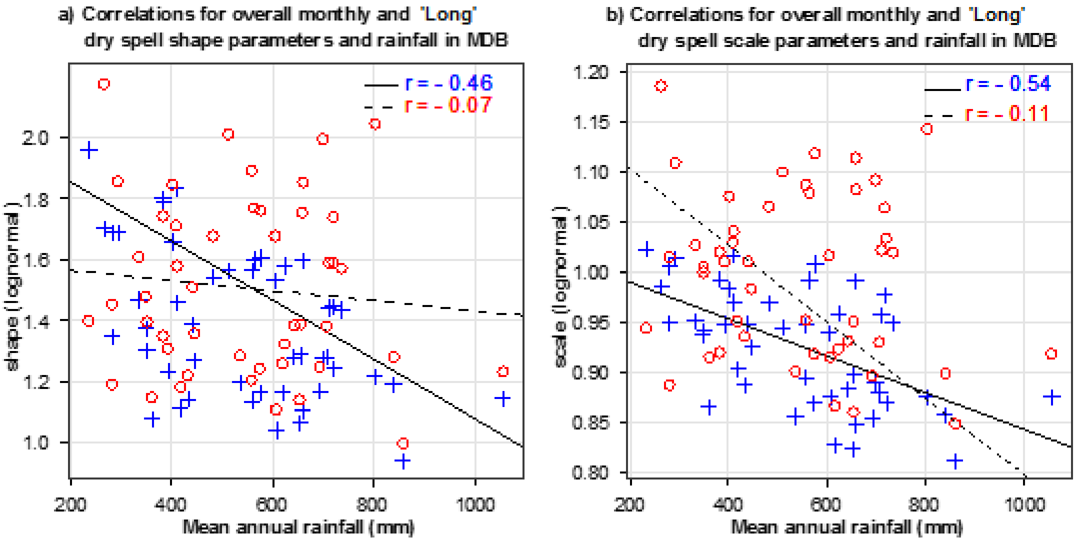


Figure 3.6: Scatter plots for the overall monthly and 'Long' dry spell lognormal parameters and rainfall in the MDB fitted with a linear regression (solid=monthly and dashed='Long') trend line.

3.3.4. Relationships between 'Long' monthly dry spell length distribution parameters and mean monthly rainfall

Correlations between the parameters fitted to the empirical distributions for the 'Long' monthly dry spells with mean monthly rainfall differ from those with annual rainfall. For Kenya (Figure not shown), the distribution parameters for 'Long' monthly dry spells are again negatively correlated to mean monthly rainfall ($p<0.001$), which is physically most logical. The highest correlations occur in August (r= -0.96 – -0.83) and the weakest in October and November. As would be expected, correlations with the shape (log mean) parameter are higher than those of the scale (variance) parameter, suggesting that rainfall amount explains the mean dry spell length better than the variance in dry spell lengths.

As an example, the correlations related to the distribution parameters in the months of April (normally wet) and August (normally dry) are given in Figure 3.7. Note that the trend in April (wet) is linear but the trend for August (dry) is actually non-linear. In general, the parameters for the normally dry months of January, February, June through September indicate non-linear patterns while the wet months indicated linear patterns with the exception of May (normally wet) where the shape and scale parameters indicated opposite (linear and non-linear) patterns respectively.

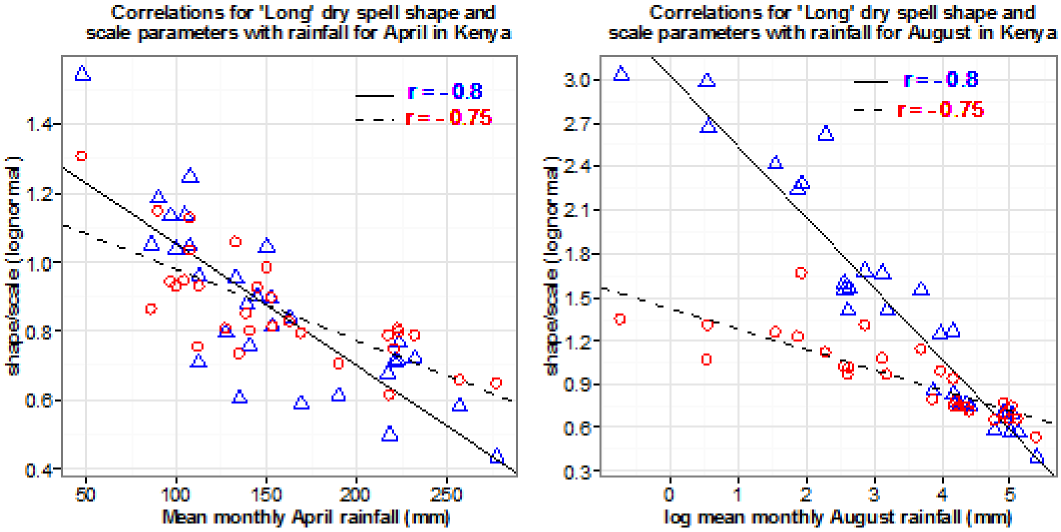


Figure 3.7: Scatter plot for 'Long' monthly dry spell lognormal parameters (shape= 'o', scale= 'Δ') and monthly mean rainfall for April (left) and a log-log plot for August (right) in Kenya fitted with linear regression line (April: solid=shape, dashed= scale).

In the MDB, the negative correlations between the parameters of the 'Long' monthly dry spell distributions and monthly mean rainfall are significant in most months ($p < 0.05$) but the strongest correlation coefficients occur in August, September and December and the weakest in May. Interestingly, non-linear relationships in the MDB occur from May - September (End of autumn - start of spring), similar to Kenya, but linear patterns occur in November - March. In contrast, the shape and scale parameters had a linear and a non-linear pattern in October. This might also explain why in the MDB, in May through July the scale parameter is more correlated to monthly rainfall than the mean (shape parameter). Thus, variations in monthly mean rainfall in space cannot explain the variation in the mean dry spell length. Similar results were visible when all months were considered together (Figure 3.6).

The correlation results for Kenya and MDB, suggest that both the mean dry spell length and the variability of the dry spells decreases with increasing rainfall across the region. Linear patterns are indicated in the normally wet and non-linear patterns in the normally dry months in Kenya. Similar patterns occur in the MDB, with May (in Kenya) and October (MDB) as exceptions. This might be because these are transitional months, where May marks end of the long (growing) rain seasons and October the peak of spring season.

3.3.5. Analysis of seasonal patterns in the lognormal dry spell length parameters

The monthly analysis suggests that the spatial pattern of the parameters of the distributions for all dry spell types varies by season. In Figure 3.8, the main dry seasons in Kenya are January - February (JF) and June - September (JJAS), while March – May (MAM) and October – December (OND) are the wet seasons. The results for the monthly dry spells are not presented here as they are similar to those of the 'Long' monthly dry spells. The magnitudes of the shape parameters, representing the log mean dry spells, in Figure 3.8(a) are evenly distributed in each season with half of values being below or above the median shape parameter. The widest spatial variability across the region in the mean and the variance (scale parameter) occurs in the JJAS dry season. Surprisingly for the scale parameter (3.8b), values are relatively high in the wet (MAM & OND) seasons, which would be expected to have fairly short dry spells. It is possible that this variance is caused by one or two longer dry spells skewing the distribution. Such longer dry spells would have a greater impact on the distribution in the wet season than in the dry season. It appears that the median of the log normal parameters representing the 'Long' dry spell distributions decreases from the start (JF) to the end of the year (OND).

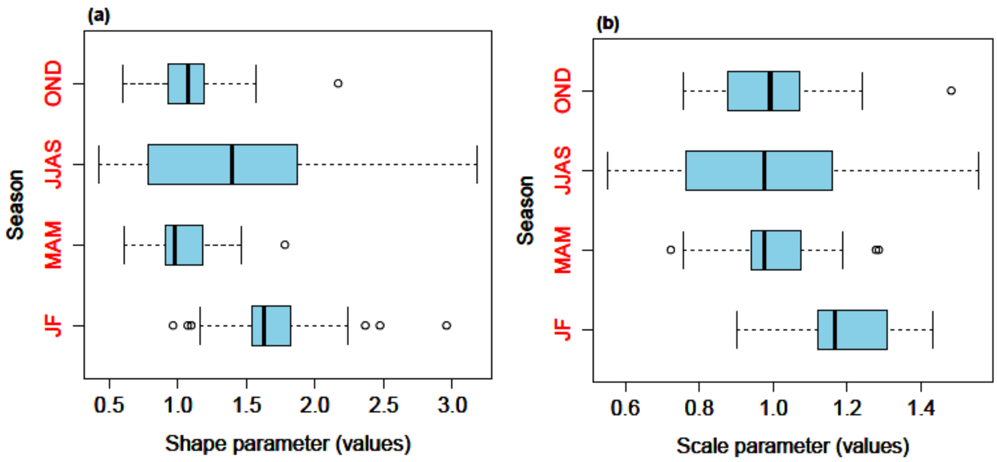


***Figure 3.8:** Box plots of (a) shape and (b) scale parameters for the lognormal distribution for all seasons in the 'Long' dry spells for the period 1961-2010 in Kenya. The JJAS seems to be the most uncertain but longest period.*

In the MDB, there are 4 distinct seasons: summer (December – February), autumn (March - May), winter (June – August) and spring (September – November). The temporal rainfall distribution is mainly summer dominant in the north and winter dominant in the south. Therefore the analysis is split between the northern (N) and southern (S) parts (Figure 3.9).

The shape parameter for the ‘Long’ monthly dry spell distribution has substantial spatial spread in the northern winter and autumn seasons with values ranging from 1.25 to greater than 2.0. Moreover the shape parameter seems to increase from the northern summer to autumn but roughly decline thereafter. In contrast, the lowest variability in the shape parameters occurs in winter and spring in the south, indicating that locations in space are more similar in this region (Figure 3.9a).

Similarly, the scale parameters indicates the greatest spatial spread in the northern autumn with values ranging from 0.95 to >1.2. In contrast to the shape parameter, the scale parameter appears to decline from autumn in the north through to spring in the south. The spatial variation is similar for the scale parameter, but smaller in the shape parameter between the MDB than in Kenya.

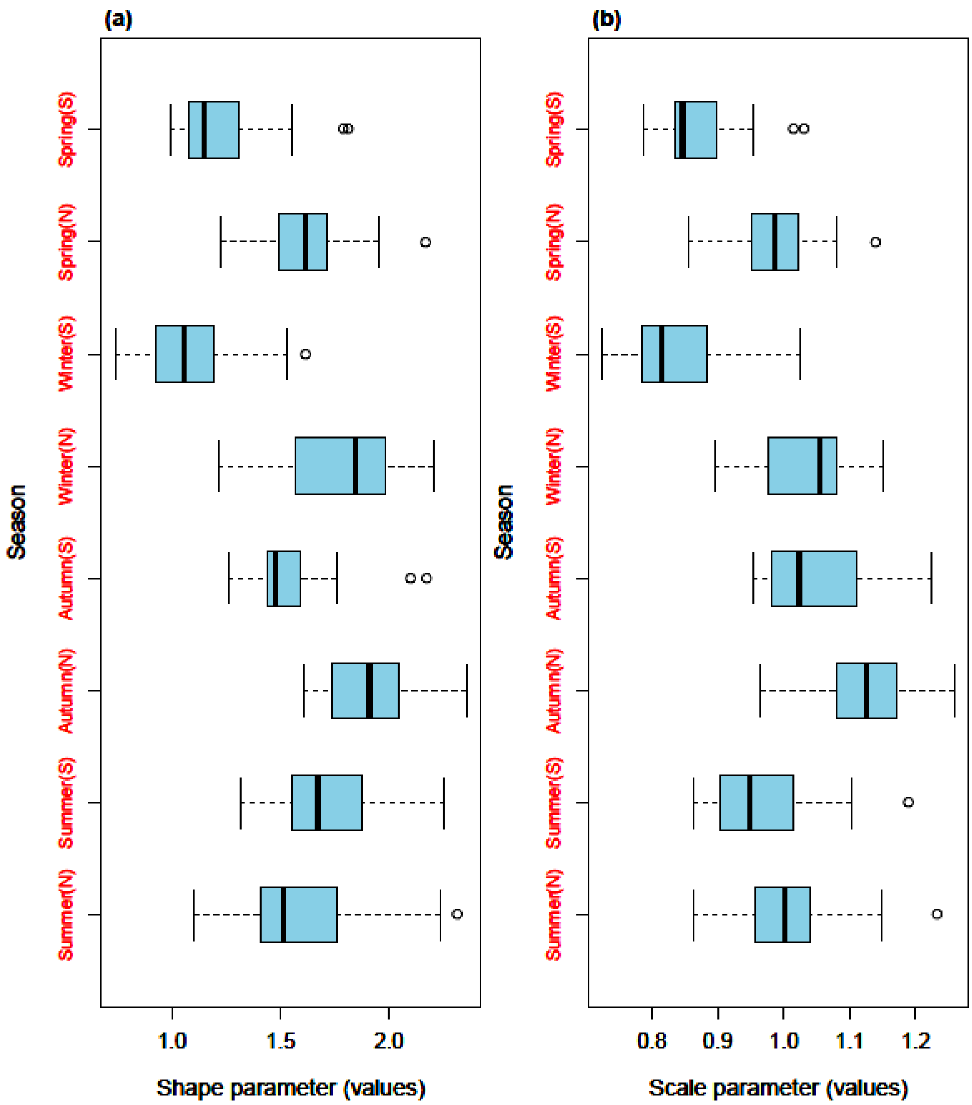


Figure 3.9: Box plots of (a) shape and (b) scale parameters for the lognormal distribution in MDB for all seasons in the ‘Long’ dry spells split by northern (N) and southern (S) regions

3.3.6. Spatial patterns in the distribution parameters

For the monthly dry spells, the spatial distribution in the shape parameters in Kenya generally increases with latitude and longitude, with the lowest values occurring at the equator and in the western regions (humid regions), as would be expected.

Latitude is a significant predictor ($p \leq 0.03$) of the log mean (shape) of the distribution of the monthly dry spells (Model 1) and explains 30% of the spatial variance (r^2) in the shape parameter (Table 3.4). Combining latitude and longitude (Model 2), explains 93% of the spatial variation.

The spatial trend in the scale parameter for the monthly dry spells (Figure not shown) shows a slightly stronger trend with longitude (r^2 = 34%) than with latitude (r^2 = 30%) suggesting a minor west - east generally increasing trend. While the mean monthly length of dry spells was more related to latitude (North – South), the variability of the dry spells thus shows more of an East-West trend. The spatial distributions for shape and scale parameters in Kenya look similar (Figure 3.10), meaning that, on the average, longer mean dry spells are related to higher variability in dry spells.

Table 3.4: GAM models to predict the shape parameter (mu) and scale of the monthly and 'Long' dry spells in Kenya and the MDB

GAM model	Measure of fit (AIC)		Variance explained (r^2)	
(a) Monthly dry spells (shape)	**Kenya**	**MDB**	**Kenya**	**MDB**
Model 1 (mu ~ Lat)	12.8	-23.3	0.30	0.46
Model 2 (mu ~ (Lat, Lon))	-55.8	-73.4	0.93	0.84
(b) Monthly dry spells (scale)				
Model 3 (sigma ~ Lat)	-44.1	-151.5	0.30	0.38
Model 4 (sigma ~ (Lon))	-49.1	-134.5	0.34	0.13
Model 5 (sigma ~ (Lat, Lon))	-89.6	-210.3	0.85	0.85
(c) 'Long' dry spells (shape)				
Model 6 (mu ~ Lat)	14.7	-9.1	0.29	0.47
Model 7 (mu ~ (Lat, Lon))	-66.45	-61.3	0.95	0.85
(d) 'Long' dry spells (scale)				
Model 8 (sigma ~ Lat)	-27.0	-117.7	0.30	0.38
Model 9 (sigma ~ (Lat, Lon))	-91.6	-177.3	0.93	0.85

Similar to the monthly dry spell lengths, latitude explains 30% of the spatial variation in the shape and scale parameters of the 'Long' dry spells. The patterns in space suggest that the shape and scale parameter for these 'Long' dry spells increase with latitude (northwards) confirming the earlier relationship with the rainfall trend in Kenya (Figure 3.10a). The interaction between latitude and longitude describes more variability in the parameter distributions of the 'Long' dry spells (Table 3.4d).

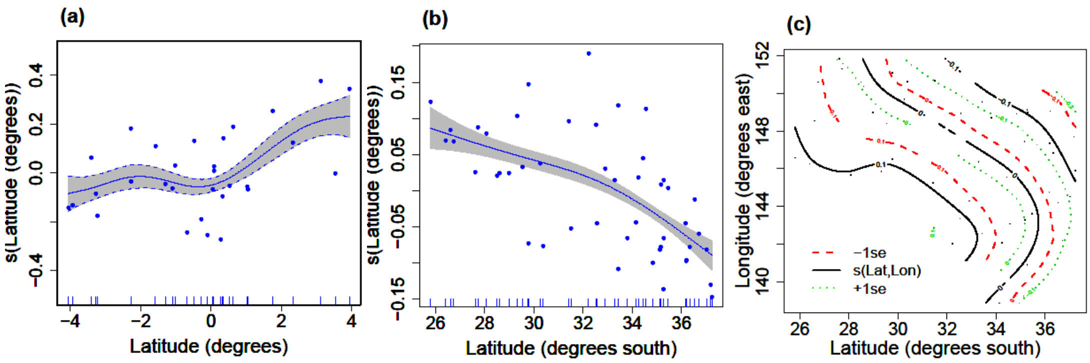


Figure 3.10: Effects of latitude on the (a) shape parameter of the 'Long' dry spells in Kenya and (b) scale parameters of the 'Long' dry spells in MDB and (c) combined effect of latitude and longitude on the scale parameter in the MDB and partial residuals (blue dots) and upper and lower 95% confidence limits of the GAM estimate (grey shade-dashed lines) overlaid.

In the MDB, latitude explains 47% of the variance in the shape and 38% of the variance in the scale parameter, of the monthly dry spell length (Table 3.4). The relationships for the 'Long' dry spell lengths were similar in explaining power. The interaction between latitude and longitude explains about 85% of the variation in the shape and scale parameter for the monthly dry spell length again indicating relatively strong spatial trends. Both the shape and scale (Figure 3.10b) parameter for the 'Long' dry spell lengths increase in southerly direction and with increasing rainfall (Figure 3.7b).

This is interesting as rainfall in the MDB is normally considered to have a strong East-West trend (Longitude) (Drosdowsky 1993, Cook & Heerdegen 2001, Ummenhofer et al. 2008). Possibly the variation in dry spell lengths is more related to the variation in summer and winter rainfall between the North and South of the basin.

The rest of the analysis concentrates on the 'Long' monthly dry spells, due to the similarities in results with the regular monthly dry spells.

3.3.7. Probability of dry spell occurrence/exceedances in the growing seasons

As an example of the application of the derived 'Long' dry spell distributions, the probabilities of exceeding (PE) certain dry spells lengths can be useful in agricultural planning. In Kenya, the empirical probabilities of exceeding 5 dry days in the growing season range from about 30% in the southern locations to a maximum of about 63% in the northern regions (Figure 3.11a).

As it would be expected, slightly lower empirical probabilities (20% - 40%) are indicated for exceeding 10 dry days, whereas they vary from 3% - 38% for exceeding 15 dry days. In contrast, and during the flowering and grain filling stage (Figure 3.11b), the empirical probabilities, for exceeding the 3 dry spell lengths, are slightly lower, ranging between 2% and 50%.

Overall, the empirical probability of exceeding the dry spells in Kenya increases from south to the north. This confirms that the risk of dry spells, lasting at least 5 days or more in the growing season, are higher in the northern ASAL regions than in the relatively wet southern areas.

The overall dry spell probabilities were based on the empirical data directly, however, more useful would be if these can be estimated from the parameters derived earlier (i.e. based on the shape and scale parameters) or directly from the relationships with mean rainfall and latitude and longitude (sections 3.3.3 -3.3.6). In some instances, the estimated probabilities (Figure 3.11c – h) over and under estimate the empirical probabilities (Figure 3.11a – b). Over a crop season, the overall mean estimated probability for exceeding 5 dry days is slightly higher than the empirical probabilities (Table 3.5). However, this is lower (up to 40%) for the estimated probabilities of exceeding 10 or 15 dry days in the season. The over or under estimation of the empirical probabilities is logical due to the uncertainty in the earlier model fits.

In contrast, the estimated probabilities during the flowering and grain filling stages are higher than the empirical probabilities and with the highest difference of 86% occurring for the estimated probability based on the mean rainfall parameters.

Overall, the differences are higher in the (shorter) flowering stage than over the whole cropping season. The higher difference for the shorter flowering stage is most likely due to the downscaling of the relationship between monthly dry spell length distribution parameters and mean annual rainfall (or spatial coordinates) to the shorter time frame.

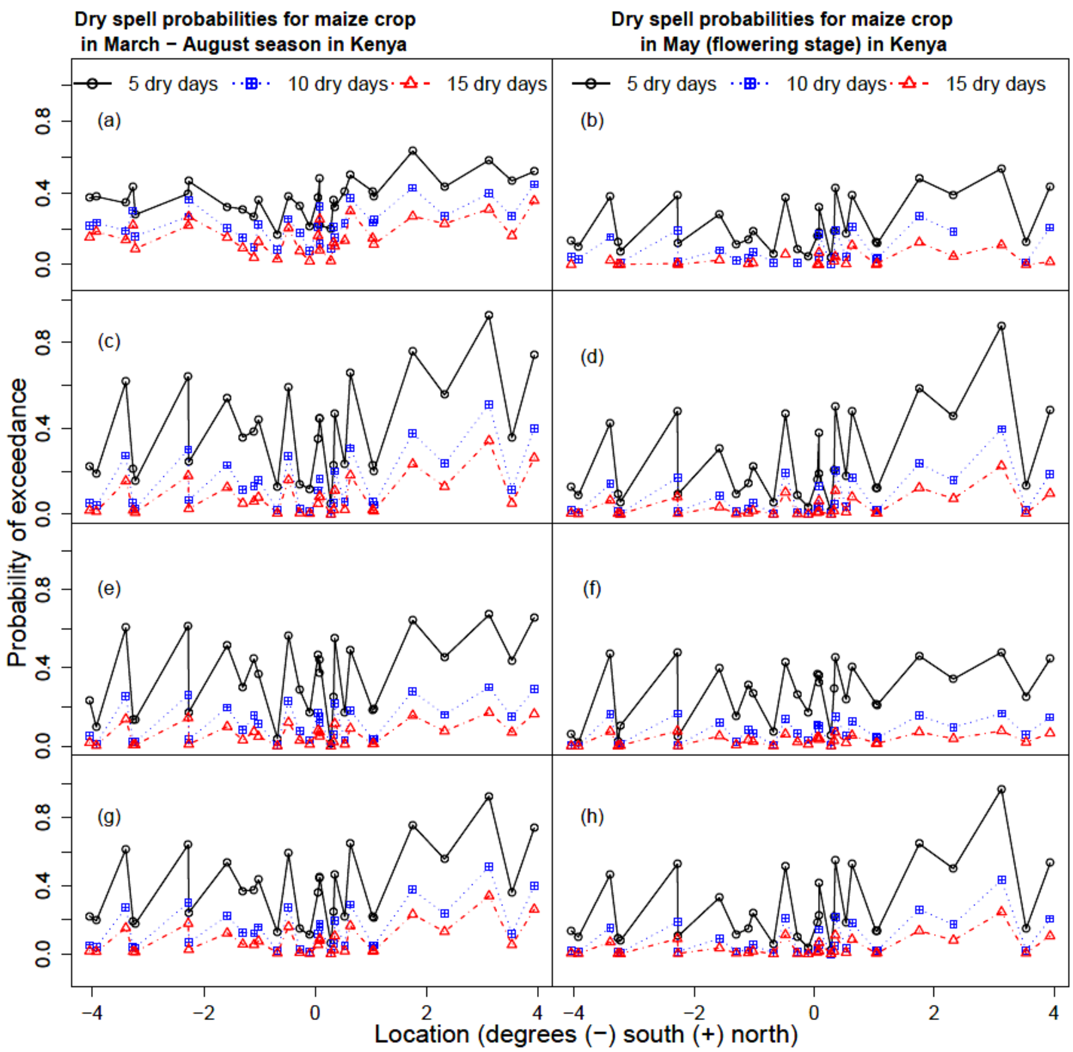


Figure 3.11: Probabilities of exceeding dry spells of 5 (circled lines), 10 (squared lines) and 15 (triangle lines) days for: (a) March - August season and (b) May (flowering stage) for maize in Kenya compared with the probabilities of exceedances for the parametric distribution estimate (lognormal) (c & d), parameter estimated from mean annual rainfall (e & f) and parameter estimated from latitude and longitude (g & h).

Table 3.5: Probabilities of exceedances for maize and wheat growing seasons in Kenya and the MDB estimated from the observed dry spell length (observed), parameters of the fitted density functions of dry spell lengths, mean annual rainfall and latitude and longitude.

Probability Variable in Kenya		**Growing season**			**Flowering stage**	
	5days	10days	15days	5days	10days	15days
Observed	0.38	0.23	0.16	0.22	0.08	0.03
Fitted distribution	0.39	0.15	0.08	0.28	0.09	0.04
Mean Annual Rain	0.36	0.12	0.06	0.38	0.39	0.39
Latitude and Longitude	0.39	0.15	0.08	0.28	0.09	0.04
Probability Variable in MDB		**Growing season**			**Flowering stage**	
	5days	10days	15days	5days	10days	15days
Observed	0.48	0.27	0.17	0.38	0.20	0.09
Fitted distribution	0.66	0.28	0.16	0.58	0.23	0.13
Mean Annual Rain	0.46	0.15	0.06	0.56	0.20	0.10
Latitude and Longitude	0.57	0.22	0.12	0.40	0.23	0.12

In the MDB, the probability of experiencing more than 5 dry days in the wheat season ranges between 15% and 77% (Figure 3.12a). On the other hand, the probability of exceeding 10 dry days lies between 4% and 57% and for 15 dry days between < 1% to 37%. Interestingly, the exceedances probabilities during the flowering/grain filling stage in the MDB are similar to those in the entire season (Figure 3.12b) in most locations. Similar to Kenya, the probabilities of dry spell occurrence in the MDB decline southward, even though this is not the general rainfall trend in the MDB, but is again related to the North South summer-winter gradient in the rainfall. The winter rainfall season in the south is more aligned with the wheat growing stages.

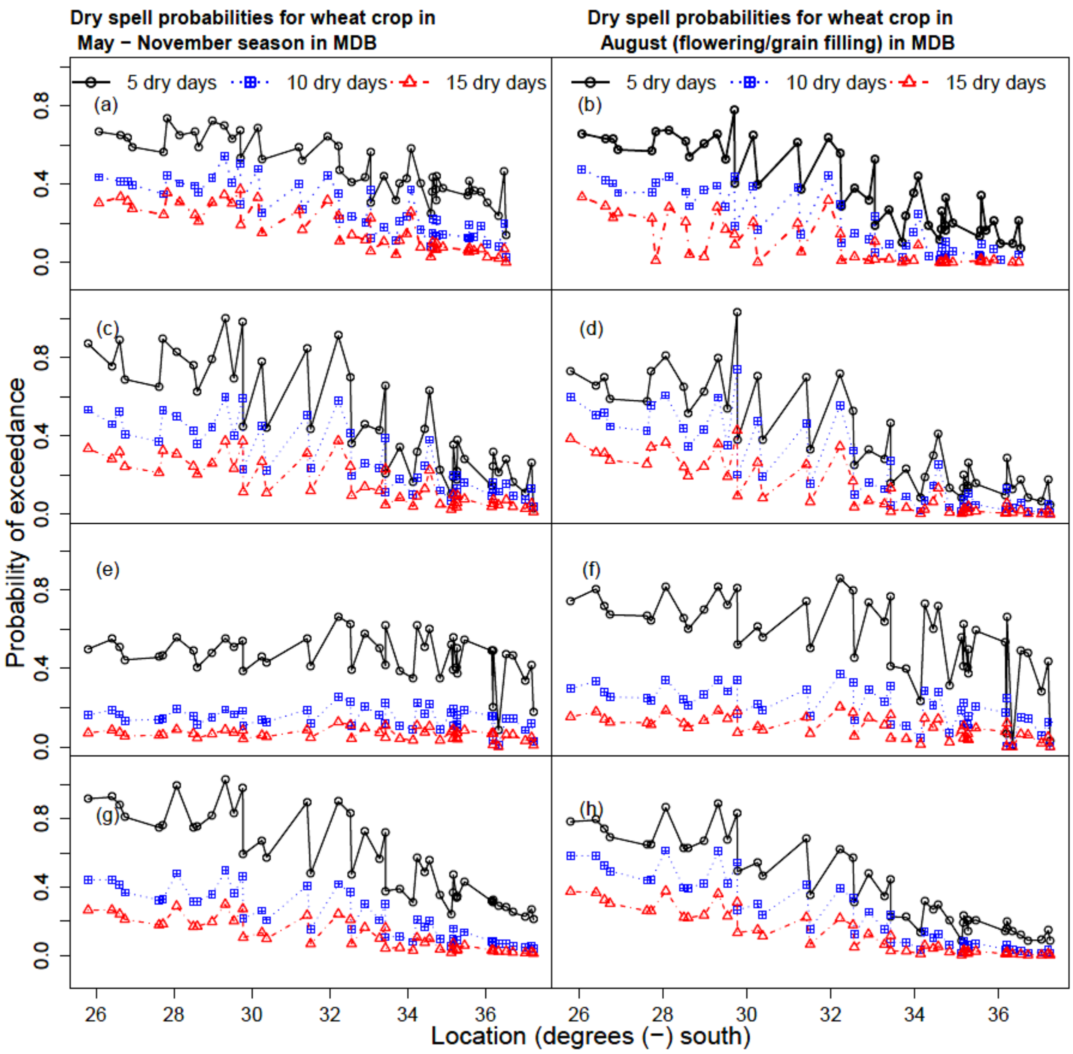


Figure 3.12: Probabilities of exceeding dry spells of 5 (circled lines), 10 (squared lines) and 15 (triangle lines) days for: (a) May - November season and (b) August (flowering stage) for wheat crop in the MDB compared with the probabilities of exceedances for the parametric distribution estimate (lognormal) (c & d), parameter estimated from mean annual rainfall (e & f) and parameter estimated from latitude and longitude (g & h).

The estimated probabilities exceed the empirical probabilities by 8% to 40% in the 5 dry day category but the estimated probabilities are lower for dry spells longer than 5 days across the cropping season (Table 3.5). In the critical flowering/grain filling stage the estimated probabilities exceed the empirical probabilities from <1% to 20% but in some cases are less than 44%.

Comparing the two regions, the overall exceedances probabilities of the specific dry spell lengths are higher in the MDB than in Kenya, thus indicating a higher drought risk in the MDB.

While the estimated probabilities are uncertain relative to the empirical probabilities, they offer a first cut approximation of drought risk that is not dependent on a long rainfall series to estimate the empirical dry spell distributions.

3.4. Discussion

3.4.1. Dry spell distribution patterns

In spite of several studies on climate variability and drought in Kenya and Australia, there is still limited knowledge regarding the temporal and spatial characteristics of dry spells in these regions. This is most likely the first attempt to study the spatial characteristics of the actual dry spells lengths in these regions.

The dry spell patterns in Figure 3.2 show that ‘Long’ dry spells are more variable and longer compared to monthly dry spells. Subsequent results indicate that the parametric distributions of longer (‘Long’) dry spells compare well with the actual variations and patterns of the observed dry spells lengths, while the parameters of the distributions understandably show some correlation with precipitation and latitude in the two regions.

In general, dry spells lengths appear to follow a lognormal distribution in both Kenya and the MDB despite differences in their rainfall patterns, similar to other studies in Africa (Tilahun 2006, Mzezewa et al. 2010). While other distributions have been suggested (Tate & Freeman 2000), the current results indicate that there is little difference between the fits of the different distribution functions. In this case, the often used GEV distribution (Lana et al. 2006; Sushama 2010) is less relevant, as this study is interested in the full distribution rather than estimating the extremes.

This contrasts previous work in Kenya (e.g. Sharma 1996, Ochola & Kerkides 2003) in which the cumulative density functions of dry spells in single sites underestimated the observed dry spell lengths probably due to the truncation of transitional probabilities of the dry spell lengths at monthly boundaries. A recent study by Chowdhury & Beecham (2013) is perhaps the only analysis to fit theoretical distributions to dry spells in the MDB (Australia). Consistent with our results, the study indicated that the theoretical distributions fitted to dry spells for Adelaide and Melbourne agreed with the observed dry spells. However the above studies were based on periods prior to 2004, which might not be representative of the current patterns in the climate for the last 10 years. Moreover, the previous studies did not account for dry days going into the next month which suggests the dry spell distributions are truncated. The study of Chowdhury & Beecham (2013) contrasts Suppiah & Hennessy (1998) which looked at trends in the number of dry days rather than dry spells over Australia during the November–April and May–October periods between 1910 and 1990. Suppiah and Hennessy (1998) found that, in that period, the number of dry days decreased by 9% over south eastern Australia (MDB) during the winter half year (May – October) season.

While the mean monthly dry spell length is commonly used to represent drought conditions (e.g. Gong et al. 2005) the results from this study suggest that this should be used with caution. Results in Figure 3.3 demonstrated that, the mean monthly dry spell lengths had a truncated distribution and do not represent the underlying observed dry spell length. This means that the mean monthly dry spell length would underestimate the mean of the actual dry spell length ('Long') at the monthly scale as this can include dry days from the previous month or in the following months.

Different physical processes might be related with the observed dry spell lengths spatial patterns in these two regions. In Kenya and the MDB, local or large-scale effects such as topography, monsoon (easterly) trade winds and the El Niño Southern Oscillation [ENSO] have considerable influence on rainfall and drought patterns in these regions (Pittock 1975, Anyamba & Eastman 1996, Mutai & Ward 2000, Cook & Heerdegen 2001). The interaction between all these factors would influence the observed spatial and temporal dry spell patterns. Trenberth & Guillemot (1996), found that the temporal variation in drought was linked to extreme SST anomalies. Other studies (e.g. Parry 2007, Taylor et al. 2012, Van Lanen et al. 2012) also suggest that climate factors are associated with prolonged dry spell occurrence. Some of the spatial variations are related to general rainfall trends away from the coast in the MDB. In contrast, in Kenya, elevation and monsoon seasons appears to be a major factor, such as related to the eastern highlands which intercept the monsoon. Future research could focus on investigating these links.

3.4.2. Relationships (and variability) between dry spell distribution parameters and rainfall amounts

The substantially weaker or non-existent relationship between dry spells distribution parameters in the MDB compared to Kenya may be due to the relatively larger spatial variability in the rainfall patterns (Nicholls 2004, Lodge & Johnson 2008, Potter et al. 2010, Nicholls et al. 2012). Possibly, the lack of correlation with mean rainfall in the MDB suggests stronger large scale climate influences affecting the year to year variability, rather than within year variability. For example, Smith et al. (2008) suggest that climatic drivers, such as ENSO, affect the duration of seasonal events rather than the mean.

Furthermore, the rainfall patterns in the MDB are possibly more complex. For example, in the southern MDB, frontal systems dominate and the variability in the dry spells parameters is relatively small (Figure 3.11) while the northern MDB is affected by monsoonal troughs (Evans & Allan 1992, Bonell et al. 1998).

Therefore, weaker correlations between the shape parameters (representing the mean dry spell length) and the mean annual rainfall in the MDB, compared to the scale (representing the variance) parameter and the mean annual rainfall, highlight the local variability in the occurrence of dry spells periods. Part of this can be due to the spatially variable nature of convective rainfall in summer (Holland 1986).

The stronger trend between the mean annual and monthly rainfall and the monthly dry spells do not occur with the ‘Long’ dry spell parameters. In this case dry days from earlier months can be part of the monthly distribution. Hence, the direct relationship between monthly rainfall and dry spells is broken. This means, the month where the long dry spell ends does not necessarily have the lower rainfall and thus the “monthly” rainfall comparison for the ‘Long’ dry spell length parameters might not be valid possibly because the estimates of PE for the latter might be worse than for the normal dry spell length (monthly). Overall, dry spells lengths in MDB are shorter than in Kenya probably as a consequence of the monsoon effect in Kenya.

Slightly stronger spatial trends in dry spells with latitude than with longitude in Kenya and MDB would possibly be related to local and synoptic scale factors that influence climate variables such as drought and precipitation in the tropics (Wagesho et al. 2013).

3.4.3. Risk of drought in the growing seasons

According to Barron et al. (2003), maize crops in Kenya tend to experience dry spells longer than 10 days more than once in their development stages, which is consistent with this analysis. In the MDB, probabilities of exceeding decile 1 (lowest 10% precipitation) dry spells range from 10% - 40% in different seasons (Mpelasoka et al. 2008). In northern Australia, the probability of 10-dry days occurring ranged from <10% in the wet monsoon season to over 80% in the dry season (e.g. Cook & Heerdegen 2001). The previous analyses seem to indicate lower probability values than our analysis, probably because they were for shorter periods prior to 2004, and thus did not include the extreme droughts of 2001 – 2009. The lower probability values may also have been due to a focus on a shorter (rainfall/season) period rather than the entire growing season. The probabilities in the MDB are much higher compared to Kenya reflecting the local climate conditions. In particular the alignment of the growing season with the monsoon rainfall in Kenya reduces drought risk which in practical terms may not necessarily be the case as the cropping season is normally longer than the monsoon season alone. Nevertheless, consistent with one recent study which considered the Australian wheat belt regions (MDB), severe stress can be common starting before flowering with up to 44% occurrence and around grain filling with up to 77% occurrence (Chenu et al. 2013).

Due to a highly variable seasonal rainfall in the ASALs (Cooper et al. 2008), the estimates of PE might be useful to choose and advise on crops. Moreover, integrating this information (probabilities) with rainfall distributions and other factors like soil type may thus enhance farmers' ability to manage climate variability in ASALs.

Other studies (Ntale & Gan 2003, Van der Schrier et al. 2011) have used different drought proxies, such as the Palmer (PDSI) or the Standard Precipitation Indices (Chambers & Gillespie), to assess drought risk in these regions. In Australia, Van der Schrier et al. (2011) indicate that the PDSI underestimated drought risk by up to 30% in 70% of the region while, in contrast, Ntale & Gan (2003) showed that the SPI represented drought over most of East Africa better than other indices.

The differences between the empirical and estimated probabilities indicate further influences on dry spell length, such as elevation and other local geographical factors.

The estimated and empirical dry spell probabilities in Kenya also indicate smaller differences for locations near the equator compared to locations further away from the equator. This is probably because locations that are far away from the equator experience larger seasonal variations in temperature and other climate factors (Ntale & Gan 2003).

3.5. Conclusions

This study indicates that dry spells lengths are mainly log-normally distributed in Kenya and the Murray Darling Basin. Latitude is the single most important factor explaining the spatial variations in the mean and variance of the distributions of the dry spell lengths, but spatial location is explains the majority of the variation in observed dry spell length distributions.

Furthermore, the spatial variation in the scale and shape parameters in Kenya is more related to annual rainfall than in the MDB, but for both regions, rainfall amount is negatively correlated to the mean and variance of the dry spell length distribution at different locations. This is a reflection of the local climate distribution. In the MDB, there is more variation in space which causes the relationship with rainfall to be less strong.

The probability of exceeding 5, 10 or 15 days during the growing season indicates that there is significant drought risk in both regions and shows an application of the derived dry spell distributions as a drought indicator. This may have significant implications for agriculture planning in these regions.

Lastly, the relationships between dry spell lengths, rainfall and spatial coordinates have the potential to predict dry spell lengths at ungauged locations or into the future.

CHAPTER 4

CHARACTERISING MONTHLY DRY SPELLS IN KENYA AND THE MURRAY DARLING BASIN, AUSTRALIA PART 2: LONG TERM TRENDS IN DRY SPELLS

Abstract

Key agricultural regions in Kenya and the Murray Darling Basin (MDB) of Australia regularly experience drought. Drought severity appears to be increasing, particularly in the arid - semi arid areas where most of the agriculture activities occur. In part 1 (Chapter 3) of this series the spatial and temporal variation in the dry spell length distributions was investigated. To further improve understanding of drought occurrence, the temporal trends in dry spell length for the period 1961 - 2010 are quantified. The aim in this part is to investigate whether long term trends in the dry spell length occur at the annual, monthly and seasonal scale.

Significant increasing and decreasing trends in longer ("Long") monthly dry spells occur in Kenya and the MDB in most months. In Kenya, the greatest increases and decreases occur in July and June while in the MDB these occur in August and July. Most of the increases in Kenya occur in the southern half of the country whereas the spatial trends tended to follow the spatial rainfall distribution in both areas. Trends in longer dry spells reflected trends in the shorter ("<month") and month long ("full month") dry spells.

All the seasons in Kenya and the MDB had increasing trends in the DSL with most occurring in the JJAS season in Kenya and autumn and winter seasons in the MDB. Annual dry spells increased, while maximum annual dry spells indicated little change in both regions. Bootstrap analysis confirmed that the number of locations indicating trends in observed dry spells is statistically significant in most of the periods.

Dry spell length increased from 0.02 - 0.75 days per year and declined from 0.001 - 0.46 days per year in Kenya and rose from 0.02 - 0.21 days per year and declined between 0.02 and 0.29 days per year in the MDB. The current trends reflect the historical rainfall data in the two regions, but also point to possible future problems with increasing droughts.

4.1. Introduction

Trends in drought have attracted many studies (Dai & Trenberth 1998, Easterling et al. 2000, Sheffield & Wood 2007, Alexander & Arblaster 2009, Funk et al. 2010).

Trends in drought and precipitation are important to detect changes in drought severity which has direct implications on people, property and the environment (Tsakiris & Vangelis 2005, Ghosh et al. 2009).

Hoerling et al. (2006) report declining seasonal rainfall in northern and southern Africa since the 1950's, while prolonged declines have been shown over west Africa and the African Sahel by Nicholson (2001). Mixed trends are indicated over eastern Africa (Nicholson 2000, Lu & Delworth 2005) while increasing rainfall trends occurred in Turkey from 1951 - 1998 (Karabörk 2007), in northern China (Zhai & Pan 2003) and over most of the United States (Andreadis & Lettenmaier 2006).

In recent times, trends in droughts have shifted to more severe droughts in the Horn of Africa (HOA), with serious impacts (Wolff et al. 2011, Viste et al. 2013). Coincidentally, the frequency of drought over Eastern Africa has also increased to more than one drought in every 3 - 5 years in the last decade (Herrero et al. 2010). The latest severe drought occurred in 2010 – 2011 (Dutra et al. 2013). Williams & Funk (2011) and Lyon & Dewitt (2012) suggest that the March - May (MAM) rainfall season over the region has been drying since 1999. The MAM season contributes over 70% of the annual rainfall and is the most important to agricultural production in Kenya and the region. These patterns are consistent with those of Williams et al. (2012) and Omondi et al. (2014) which show that precipitation over the region declined since 1980. In contrast, Sheffield et al. (2012) suggest that there has been little change in drought globally over the past 60 years.

Regardless, the drying patterns in Kenya are possibly linked with anomolous warming in the Atlantic and Indian Ocean, which tends to suppress the moisture incursions to the inland areas of the region (e.g. Williams & Funk 2011) and the shifts in Pacific sea surface temperatures (SSTs), which tend to intensify the Walker Circulation (Lyon & DeWitt 2012). However, Tierney et al. (2013) suggest that the Indian Ocean SSTs remain the main drivers of the East African rainfall on the multidecadal time scales while Williams et al. (2012) is of the view that the underlying causes of the drying climate in the region remain unclear.

Drought is a regular occurrence in Australia. According to Plummer et al. (1999), there has been extreme dryness over much of Australia prior to 1990's, whereas winter rainfall appears to have decreased over south-western Australia since the 1960's (Allan & Haylock 1993). Between 1995 and 2010, rainfall has reduced significantly over south eastern Australia (Dijk et al. 2013, Risbey et al. 2013).

Numerous mechanisms driving the changes in the drought patterns in this region have been suggested: El Niño Southern Oscillation (ENSO) (Ummenhofer et al. 2011, Smith & Timbal 2012), Indian Ocean Dipole (Ummenhofer et al. 2009) and Southern Annular Mode (SAM) (Cai et al. 2014). However, there is still ongoing debate on the relative roles of Indian and Pacific Ocean in driving climate variability over the region (e.g. Nicholls 2009, Cai et al. 2011, Smith & Timbal 2012).

For both Kenya and the MDB, it is suggested that dry conditions have increased in recent decades. Focus of most studies seems to be on long term changes in prolonged dry periods (drought) while very little investigation has been done on the changes in the trends of short dry periods or dry spells which normally cannot be defined as drought. Changes in dry spells can have adverse effects on crops, especially if they occur in the critical flowering and grain filling stages (e.g. Kassie et al. 2013). Understanding the changes in the patterns and trends of dry spells may benefit the semi-arid agricultural systems in Kenya and the MDB.

In the MDB, both decreases (Suppiah & Hennessy 1998) and increases (Deo et al. (2009); Nicholls (2006)) have been indicated, possibly due to the marked dry periods from 1996 through 2007 (Murphy & Timbal 2008). In contrast, Donat et al. (2013) suggest non-significant trends in consecutive dry days over eastern Australia. In Kenya limited studies focus on some seasonal attributes of dry spells. For example, Mugalavai et al. (2013) concluded that reduction in seasonal rainfall and increasing temperatures between 1982 and 2009 over western Kenya reflected increasing dry spell occurrence in the region. Global climate models suggest a dry future in both Kenya and the MDB (Schreider et al. 1996, Butterfield 2009).

Cumulative rainfall (Williams et al. 2012, Gitau et al. 2013, Verdon-Kidd & Kiem 2013) and stochastic models (Sharma 1996) are often used alongside other indices (Mpelasoka et al. 2008, Rojas et al. 2011) to estimate dry spells and drought in these regions. Both parametric (model-based) and non-parametric methods (Suppiah & Hennessy 1998, Chenu et al. 2013) have been used to estimate temporal trends in these regions. Trends estimated using different ways may differ slightly but overall indicate similar patterns in the dry spell (e.g. Mpelasoka et al. 2008, van der Schrier et al. 2011).

No studies have systematically looked specifically at historical trends in dry spell lengths in space and time for the two regions. The earlier analysis of the distribution of dry spell lengths in chapter 3 suggested some spatial coherence in the dry spell patterns but it is not known whether these patterns also occur in time.

The objective of this study therefore is to investigate characteristics of the trends in the historical data for the 2 regions: 1) whether there is evidence of temporal and spatial long term trend in the dry spell lengths at the annual scale 2) if long term historical trends exist in the dry spell lengths at the month and seasonal scale.

4.2. Methods

4.2.1. Data and study area description

The study areas are Kenya, between latitudes 5^0N - 5^0S and longitudes 34^0 E - 42^0E, and the MDB, between latitudes 24^0S - 38^0S and longitudes $136^{\,0}$ E- 153^0E. Rainfall in Kenya is mainly bimodal (March-May & October-December) and ranges from 2000mm in western to < 300mm in the northern and south eastern regions. In the MDB, rainfall occurs mainly in summer (north) and in winter (south) and ranges from ≤ 400mm in the west to > 1000mm in the southern and eastern parts of MDB. Much of the 2 regions are semi-arid or arid with annual potential evaporation ranging from 1700mm in the north to 1000mm in the south in both regions.

Dry spell calculation methods and data are similar to those used in chapter 3, which described the distribution of dry spells. The analysis of dry spells is based on the 1961 - 2010 period daily rainfall for 30 locations in Kenya (obtained from Kenya Meteorological Department) and 47 locations in the Murray Darling Basin (obtained from the Australian Bureau of Meteorology (http://www.bom.gov.au/climate/data/)). In Kenya, the analysis and homogeneity of the rainfall time series (as well as continuity) for these periods/locations has been a focus of many studies (e.g. Bärring 1988, Ogallo 1989, Funk et al. 2010) suggesting that, it represents the regions' climate well. Similarly, in the MDB, this period was considered ideal as it represents reasonably, historical patterns consistent with most other studies on extreme droughts or wet periods in this region (e.g. Whetton 1988, Nicholls et al. 1997, Suppiah & Hennessy 1998, Nicholls et al. 2012).

A preliminary examination of the historical rainfall records from the 2 regions was done to see whether it characterises the longer historical data correctly. Rainfall data for 4 locations in Kenya and 4 locations in the MDB was used (Figure 4.1). In Kenya (Figure 4.1a), the coefficient of variation (CV) for the monthly rainfall across the locations in 1935 - 1960, ranges from 130.6% - 181.8%, 143.5% - 197% in 1961 -

2010 and 146.5% - 194.8% in the overall period (Appendix A3). This suggests that, rainfall variability in the current period (1961-2010) is not very different from the preceding or the overall period. Further, a paired-test of the means (and CV) between the 3 respective periods (1935-1960, 1961-2010, 1935 - 2010) in Kenya, indicate that, the rainfall data for these locations do not provide any evidence that the means/CV differ ($p<0.05$).

In the MDB (Figure 4.1b), the CV of the monthly rainfall across the 4 locations varies from 71.7 - 118.7 % overall, with the highest variability being indicated between 1910 and 1960 (Appendix A3). Although the t-test results suggest that the means differ between the 4 locations, CV between the respective periods do not suggest a strong difference between the rainfall series ($p<0.1$).

The above suggests that, the historical rainfall represents the climate variability in those locations and the region.

A dry day was taken to be a day with a threshold $q \leq 0.1$mm daily and a dry spell was defined as the number of successive dry days within a month. Two categories of dry spell lengths were calculated: (i) monthly dry spells (dry spells within monthly boundaries) and (ii) "Long" dry spells (dry spells including those dry spells that continue into consecutive months).

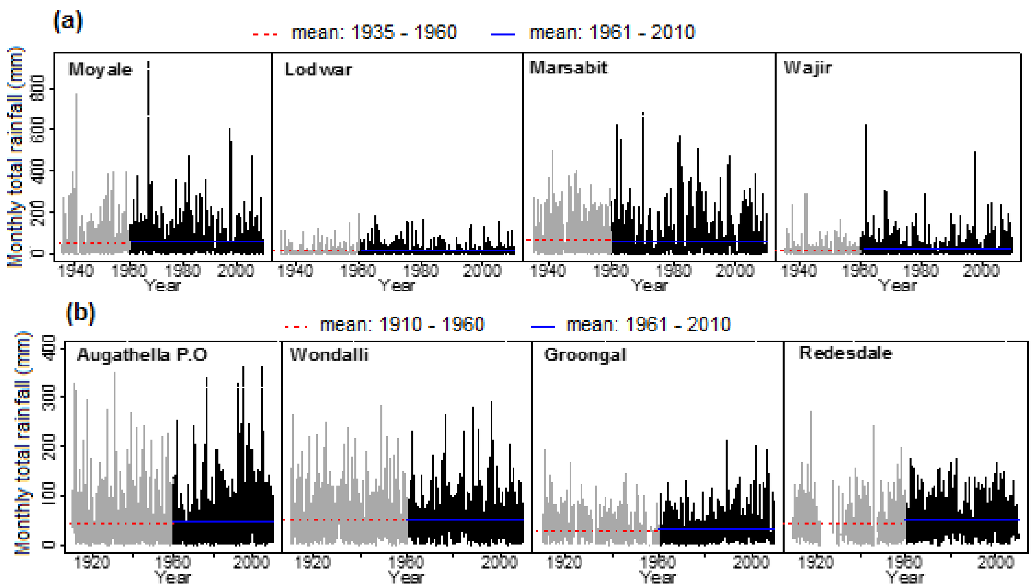


Figure 4.1: Monthly total rainfall for Moyale (3.53^{0}N, 39.05^{0}E), Lodwar (3.12^{0}N, 35.62^{0}E), Marsabit (2.32^{0}N, 37.98^{0}E) and Wajir (1.75^{0}N, 40.07^{0}E) in (a) Kenya from 1935 – 2010 and for Augathella P.O (25.8^{0}S, 146.59^{0}N), Wondalli (28.5^{0}S, 150.59^{0}E), Groongal (34.44^{0}S, 145.56^{0}E) and Redesdale (37.02^{0}S, 144.52^{0}S) in the MDB from 1910 – 2010.

4.2.2. Analysis of trends

4.2.2.1. Binomial model

A binomial model (Cox et al. 1979) can be applied to monthly dry spells that are equal to the month length (also defined as “full month”) against dry spells that are shorter than a month (also defined as “<month”). This is because dry spells that are exactly as long as a month (“full month”) might be truncated dry spells running into consecutive months. Trends in the “<month” dry spells are then analysed separately within a generalized linear model. In the analysis, dry spells running into consecutive months are “Long” dry spells as defined in chapter 5.

4.2.2.2. Generalized Linear Model

More generally, the trends in the monthly and annual dry spells in Kenya and MDB for the period 1961 - 2010 are analysed using a Generalized Linear model (GLM) (Nelder & Wedderburn 1972). Generalized linear models have been used widely to examine climate relationships (Mestre & Hallegatte 2009, Wang et al. 2010). A GLM is a linear predictor that allows a wide range of distributions and can be expressed as:

$$g(\mu) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n + \varepsilon \qquad \textbf{[4.1]}$$

Where a link function g (.) describes how the mean (μ) relates to the linear predictors and a variance function similarly relates the variance to the predictors. However this analysis only concentrates on the mean function. The $\beta_{i=1 \ldots n}$ are linear regression coefficients and describe the partial rate of change of the response variable g (μ) as a function of changes in the predictors. The error term (ε) is the noise in the linear relationship. Because dry spells are typically positively skewed and best described by a lognormal distribution in the study areas, we directly model the dry spell data within the GLM framework using a log link function (Chambers & Hastie 1992).

The regression coefficients were estimated by maximum likelihood or MLE method (Chambers & Hastie 1992) using R (R Development Core Team 2010). Compared with the traditional Ordinary Least Squares estimation (OLS), MLE is less biased and efficient for non-zero mean and highly skewed data like dry spells (Buntin & Zaslavsky 2004).

(a) Long term dry spell trends

The fitted GLM models for each month are as follows:

Model1: **glm** (dryspell_length (Month (i)) ~Year, data=dryspelldata, family=binomial ())

Model2: **glm** (dryspell_length (Month (i)) ~Year, data=dryspelldata, family=gaussian (link="**log**"))

Where, Model1 is for "full month" and Model2 is for "< month" and "Long" dry spells. Note in Model 2 that the "dryspelldata" for each of the 2 dry spell types is different.

For statistically important trends, only values in months with p-values between 0 to 0.1 were extracted as these are commonly used in most climate studies as evidence of statistically significant or strongly insignificant trends (e.g. Singh & Kripalani 1986, Cayan et al. 1998, Hannaford & Marsh 2006, Chamaillé-Jammes et al. 2007, Ellis et al. 2009, Batisani & Yarnal 2010, Shahabfar et al. 2012).

In Kenya the growing seasons are defined as March to May (MAM or long rains) and October to December (OND or short rains) while the dry seasons are January to February (short dry) and June-September (long dry). Similarly, in the MDB, May – October is defined as the growing season for important winter crops such as wheat (Nicholls 2004) as well as summer (December-February or DJF) and autumn (March-May or MAM). May-August (MJJA) is defined as winter and September-November (SON) as spring.

(b) Testing trend significance by bootstrapping

A bootstrap resampling procedure similar to Westra et al. (2012) is used to investigate the reliability of the regression results. This approach constitutes jumbling the temporal structure of the dry spell series such that the coupling between the time (years) and dry spells is lost but the spatial dependencies are preserved. This enables testing whether trends in observed dry spells are statistically significant by chance or not.

For all series, 1000 bootstrap realisations were sampled and the percentage of locations showing significant trends recorded. This percentage of trends would occur purely by chance in random data (Westra et al. 2012). The percentage of locations from the bootstrap analysis is compared with the percentage locations from the original observations (regression results). This indicates whether the percentage locations with significant trends are purely by chance (within the bootstrap distribution range) or real (outside the bootstrap distribution range).

4.3. Results

As an example of a typical time series, the monthly and "Long" dry spells for Katumani (latitude 1.58^0 S, longitude 37.23^0 E) in Kenya and Tongio (Brooklands) (latitude 37.18^{0}S, longitude 147.71^0 E) in the MDB are highlighted in Figure 4.2. For comparisons, the 2 locations were selected as they depict the dry agro-climate of the 2 regions, both are the southern parts and have relatively low mean annual rainfall (Katumani = 731.1mm, Tongio = 618.3mm).

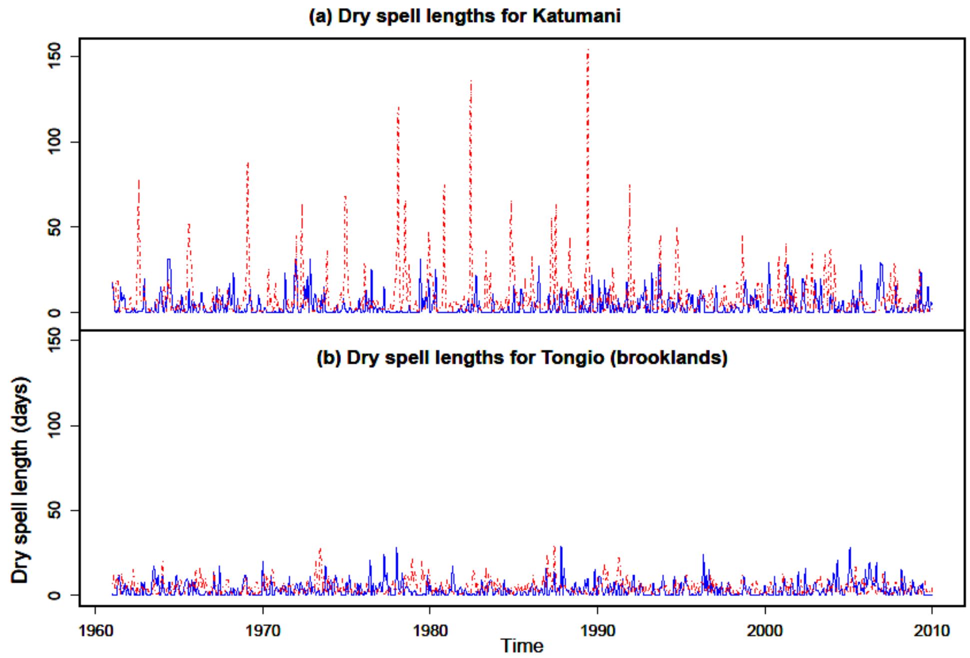


Figure 4.2: Monthly (blue-solid) and "Long" (red-dashed) dry spells length for (a) Katumani and (b) Tongio (Brooklands) for the period 1961 -2010

The dry spell series in Figure 4.2 indicate different patterns for the two semi-arid locations. At Katumani, the monthly dry spells are typically about a month long, while the "Long" dry spells can be over 50 days long. In contrast both the monthly and "Long" dry spells over Tongio-Brooklands never exceed the length of the month. At the Kenyan location, the monthly dry spell lengths are far less than the actual dry spell lengths. Given this shortcoming the monthly dry spells are analysed in two parts as a binomial model and a GLM as discussed in the methods.

4.3.1. Long term trends patterns in Kenya and Murray Darling Basin

In Kenya and MDB, significant trends ($p < 0.1$) in all the 3 dry spell types vary and occur in most months. As would be expected, fewer trends occur in the "full month" dry spells in both regions. The actual trends in days per year (increase and decrease) in the "Long" dry spell lengths in Kenya and the MDB for the period 1961 - 2010 is given in Table 4.1. Overall, increases in the dry spell lengths ranged from about 0.026 days/year in December with a standard deviation (SD) of 0.01 days/year to an average of 0.75 days/year in August (SD = 0.33 days/year). This equates to a 1 day to 37 days increase over the whole time period. Notably, high increases are indicated in the normally wet months of March ranging from 0.15 - 0.37 days/year. Conversely, decreases range from < 0.01 days/year to a maximum of 0.46 days/year in June which equates to 23 days decrease over the entire period.

Table 4.1: Range of trends (days/year) of increase and decrease ($p < 0.1$) in "Long" dry spells lengths in Kenya and MDB

Month	Kenya (Trends in days/year)		MDB (Trends in days/year)	
	Increasing	decreasing	Increasing	decreasing
January	0.1 - 0.32	0.11 - 0.16	0.05 - 0.19	0.05 - 0.12
February	0.03 - 0.48	0.09 - 0.14	-	0.04 - 0.18
March	0.15 - 0.37	0.09 - 0.33	0.07 - 0.17	0.08
April	0.05 - 0.09	-	0.11 - 0.20	0.06
May	0.03 - 0.21	0.001 - 0.01	0.04 - 0.15	0.03 - 0.19
June	0.12 - 0.33	0.02 - 0.46	0.03 - 0.04	0.02 - 0.24
July	0.03 - 0.65	0.02 - 0.23	0.03	0.03 - 0.29
August	0.02 - 0.75	0.03 - 0.32	0.02 - 0.21	0.23
September	0.03 - 0.46	-	0.02 - 0.13	0.02 - 0.04
October	0.05 - 0.22	0.02 - 0.30	0.07 - 0.20	0.03
November	0.03	0.03 - 0.16	0.02 - 0.06	0.03 - 0.14
December	0.026 - 0.034	0.08 - 0.33	-	0.03 - 0.16

4.3.2. Trends in the monthly dry spell lengths in Kenya

The p-values for significant trends for "< month", "full month" and "Long" dry spells in Kenya are given in Figure 4.3. In the "< month" dry spells, significant increasing trends occur in all the months and the greatest numbers of locations (23%) with such trends are in February. Significant declining trends occur again in all months but the greatest number of locations (13%) is in June. Unlike the “<month> trends, increasing trends in the “full month” dry spells only occur in January, February, June, August and September in 3% of the locations. Declining trends, however, occur in most of the months apart from March, April, August and November but at only a few locations (3 - 17%).

Significant increasing trends in the “Long” dry spells occur in all months, but most occur in July. Similarly, significant decreasing trends are shown in all months except April and September and most (27%) of the declining trends occur in June, confirming the “< month” and “full month” results. It seems that, increasing trends in the “< month” and “Long” dry spells occur in monsoon seasons/months (April and May) (long rains) and October to November (short rains)) in Kenya.

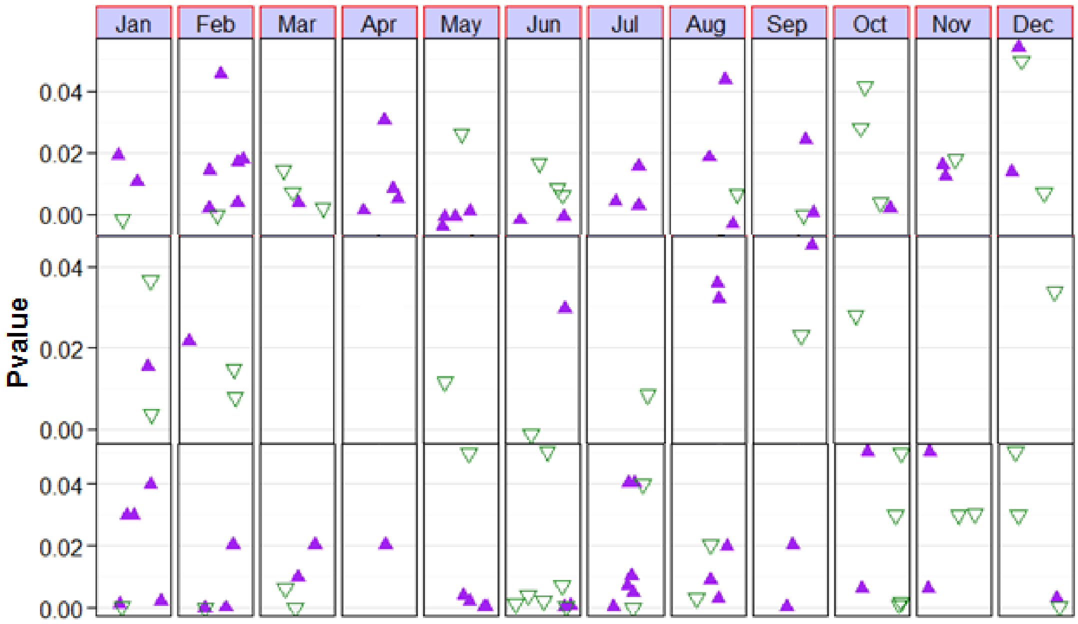


Figure 4.3: Scatter plots of trends by month showing positive/increasing (▲) and negative/declining (▽) trends at $p < 0.05$ (y-axis) for “< month” (top panel), “full month” (middle panel), and “Long” dry spells lengths (bottom panel) for locations in Kenya. The scatter plots for the trend patterns for < month and the ‘Long’ dry spells show some similarities while such pattern is missing in most of the months for to the ‘full month’ dry spells.

4.3.3. Trends in the monthly dry spell lengths in the Murray Darling Basin

In the MDB, increasing significant trends in the “<month” dry spells occur in January, March, May, July and August (Figure 4.4) with most of the increasing trends occurring in 28% of all locations in August. Declining trends occur in most months except in March, April, August and October although these trends occur

consistently from September - December. However, the largest number of locations (26%) with declining trends is in June. In the "full month" dry spells, increasing trends occur only in April, May, August and September in 4 - 6% of the locations while declining trends occur in 2% of the locations in May through July and November. As indicated earlier only very few locations in the MDB had any full month dry spells.

In contrast, increasing trends in "Long" dry spells lengths occur in most months but mainly in January, March - May, and July - October with 17% occurring in August, confirming the "<month" and "full month" result. While this suggests that "Long" trends capture the monthly dry spells patterns well, increasing trends only occur in April and October in the 'Long' dry spells and not in the later (<month).

Similarly, decreasing trends are shown in all the months apart from April and October with most of the declining trends occurring in July (19% of all locations). It seems for the '<month' and 'Long' dry spells, February, June, July, November and December indicated declining trends relative to the other months (Figure 4.4, top and bottom panels). In contrast, May and August had increasing trends for both methods.

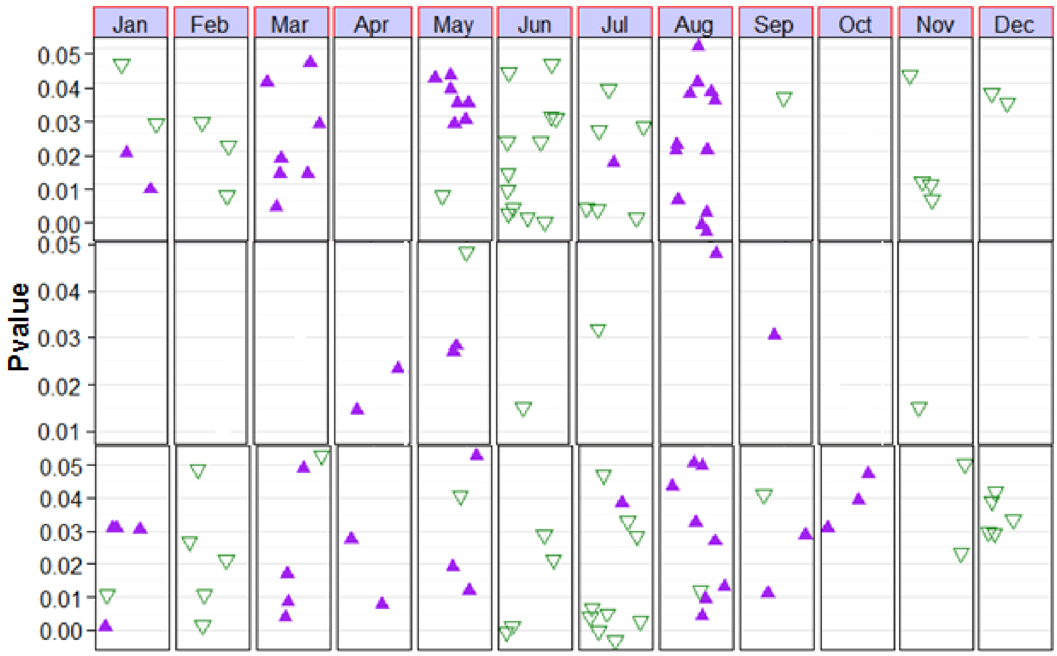


Figure 4.4: Scatter plots of trends by month showing positive / increasing (▲) and negative/declining (▽) trends at $p < 0.05$ (y-axis) for "< month" (top panel), "full month" (middle panel), and "Long" dry spells lengths (bottom panel) for locations in the MDB. The scatter plots for the trend patterns for < month and the 'Long' dry spells show some similarities while such pattern is missing in most of the months for to the 'full month' dry spells.

Dry spell length increased from less than 0.021 - 0.21 days per year (SD = 0.05 days/year) with the highest increases being in August. In contrast dry spell length declines varied from 0.02 - 0.29 days per year which translates to a maximum decrease of about 15 days over the entire period in July (SD = 0.08 days/year) (Table 4.1).

Comparing trends between Kenya and the MDB, significant increasing and declining trends in the “<month” dry spells occur across all months in Kenya, and in specific months in the MDB. The trends in the “full month” dry spells generally differ (months) for increasing trends in both areas and again for declining trends which occur over most months in Kenya but concentrate in only a few months in the MDB. This might be due to the limited number of “full month” dry spells in the MDB. In Kenya, increasing trends in the “Long” dry spells occur in few locations but in relatively more locations in the MDB.

Interestingly however, trends in the “Long” dry spells roughly appear to be similar in Kenya and MDB between March and June (evenly increasing and decreasing) and November and December (mostly declining trends) but indicating opposite trends in February.

4.3.4. Seasonal trends in the “Long” dry spells.

The above results suggest that dry spells are seasonal. In Kenya, increasing trends in the “Long” dry spells occur in all the seasons with the highest number of locations (23%) showing significant increasing trends in the JJAS season (Figure 4.5: solid asterisk and red lines). Interestingly, declining trends also peak (13% of locations) during the JJAS season although similar trends occur in all the seasons, but only in a few locations.

In the growing seasons (MAM and OND), only 3% of locations had an increasing trend during the “Long rains” season while 7% of locations indicated an increasing trend in the “Short rains” (OND) season. Declining trends only occurred in 2 locations (7%) in each of the seasons. Compared with results in Table 4.3, it seems that the seasonal trends mainly occur in the short (“< month”) and “Long” dry spells during MAM and OND seasons.

Table 4.2 shows the increase and decrease in days per year in the seasonal and annual dry spell lengths in Kenya and MDB. In the wet seasons, it seems the largest increases and smallest declines occurred in MAM compared to OND. These rain seasons in Kenya normally follow the driest months of the year and this probably influences trends in the dry spells lengths in the following months. For example, the

90th percentile dry spells length for March and October (start of the 2 rain seasons in Kenya) were similar to those of the previous months (January and February and June-September) which are normally dry. This suggests either the actual onset of rainfall in these months is delayed, or relatively low rainfalls occur.

In MDB, increasing trends in the “Long” dry spells were significant in all the seasons although the highest number of locations (15%) with increasing trends occurred in the autumn and winter (JJA) seasons (Figure 4.5). Declining trends were mainly in Summer (DJF) and in winter (JJA). The largest number of locations (17%) with declining trends occurred in winter. In summary, increasing and decreasing trends in “<month”, “full month” and “Long” dry spells occur in most of the months and in all seasons in Kenya and the MDB. In the growing seasons, these trends appear more pronounced in the short rains season in Kenya and in winter in the MDB.

In comparison, it appears that increasing trends in the dry spell lengths at the monthly scale in Kenya are much higher than in MDB (Table 4.1). For example, the greatest increasing trends were in August for both regions: 0.75 days per year in Kenya and 0.21 days per year in MDB. Both the seasonal and the annual trends are greater in Kenya than in the MDB with the exception of the MAM (autumn) season. In contrast, declining trends at the monthly and seasonal scales are roughly similar in both regions with some differences: January, the JF and JJAS seasons and the annual scale had greater declining trends in Kenya than in the MDB.

Table 4.2: Trends (days per year) of increase and decrease in seasonal and annual dry spells lengths in Kenya and MDB between 1961 and 2010

Season & Annual	Kenya (Rates in days/year)		Season & Annual	MDB (Rates in days/year)	
	Increasing	Decreasing		Increasing	Decreasing
JF	0.30	0.13	DJF	0.038 - 0.042	0.04 - 0.33
MAM	0.01 - 0.10	0.01 - 0.02	MAM	0.04 - 0.17	0.05
JJAS	0.02 - 0.60	0.02 - 0.14	MJJA	0.01 - 0.05	0.01 - 0.06
OND	0.01 - 0.04	0.02 - 0.04	SON	0.02 - 0.03	0.01 - 0.04
Annual	0.27 - 1.90	0.31 - 0.95	Annual	0.34 - 0.54	0.27 - 0.60
Annual maximum	0.59 - 0.67	0.38 - 0.66	Annual maximum	0.21 - 0.46	0.30 - 1.1

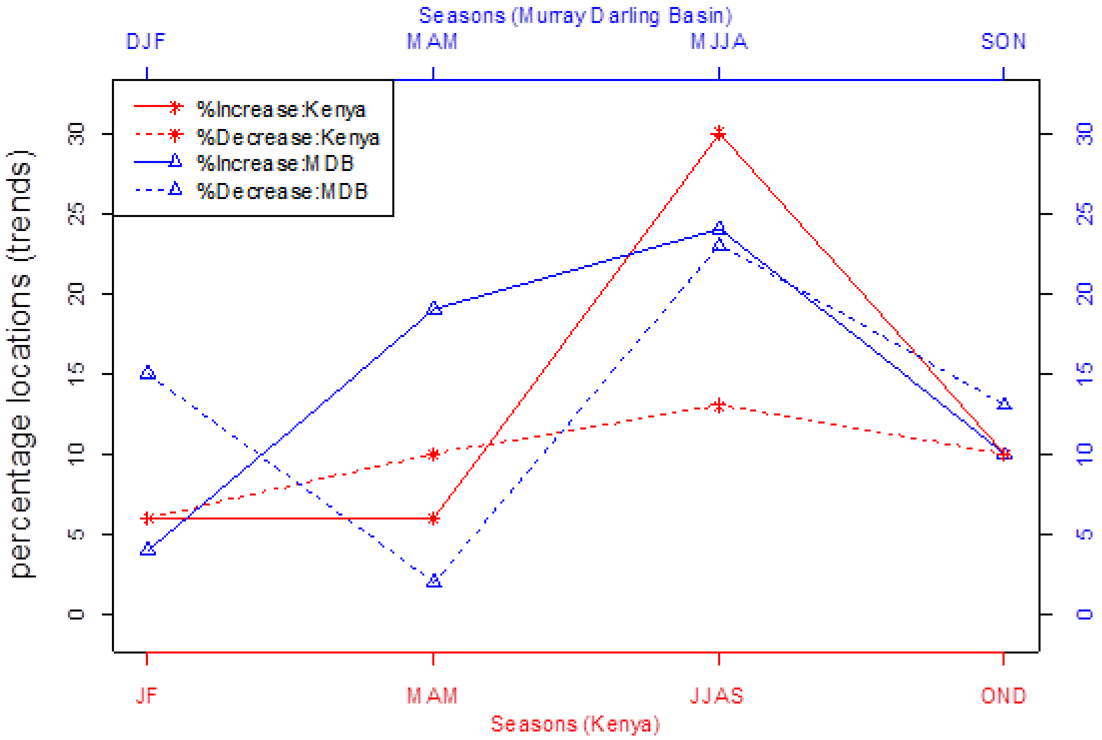


Figure 4.5: Proportion of locations (%) showing significant trends at p < 0.05 for "Long" dry spells in JF, MAM, JJAS, and OND seasons in Kenya (red lines/dashes with asterisks) and in DJF, MAM, MJJA (growing season), and SON seasons in the Murray Darling Basin (blue lines/dashes with triangle symbols). Increasing and decreasing trends are shown in solid and dashed lines respectively. Note that winter includes the month of May for MDB to indicate the growing season as defined in the methods. In addition, the seasons for Kenya and MDB do not exactly overlap

4.3.5. Dry spell trends at the annual scale

Annual trends are vital indicators for socio-economic impacts such as food insecurity (Butterfield 2009). Increasing trends in the maximum annual dry spell lengths (MDL) in Kenya occurred in 7% of locations but for the annual dry spells (ADL) this occurred in more locations (17%). Declining trends in the MDL occurred in 17% of locations while such trends in the regular ADL occurred in 13% of locations.

Similarly, in the MDB, only 6% of locations suggest upward trends in the maximum annual dry spells compared to 11% of locations with such trends in the annual dry spells. Significant declining trends in the MDL occurred at extremely few locations whereas, a modest number of locations (19%) indicate declining trends in the ADL.

In summary, for the annual series, increasing trends in Kenya and MDB occur mostly in the ADL rather than in the MDL. Increasing trends in ADL are relatively even in both regions although, as mentioned earlier, the annual trends are much greater in

Kenya than in the MDB. More declining trends occur in the MDB relative to Kenya but again the trends are much greater in Kenya.

4.3.6. Bootstrap resampling results

For trends in Kenya, the observed proportion of locations with increasing and decreasing trends tended to be outside the null (bootstrap) distribution (Figure 4.6a & b), suggesting that the calculated fraction of locations with trends was not a random occurrence. For instance, the percentage of locations in the random bootstrap sample showing significant increasing trends in January ranged from 4.1 - 6.4 % (Figure 4.6a), but the calculated trends based on the observed data occurred in 17% of locations (asterisk points). In contrast, percentage of locations with increasing trends in the observed data in April and locations with decreasing trends in January and February occurred inside the bootstrap range (Table 4.3).

In the MDB, the observed percentage of locations with increasing trends in the observed data (Figure 4.6c, triangles) was within the boundaries of the bootstrap distributions in September (Table 4.3). Similarly, in January, August and September, the observed percentage of locations with declining trends was within the bootstrap range (Figure 4.6d). Locations in January (summer season), August and September (Winter/Spring) therefore can be considered to show no trends as they fall within the bootstrap distribution.

From the bootstrap analysis in both regions, it can be concluded that for at least part of the year the observed data showed a much higher proportion of locations with significant trends than would be expected from purely random chance.

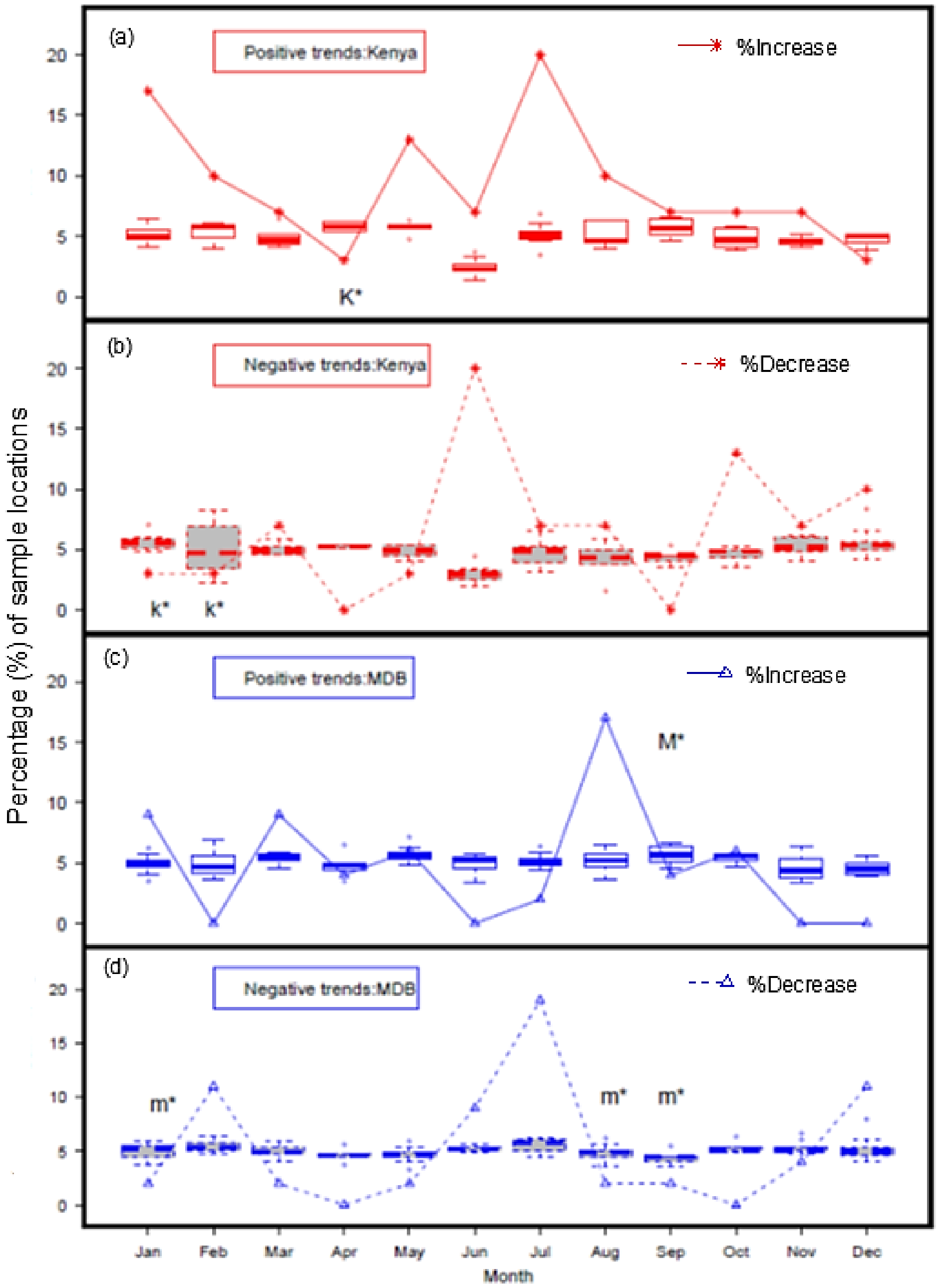


Figure 4.6: Line graphs for percentage of locations (legend: % increase or decrease) showing observed trends in the "Long" dry spells and box plots of the percentage of locations from 1000 bootstrapped replicates (sampled) trends in (a) & (b) Kenya and (c) & (d) MDB ($p < 0.05$, significant increasing/positive (red/ blue solid box plots) and decreasing/negative (red/ blue dashed box plots) trends). The y-axis in all the panels shows the percentage of locations with observed significant increasing (solid lines) and decreasing (dashed lines) trends in Kenya (asterisk points) and MDB (triangle points) while solid and dashed box plots indicate the percentage of the bootstrap samples (locations) with increasing/decreasing trends respectively. The months where observed trends are within the bootstrap range are marked with "K*" (increasing) and "k*" (decreasing) for locations in Kenya and "M*" (increasing) and "m*" (decreasing) for locations in MDB.

Table 4.3: Proportion (%) of locations showing trends at p < 0.05 in the "<month", "full month" and "Long" dry spells in Kenya and MDB. The proportion of locations (% range) for the bootstrapped trends for the "Long" dry spells at p < 0.05 is also shown. The bootstrap range in which the significant observed trends at p < 0.05 occur is in bold and underlined

	% Observed (locations) in Kenya (at p<0.05)						Bootstrap range ("Long" dry spells) (at p < 0.05)		% Observed (locations) in MDB (at p<0.05)						Bootstrap range ("Long" dry spells) (at p < 0.05)	
Dry spell type	<month		full month		Long				<month		full month		Long			
Month	Increasing	Declining	Increasing	Declining	Increasing	Declining	Increasing	Declining	Increasing	Declining	Increasing	Declining	Increasing	Declining	Increasing	Declining
Jan	10	10	3	17	17	6	4.1 - 6.4	**<u>3.3 - 7.1</u>**	13	8	-	-	28	6	3.5 - 6.2	**<u>3.7 - 6.0</u>**
Feb	30	3	3	10	13	6	4.0 - 6.0	**<u>2.3 - 8.3</u>**	-	10	-	-	-	24	3.6 - 6.9	4.7 - 6.4
Mar	3	17	-	-	7	10	4.1 - 6.4	4.6 - 5.9	17	-	6	-	9	4	4.6 - 5.8	4.1 - 5.9
Apr	20	7	-	-	6	-	**<u>5.4 - 6.2</u>**	5.1 - 5.4	6	4	4	-	8	2	3.5 - 6.5	3.7 - 5.6
May	13	3	3	7	16	3	4.7 - 6.3	4.1 - 5.4	23	2	-	2	17	6	4.8 - 7.1	3.3 - 5.9
Jun	7	23	6	6	10	27	1.4 - 3.7	2.0 - 4.4	-	35	-	2	6	18	3.4 - 5.7	4.9 - 5.6
Jul	23	3	3	3	33	10	3.4 - 6.8	3.2 - 6.5	2	19	-	2	2	21	4.4 - 6.4	4.4 - 6.3
Aug	10	3	3	-	13	7	4.0 - 6.3	1.6 - 5.9	39	-	6	-	28	4	3.6 - 6.5	**<u>3.6 - 6.2</u>**
Sep	10	3	3	10	20	-	4.6 - 6.6	3.6 - 5.4	-	4	-	2	6	4	**<u>4.6 - 6.6</u>**	**<u>3.6 - 5.4</u>**
Oct	6	10	-	6	7	20	3.8 - 5.8	3.6 - 5.2	2	-	-	-	8	2	4.7 - 5.7	4.9 - 6.3
Nov	14	7	-	-	7	17	4.1 - 5.1	4.1 - 6.2	2	17	-	2	2	13	3.4 - 6.4	4.8 - 6.6
Dec	7	14	-	6	13	17	3.5 - 5.1	4.2 - 8.4	-	17	-	4	2	30	3.9 - 5.6	4.1 - 7.9

4.3.7. Spatial trends in dry spells

Figure 4.7 gives the spatial distribution of trends in the “Long” dry spells in Kenya. Increasing trends in the “Long” dry spells occur mostly in July, and mainly in locations in the southern half of the country, but this is somewhat similar to the patterns throughout the year. The patterns in the “Long” dry spells suggest two regions. The northern transect, being mostly arid-semi arid, is associated with no significant increasing trends and the southern transect, constituting humid - semi humid locations, is linked with increasing trends. An exception to this generalisation is the coastal region where consistently decreasing trends are shown in most of the months. In June significant decreasing trends occur in the majority of locations and yet again most are in the coastal region. This pattern is again indicated in the normally wet months of October and December.

In the “<month” dry spells (not shown), increasing trends occurred mostly in locations in the northern half of the country and appear to shift to locations southward from July – September. Declining trends however, are indicated mostly in the coastal regions in most of the months but at a few locations. In contrast such patterns are less visible in the “full month” dry spells. In other words, the spatial patterns for the shorter dry spell lengths were different to the more general “Long” dry spell length spatial pattern.

At the seasonal level, some replication of the monthly scale patterns occurs (not shown). Increasing trends are indicated in the JJAS season in the southern transect. This could be expected as this is the longest dry period in Kenya. In contrast, significant decreasing trends during JJAS season occur at the coast.

Interestingly, dry spells at the annual scale exhibit somewhat opposite patterns to the seasonal trends. At the annual scale, significant trends appear to be mainly in the western half of the country. An increasing trend in maximum annual dry spells is indicated in only one location in the eastern and southern regions. In contrast, increasing annual dry spells trends occur in locations in western, southern and central highlands. However, decreasing trends for both maximum annual and annual dry spells are indicated in some locations in eastern, southern and coastal areas.

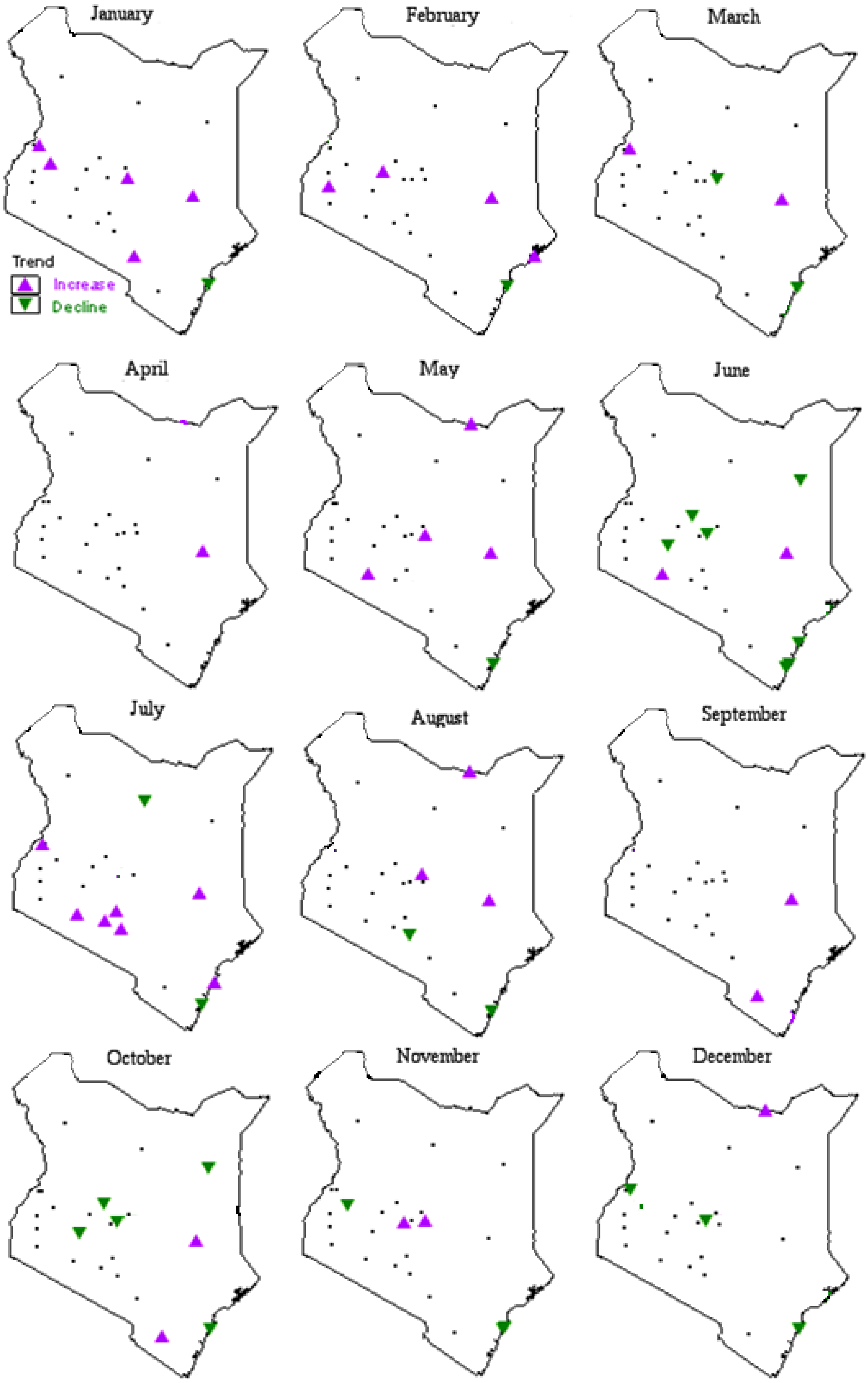


Figure 4.7: Spatial (increasing (▲) and decreasing (▼), $p < 0.05$) trends by month in the "Long" dry spells for the period 1961 – 2010 in Kenya.

4.3.8. Spatial trends in the Murray Darling Basin

The spatial distribution trends for the “Long” dry spells in the MDB are given in Figure 4.8. Increasing trends in the “Long” dry spells in August predominantly occur from north to south and mostly in eastern locations. The declining trends in July are mainly in locations to the east, west and south of the basin. Declining trends in February and December are only in locations in the extreme north eastern parts of the basin (Queensland). While the number of locations showing significant trends was not different from the random boot strap sample in these months, the spatial organisation might suggest it is not a random occurrence. Increasing trends in the “<month” dry spells in August occur from north to south of the MDB, while in March (start of autumn) they occur in locations in the north and in May (end of autumn) in locations in the south (Figure not shown). In contrast, decreasing trends mostly dominate June (start of winter) in several locations across the whole basin except in extreme north western parts and the same trends continues into July but with a slight shift to locations southwards. Again, the number of locations was not different from the bootstrap sample, but the spatial organisation might suggest differently.

Just as in Kenya, extremely few trend patterns are shown in the full month dry spells. The patterns in the “<month” spells suggests that dry spells in the MDB reflect the summer and winter dominant rainfall patterns in the north and south respectively.

Again, the trends in the monthly dry spells suggest patterns similar to the rainfall modes in the MDB (i.e. winter and summer). In MJJA/winter season, both increasing and decreasing trends occur in several locations across the entire basin except in central and extreme north/south-western parts of the MDB. However, in DJF (summer season), decreasing trends are dominant mainly in locations in the east of the MDB. Contrasting the trends in summer, increasing trends dominate the MAM/autumn season in the north and southern areas.

Significant increasing trends in maximum annual dry spells occur only in locations north of the basin while declining trends are only in a few locations in the south and southwest of the basin. Compared to trends in the maximum annual dry spells, declining trends in the annual dry spells are indicated in locations in the north and south of MDB. However, a substantial number of locations in the southern parts of the basin show significant increasing trends.

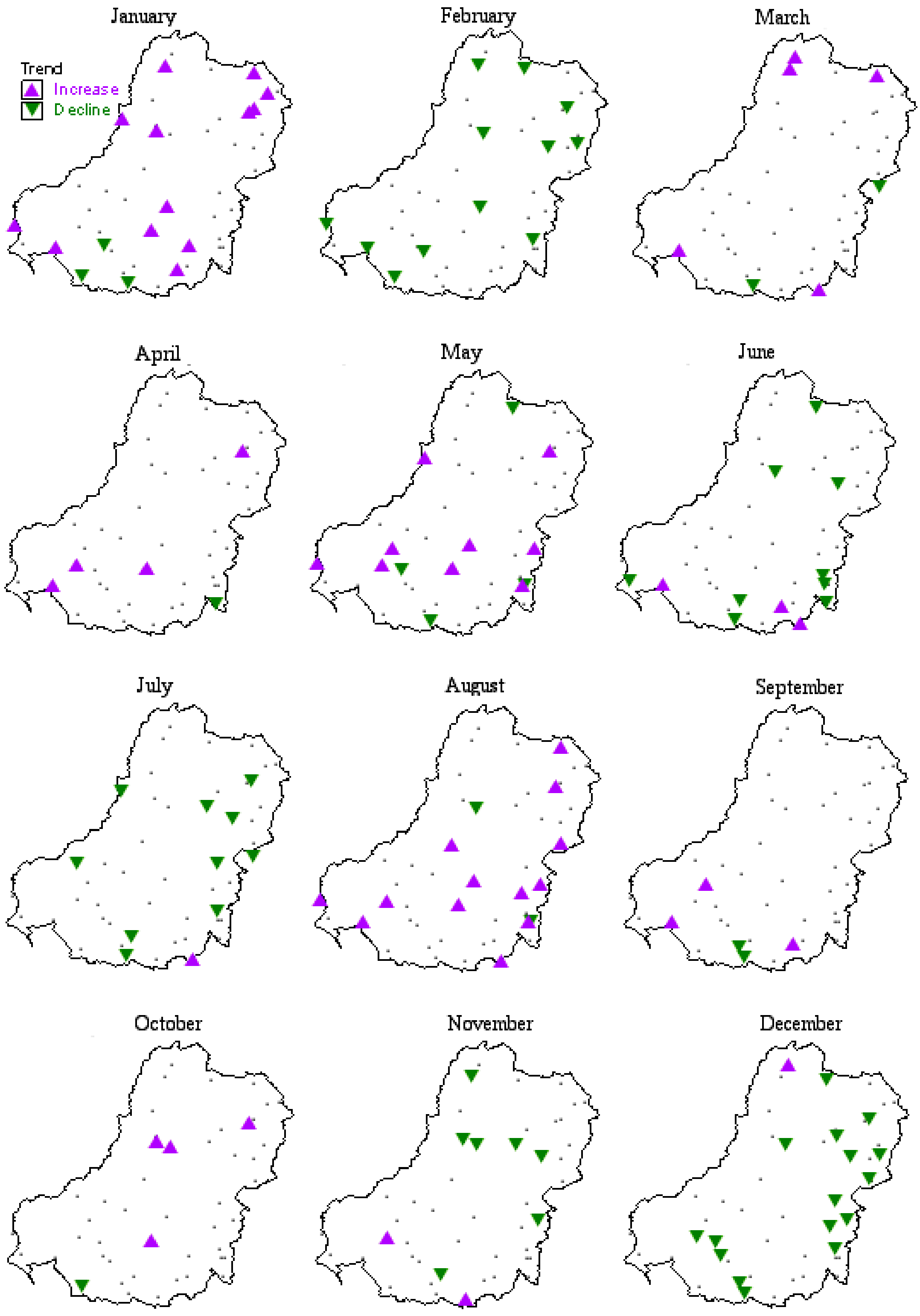


Figure 4.8: Spatial (increasing (▲) and decreasing (▼), $p < 0.05$) trends by month in the "Long" dry spells for the period 1961 – 2010 in MDB

4.3.9. Long term trends using Generalised Additive Models (GAM)

It is possible that the trends in dry spell lengths observed in this study are non-linear rather than linear, and analysing linear trends might overstate the magnitude of the trend. As a test, a generalised additive model (GAM) was fit to the “Long” dry spells for 4 locations from each region. GAMs extend GLMs (McCullagh & Nelder 1989) and allow flexibility in modeling underlying long-term trends in a data series using smooth functions (Underwood 2009) and for being able to capture non-linear trends. The GAM model for each location was:

$$g(dryspell) = f(year),\ family = gaussian(link = "identity"), data = dryspelldata) \quad \textbf{[4.2]}$$

Where, g () and f () are the link and smooth functions respectively, with the year term as the only covariate. Temporal trends were examined from the patterns indicated in the GAM plots. Again, our analysis concentrates on the mean function and not the variance.

The GAM results in Figures 6.9 shows that dry spells in Kenya and the MDB exhibit both linear and non-linear behaviours. As an example, a non-linear pattern occurs at Malindi in Kenya (Figure 4.9d) while a linear pattern is indicated at Kisumu (Figure 4.9c).

The GAM results suggest more complex behaviour in the trends than can be concluded from the previous linear analyses. However, for several locations, the non-linear trend could be summarized with a linear trend such as in Chinchilla, Narrabri, Pinnaroo, Colcheccio and Meru. Some of the non-linearity might be due to variations in major climatic drivers such as the El Niño Southern Oscillation (ENSO) which influences the rainfall patterns in the two regions.

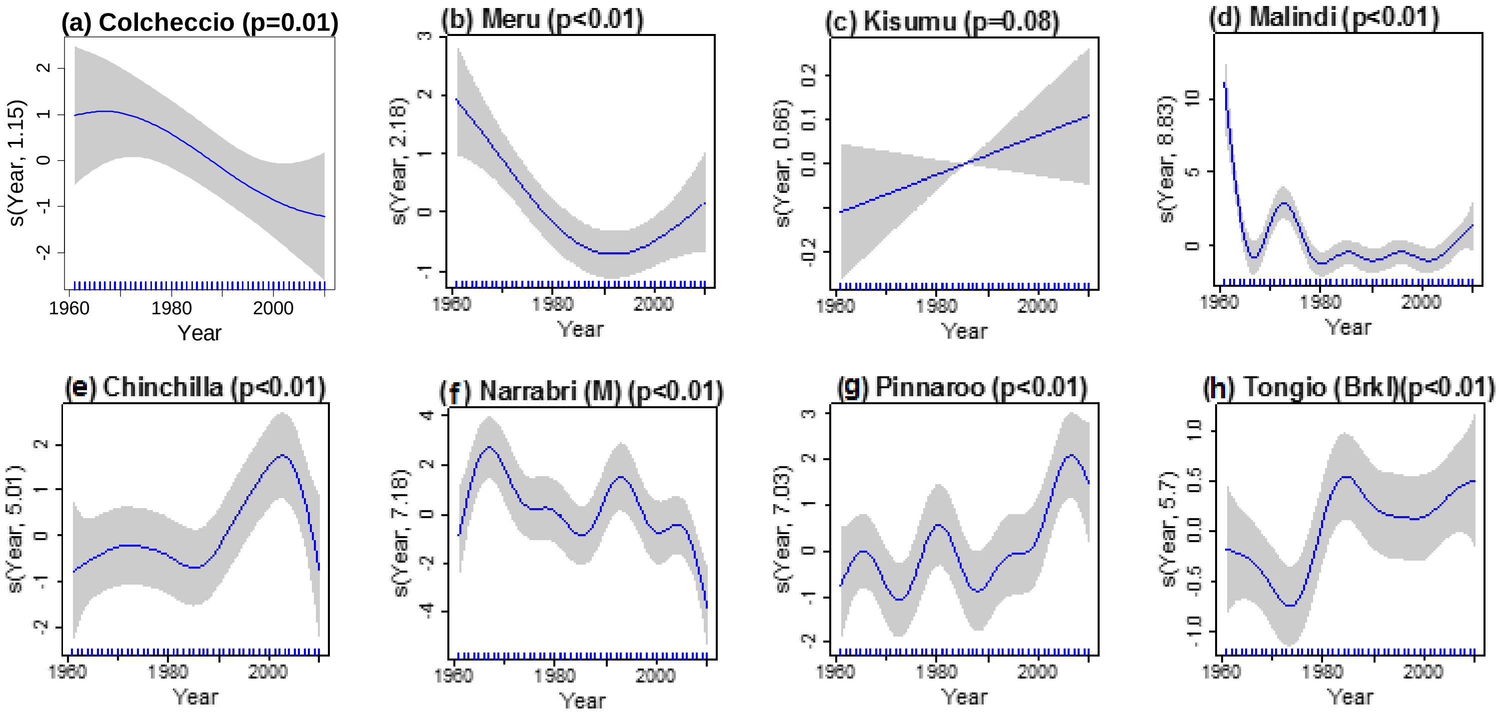


Figure 4.9:The effect of year on "Long" dry spells trends for (a) Colcheccio, (b) Meru, (c) Kisumu and (d) Malindi in Kenya and (e) Chinchilla, (f) Narrabri, (g) Pinnaroo and (h) Tongio (Brooklands) in MDB. The upper and lower 95% confidence limits of the GAM estimate are indicated by the gray shades.

4.4. Discussion

This analysis present some possible evidence of temporal and spatial long term trends in dry spell lengths in Kenya and the Murray Darling Basin (MDB) of Australia. The findings support previous assertions that there are changes in dry conditions in the two regions. This study also contrasts from the previous studies in a number of ways. Consistent with this study, a mixture of increasing and declining trends in dry spells have been reported before in both regions (e.g. Suppiah & Hennessy 1998, Usman & Reason 2004, Seleshi & Camberlin 2006, Hennessy et al. 2008, Murphy & Timbal 2008, Braganza et al. 2011). While previous studies tended to focus on the seasonal time scale, the current analysis focused in both the short, intra seasonal and annual timescales. For instance, Suppiah & Hennessy (1998) analysed block seasons/months i.e. November – April as summer and May–October as winter and identified that declining trends in the number of dry days (not dry spell lengths) occurred more in the latter period than in summer over eastern Australia (MDB).

In contrast, this study found that increasing and decreasing trends are roughly even in winter and spring (SON) in MDB, while the greatest increases are in autumn consistent with some more recent studies (Murphy & Timbal 2008, Cai & Cowan 2012), and most of the declines occurred in summer. In addition, significant trends occurred in both short and longer dry spells in Kenya and MDB with 1/3 of locations showing upward trends in the JJAS and winter seasons respectively. Even though there are limited comparative studies on dry spell trends in Kenya, in the wet/monsoon seasons, most drying trends coincided with the short rains (OND), suggesting a tendency of dryness in this period rather than in the long rain season as corroborated in some studies in the region (e.g. Funk et al. 2005, Sheffield & Wood 2008, Funk et al. 2010).

Considering the characteristics of the historical rainfall time series in these regions (Figure 4.1), it was expected that the trends in the dry spells lengths in both Kenya and MDB reflect the longer historical data and the diverse climates of the regions (i.e. arid –semi- arid - humid). In contrast to previous studies and to assist better understanding of the regions climates, the current study assessed the trends for 3 types of dry spells lengths: short, monthly and across consecutive months. In Kenya, increasing trends in short and long dry spells are more prominent in the southern transect in most of the months compared to the northern parts (e.g. Figure 4.7), possibly reflecting the homogenous nature of the region (north and south/east are mostly ASALs). A recent study found that the observed wet and dry spell characteristics in the global tropics were primarily dependent on whether a region is humid or arid (Ratan & Venugopal 2013). In contrast, in the MDB most of the increasing trends in the long dry spells occurred mainly in the relatively wetter southern half and eastern sectors of the region and declining trends in both north and southern parts (e.g. Figure 4.8). This suggest that the different patterns of increasing or decreasing trends in dry spell lengths in the region may be due to local weather patterns as well as the differences between the synoptic weather patterns in the northern – summer and southern - winter climate regimes.

While the rates of increase in dry spell length per year in the growing seasons for both regions were more or less similar, overall, the trends in Kenya were much higher than in the MDB. This could be due to the effect of the monsoon in Kenya relative to the MDB. Sheffield & Wood (2008) suggest that the largest trends in dry spells tend to coincide with the retreat of the inter- tropical convergence zone (ITCZ), such as in the JJAS season (longest dry season in Kenya) in East Africa/Kenya, when the monsoon is weakest and local convection is minimal (Verschuren et al. 2009). The ITCZ drives the inter-annual rainfall variability over eastern Africa between the wet (MAM & OND) and dry (January-February & JJAS) seasons and being an oceanic feature possibly interacts with other climatic systems (Marchant et al. 2007), such as ENSO or Indian Ocean SSTs.

In contrast with the results in this study, Williams & Funk (2011) indicate drying trends in the March – May long rains season in Kenya between 1980 – 2009 and attributed this to the warming over the Indian Ocean. This study found that more locations indicated increasing trends in the OND season compared to the MAM season. Warming of the SSTs over the western Indian Ocean tends to suppress convection and enhance dry air mass over tropical eastern Africa. Similar to William and Funk (2011), results from climate model simulations by Lyon & DeWitt (2012) confirm the declining trends in the long rains seasons but instead links this to abrupt changes in SST in the tropical Pacific. Behera et al. (2005) has shown that the variability in the short rain season (October – December) is largely linked to the Indian Ocean Dipole (IOD) in the tropical Indian Ocean rather than the El Niño-Southern Oscillation (ENSO) in the tropical Pacific although Omondi et al. (2013), shows that both the El Niño and Indian Ocean dipole modes are associated with rainfall variability in the region.

While the current trends are consistent with other studies that show increase in drought in the MDB (e.g. Speer et al. 2011, Dai 2012), the current increasing trends in dry spell length in the growing season are likely due to increase in more severe dry conditions in the last decade. For instance, Speer et al. (2011) shows that rainfall has declined at up to 50 mm per decade since 1970, whereas Chenu et al. (2013) suggest that, between 1999 and 2011 was one of the longest and most severe periods of drought since around 1940. Some studies however, suggest that the current increasing trends are due to global warming (Chiew et al. 2011, Dai 2012) and other studies have linked these patterns with the large scale climate drivers such as the El Niño-Southern Oscillation (ENSO), the inter-decadal Pacific oscillation (IPO) and the southern annular mode (SAM) and the Indian Ocean Dipole (Ummenhofer et al. 2009, Speer et al. 2011, Cai et al. 2014).

The bootstrap analysis confirmed that the number of locations indicating observed trends in dry spells in these regions did not merely occur by chance. However, varied patterns show up across months. Increasing and declining trends within the bootstrap only occur early in Kenya (April, January) (Figure 4.6) but later in MDB (August, September). In general, the majority of locations showing increase in dry spell length in both regions tend to shift from January to May and July in Kenya, and only occur in August in the MDB. Interestingly, the highest number of locations indicating increasing trends in Kenya (July) and MDB (August) follow after declining trends occur in the largest number of locations in the two regions (Kenya (June) and MDB (July)).

The results of this study have implications for agricultural production in these regions depending on how we interpret the changes in the dry spell trends in different seasons. The occurrence of significant increasing trends in the “Long” dry spell in March, April and May compared to June and July suggest that agricultural production in the MDB may experience higher drought risk in autumn than in winter. This echoes previous findings that rainfall in autumn has declined in south eastern Australia (e.g. Cai & Cowan 2008, Potter & Chiew 2009). Rainfall in autumn, although not as reliable as in winter, has the greatest impact on crop and pasture production in MDB (Austen et al. 2002, Clark et al. 2003). Therefore any increase in dry spell lengths in this period is crucial for Australia’s agricultural economy. In

Kenya, the long rain season, although more abundant, is less reliable for crops and pasture for ASAL regions than the short rain season, suggesting that increased dryness in the short (OND) season can also have profound effects on agriculture in the region.

Dry spells vary at different time and space scales (Table 4.3). The fact that shorter dry spells to a large extent indicated similar spatial trends as longer dry spells suggests an overall increase in drought risk. In relation to part 1 (Chapter 3) of this series, this would be a shift in the shape parameters of the derived distributions. Our analysis cannot establish whether there would also be an equivalent change in the scale parameter.

From a farmers point of view, short maturing crops should be promoted where increasing drying trends are anticipated (Singh & Reddy 1988, Sivakumar 1992). For example, extended drying may lead to a delay in the onset of the growing season such as for the long rain season in western Kenya and farmers may still benefit by planting early maturing crops such as millet instead of maize (Mugalavai et al. 2008). Water harvesting for supplementary irrigation might become a key strategy under a drying trend.

As mentioned earlier, the temporal and spatial patterns in dry spells trends might be linked to the large scale and regional climate factors like the sub-tropical cut-off lows, SSTs and ENSO (Nicholson 1989, Drosdowsky 1993, Mutai & Ward 2000, Camberlin & Philippon 2002, Murphy & Timbal 2008, Risbey et al. 2009) as they principally drive rainfall in these regions. A warmer Pacific and negative Indian Ocean SSTs are strongly associated with drought patterns in eastern Australia or MDB (Nicholls 1985, Drosdowsky 1993) while the opposite patterns are associated with drier conditions in Kenya (Anyamba et al. 2002, Funk et al. 2008).

Although no climate change (CC) was considered in this analysis, it is prudent to examine the trends in terms of the CC studies in these regions. Most model studies focus on low rainfall as an indicator of drought rather than dry spells in relation to future changes. Findings from GCM models suggest declining rainfall trends in the winter half of the year over much of MDB (eastern and southern) under enhanced GHGs and associated increasing rainfall trends in summer half of the year (e.g. Kothavala 1999, Hughes 2003, IPCC 2007). More recently, Mpelasoka et al. (2008), indicate 20-30% increases in drought frequency by 2030 under CC scenarios over most of Australia based on the 1975-2004 historical data. Compared to our results in the winter months, the observed declining trends in June and July in the MDB seem to affirm the previous findings. Moreover the observed increasing trends in autumn could also be a reflection of the decline in winter rainfall predicted by GCM models. In contrast, in a recent study (Fu et al. 2013), GCM results indicated mixed results such that some models project simultaneous declines and increases in summer rainfall while others predict a decrease in winter rainfall and increase in the maximum length of dry spells in the southern MDB.

Similar studies in Eastern Africa (Hulme et al. 2001, Shongwe et al. 2011) suggest a decline in drought in the Austral summer (DJF) and increase in the JJAS season under enhanced GHGs. In contrast, our study found increasing trends in the DJF months. However, in the JJAS months, our study also found increasing trends. Kabubo-Mariara & Karanja (2007) suggest that the number of drying trends in arid - semi areas is higher than in relatively humid areas although the current analysis found more trends in the wetter and coastal areas. In Kenya for instance, the IPCC and other studies seem to suggest that the warming in the Indian Ocean SSTs is related to global warming and is partly responsible for extreme dryness in the recent years (e.g. Anyamba et al. 2002, IPCC 2007, Marchant et al. 2007, Funk et al. 2010).

4.4.1. Interpreting the difference between “<month”, “full month” and “Long” dry spells trends

In this study, trend patterns for “<month” dry spells are fairly similar to the “Long” dry spells (Figure 4.3 and 6.4). While trends occurred in more locations in the “Long” dry spells relative to “< month” trends, the overall patterns in time and space were similar. This is probably because the “< month” dry spells are a subset of the true distribution of dry spells. It also shows that the increasing trends in the dry spells occur in both the short and longer dry spells.

More importantly, trends in the dry spells appeared to be more seasonal in Kenya than in the MDB again emphasizing the differences in the climates. Increases in “<month” dry spells trends characterises the weather patterns in Kenya as most occur at the end of the short rain season (February: Figure 4.3), (gradually declines more in the following months (wet/MAM season)) and shifts to July in the “Long” dry spells (mid of the long dry season). As mentioned earlier this trend appears to be related to the ITCZ when it lies further away from the equator/country around these times. Consistent with this study, Camberlin & Wairoto(1997) suggest that, dry days are

more common in months of the long monsoon seasons (March-April) than in the short monsoon season (October-December) in which dry days over most of the country are linked with strong easterly wind anomalies at the 700hpa level.

4.5. Conclusions

In conclusion, significant increasing and decreasing trends in Kenya and MDB occurred in a number of locations and at specific times for both the shorter ("< month") and longer ("Long") dry spells. The greatest increases in dry spell lengths in the MDB over the period from 1961 - 2010 occurred in the autumn season, which has major implications for local agricultural production. In Kenya, the major increases occurred in the short rains season (OND), again related to the most important agricultural production period. Overall trends in Kenya were much higher than in the MDB, possibly linked to the difference between tropics and subtropics. Relatively very few trends occurred in the "full month" dry spells, but this could be due to a lower number of observations. The bootstrap analysis revealed that of the number of locations with observed trends in the "Long" dry spells were not merely by chance. The relationship between the "Long" and "< month" trends suggests that these trends are similarly real. The current trends reflect the historical rainfall data in the two regions, but also points to possible future problems with increasing droughts.

CHAPTER 5

SEASONAL CLIMATE FORECASTING: PROBABILISTIC FORECASTING OF DRY SPELL LENGTHS IN KENYA AND THE MURRAY DARLING BASIN

Abstract

Monthly dry spell statistics (Total dry days (TDD) and Maximum dry spell length (MDS)) are predicted for Kenya and the Murray Darling Basin (MDB) of Australia using 1-, 3- and 6 lags of the Southern Oscillation Index (SOI) phases and SSTs derived from the global Oceans. Drought forecasting at the monthly scale has received less attention in these regions compared to seasonal or longer time scale forecasting.

Using a generalized additive model (GAM), binary and continuous forecasts were constructed after identification of tangible correlations between SOI-phases and SST and dry spell statistics. Two forms of forecast evaluation were used; [1] in the binary forecast a 70/30% split calibration/validation was used and [2] a one step-ahead validation, where the model was trained on all data up to a time point and then the next relevant time point was forecast and model skill of the forecasts evaluated.

The skill of binary forecasts varied from 40% to >60% while that for continuous forecasts reached up to 67% (SOI) and 72% (SST) in both regions. The impact of SOI-phase for binary forecasts was better in the 3 months lead time in Kenya and MDB in over 35% of the locations. For continuous forecasts, the SOI-phase was most significant in lag 6 in Kenya and in lag 3 in the MDB for both MDS and TDD whereas SSTs indicated better skill in some locations.

Better forecast skill is indicated in locations near the equator (2 / 3 ^{0}S – 2^{0}N) in Kenya and in locations in southern higher latitudes in the MDB and appear to increase from southern (SOI-phases) and northern (SST) locations in Kenya and increasing southerly latitude in the MDB. These findings can have implications for agriculture in these regions.

5.1. Introduction

Forecasting drought in advance can potentially minimize agriculture losses. Studies however indicate that, drought predictability is not easy (e.g. Oguntoyinbo 1986, Peters et al. 2002, Moreira et al. 2008) although there is potential for improvement

(Cordery et al. 1999). The difficulty in forecasting drought might be because the onset of drought is slower, gradual and confusing making drought hard to identify (Agnew 2000, Tsakiris et al. 2013). Often drought is identified when the impacts have appeared or the damage has already set in.

Drought predictions in Kenya and MDB (see, among many others, Ogallo 1989, Chiew et al. 1998, Stone & de Hoedt 2000) are mainly based on regression and correlation analysis using "teleconnections" between local events (rainfall) and climatic drivers such as sea surface temperature (SST). For example, indices such as the Southern Oscillation Index (SOI), the Indian Ocean Dipole (Saji et al. 1999, Black 2003, 2005) and other SST based indices are among the strongest sources of seasonal predictability (e.g. Fiddes et al. 1974, Mutai et al. 1998, Cai et al. 2009). Research suggests that these predictors can be good estimators of the local/regional climatic factors such as rainfall and dry spell onsets (e.g. Nicholls 1992, Camberlin & Philippon 2002). For example, Kirono et al. (2010) examined the relationships between several climate predictors (SOI, Niño 3, SST etc) at 1 – 2 month lead times and seasonal rainfall across Australia and found that the strongest correlations over eastern Australia were in spring and summer.

In Australia, drought is mainly linked to El Niño and cooler Indian Ocean SSTs and in Kenya drought is generally associated with the opposite patterns (La Niña) (Verdon et al. 2004, Black 2005). The El Niño-Southern Oscillation (ENSO) is the anomalous warming of SSTs in the eastern (equatorial) Pacific and influences rainfall globally. Chiew et al. (1998) for example, show that dry conditions in Australia are closely related to El Niño. The SOI phases on the other hand have been used to predict rainfall in some parts of Australia (Fawcett & Stone 2010, McCown et al. 2012, Cobon & Toombs 2013, O'Reagain & Scanlan 2013). Over eastern Africa, the European Centre for Medium-Range Weather Forecasts (ECMWF) system has been used to monitor and assess drought. Dutra et al. (2013) show that products derived from the ECMWF (SSTs, Niño3.4 etc) correlate better with precipitation in the short rain season (October–December) than in the long rain (March-May). However, the forecast system does not accurately replicate drought response to SST patterns in the Indian Ocean. The SSTs over the Indian Ocean are believed to play a critical role in suppressing moisture and convection over eastern Africa (Williams & Funk 2011). Consistent with Dutra et al. (2013), Mwangi et al.

(2014) indicate that the skill of ECWRF has higher skill in the short (October–December) rain season compared to the long (March-May) season.

Although, statistical approaches are common tools for drought prediction in Kenya and MDB, Palmer et al. (2008) suggest that the skill of seasonal models in these regions remain relatively low. For example, the maximum correlation of SOI with rainfall of 1 - 3 months lead time was at 40% against the persistent value of 44% (Hunt 1991). There have been many attempts to improve forecast skills using; integration of SOI and SST trends (Casey 1995), bias correction (Johnson & Sharma 2009), and model simulations (Evans & McCabe 2010). Using linear regression techniques, Casey (1995) indicated a 10 % increase in the skill of seasonal forecasts for Australia. Similarly, Mwale & Gan (2005) found that artificial neural networks provided a better skill with residual errors ranging between 0.4 and 0.75 than linear correlation forecasts (rmse = 0.4 - 1.2) for the September-November season in east Africa. In the more recent time, Abbot & Marohasy (2014) using the Artificial Neural Networks (ANN) to forecast rainfall in Queensland suggest that the forecast skill was better than that of forecasts from the Predictive Ocean Atmosphere Model for Australia (POAMA) of the Bureau of Meteorology (BOM). Currently, for both Kenya and Australia, forecast skill remains unclear and is suggested to be not better or about climatology (Diro et al. 2012, Abbot & Marohasy 2014). The probability of exceeding the long term average which is normally used to gauge climate forecasts in these regions have the limitation of giving no information on the expected deviations from the median forecast value.

In other occasions, there has been failure in adequately forecasting extreme events in both Kenya and Australia. For example, the forecast models did not capture satisfactorily the extreme summer rainfall event of 2010 - 2011 which had serious social and economic impacts over eastern Australia (van den Honert & McAneney 2011) whereas the 2014 seasonal forecast in Kenya under estimated the March – May rainfall (http://www.meteo.go.ke/ranet/Wx/seasonal.pdf) where many areas experienced depressed and poorly distributed rainfall.

The above examples reiterate that the skill of rainfall forecasts in these regions are generally low or modest (Ash et al. 2007) and suggests that there is a need to accurately capture and forecast the variability of observed rainfall time series in these regions.

SOI-phases based forecasts are provided for rainfall, pasture and dry-land wheat in Australia (www.longpaddock.qld.gov.au, http://www.daff.qld.gov.au/26_6256.htm) but this has not been tested in Kenya. The SOI-Phases which has persistently been used to forecast rainfall in Australia might potentially predict drought in these regions. Similarly and as earlier indicated, SSTs which are used to forecast precipitation in these regions (Ogallo 2009, Kirono et al. 2010, Schepen et al. 2011) may also be used to model drought.

This study therefore explores climatic predictors as described earlier mainly SOI-Phases and global SSTs because of their link with rainfall patterns in Kenya and the MDB of Australia. Rather than model drought, this study forecasts dry spells which are successive dry days without precipitation as an alternative to better understand drought occurrence. It has been argued that the degree of dryness (dry conditions) requires both rainfall and evapo-transpiration (Tsakiris & Vangelis 2005). The later however is hard to determine since climatic data used to derive it is not available in many places. Under water limiting environments such as Kenya and MDB, evapo-transpiration would exceed precipitation during extreme dry conditions (dry spells), meaning that dry spells can be considered over cumulative rainfall in estimating drought. According to Usman & Reason (2004), it is preferable to consider other factors such as dry spell during the cropping season since the variability of cumulative rainfall does not fully explain impacts on agriculture and a few heavy rainfall events may lead to an erroneous impression of good (growing) season.

The aim of this study therefore is to forecast monthly dry spell statistics using a Generalized Additive Model (GAM). The selection of predictors builds on previous studies in the regions (Stone & Auliciems 1992, Jury et al. 1994, Kirono et al. 2010). In order to select predictors, correlations between the predictors and dry spell statistics are first examined using simple correlation and Principal Component Analysis (PCA) with VARIMAX rotation.

5.2. Methods

5.2.1. Data and study area descriptions

Dry spell data sets are similar to the ones used in chapters 3 and 4. The analysis is confined to the period 1961-2010 and 30 locations in Kenya and 47 locations in the MDB. Kenya [region 5^0 N - 5^0 S and 34^0 E - 42^0 E] has 2 main rain seasons: Long (March-May (MAM)) and short (October-December (OND)) seasons and annual rainfall ranges from <300mm in the northern and southern regions to 2000mm in the central and western regions. The MDB [region 24^0 S - 38^0 S and 136^0 E- 153^0 E] has summer dominated rainfall in the north and mainly winter rainfall in the south and mean annual rainfall range from ≤400 mm in the western parts to > 600 mm in the south and eastern parts.

5.2.2. Selection of predictors and modeling schemes

In this study, the SOI phases (Stone & Auliciems 1992) and SSTs are used to predict the total number of dry days (TDD) and maximum dry spell length (MDS) in a month. This study does not include dry days going across months but rather those within the 1st to the last day of a month.

In their pioneer work, Stone & Auliciems (1992) show that rainfall can be associated with 5 distinct phases in the SOI. Stone et al. (1996) define the 5 SOI phases as; consistently negative [1], consistently positive [2], rapidly falling [3], rapidly rising [4] and consistently near zero [5]. The SOI phases are based on a 2-month grouping of SOI values i.e. current value and the value in the preceding month. The data for the study period was obtained from the Queensland department of primary industries (http://www.LongPaddock.qld.gov.au/RainfallAndPastureGrowth/NSW).

Global Oceanic SSTs indices were obtained from the United States (US) National Oceanic and Atmospheric Administration (NOAA) official website (http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.oisst.v2.html) and included both in situ and satellite SST observations. A total of fourteen (14) SST indices were extracted from specific regions along the Pacific, Indian, and Atlantic Oceans (Table 5.1) based on their relative correlation with the dry spell length statistics.

Pearson's correlation and Principal Component Analysis (PCA) with VARIMAX rotation (Demšar et al. 2013) was used to examine the strength of relationships between SOI-phases and SSTs and dry spells statistics. Principal components (PCs) were calculated using the 'psych' package (Revelle 2014) in the R Statistical Program (R Development Core Team, 2013). The advantage of VARIMAX rotation compared to unrotated PCs was to achieve better physical interpretation of the PCs and extraction of localized spatial patterns of variability of underlying climatic mechanisms (Zeleke et al. 2013). Moreover, an advantage of VARIMAX rotated PCs is that they are uncorrelated (Westra et al. 2010, Daneshvar et al. 2013).

Correlations between SST indices and TDD and MDS in Kenya ranged from r = 3% - 54% (-62%) (MDS), and *r* = 1% - 53% (-72%) (TDD) (Table 5.1). In the MDB, the correlations reached up to r = 57% (-59%) for MDS and up to 67% (-70%) for TDD (Table 5.2). Subsequently, the first two predictor variables with the highest correlations (each location) with dry spell statistics were used in the forecast models.

Table 5.1: MDS and TDD predictors for locations in Kenya and the corresponding highest correlation coefficients using monthly SST

Ocean Region	Predictors	Longitude	Latitude	Pearson Correlation Coefficient (r)			
				MDS		TDD	
Atlantic	ATB1	20W - 15E	10 - 20S	0.37	-0.34	0.29	-0.45
	ATB2	20W - 15E	20 - 30S	0.50	-0.35	0.41	-0.45
	ATB3	40 - 15W	20 - 10N	0.32	-0.39	0.42	-0.33
	ATB4	40 - 10W	30 - 20N	0.35	-0.42	0.44	-0.35
	ATB5	40 - 10W	40 - 30N	0.44	-0.44	0.52	-0.37
Equatorial Atlantic	EQAT1	25 - 15W	5S - 5N	0.22	-0.42	0.26	-0.46
	EQAT2	40 - 30W	5S - 5N	0.06	-0.31	0.10	-0.32
North Atlantic	NAT1	20 - 10W	30 - 40N	0.41	-0.44	0.50	-0.36
	NAT2	50 - 40W	25 - 35N	0.43	-0.45	0.52	-0.39
	NAT3	80 - 70W	35 - 40N	0.52	-0.52	0.52	-0.48
South Atlantic	SAT1	25 - 15W	40 - 30S	0.52	-0.36	0.45	-0.44
	SAT2	5 - 15E	20 - 10S	0.42	-0.43	0.36	-0.49
	SAT4	40 - 30W	15 - 5S	0.32	-0.37	0.28	-0.45
East Atlantic	EATL	10W - 10E	5N - 5S	0.34	-0.49	0.35	-0.52
Equatorial Pacific	EQPA1	150 - 140W	5S - 5N	0.06	-0.28	0.03	-0.36
	EQPA2	120 - 110W	5S - 5N	0.04	-0.24	0.01	-0.30
North Pacific	NPA1	150 - 160E	25 - 35N	0.40	-0.46	0.50	-0.39
	NPA2	140 - 150E	10 - 20N	0.40	-0.54	0.46	-0.49
	NPA7	170 - 160W	30 - 35N	0.43	-0.46	0.50	-0.38
South Pacific	SPA1	179 - 170W	20 - 10S	0.45	-0.40	0.41	-0.44
	SPA2	160 - 170E	30 - 20S	0.53	-0.43	0.48	-0.46
	SPA3	100 - 80W	40 - 30S	0.54	-0.35	0.47	-0.44
	SPA4	150 - 160E	25 - 15S	0.56	-0.50	0.53	-0.47
Equatorial Indian	EQIND1	50 - 60E	5S - 5N	0. 10	-0.54	0.04	-0.61
Indian Ocean	INDB1	35 -70E	20 - 30S	0.53	-0.42	0.47	-0.45
	INDB2	40 - 70E	10 - 20S	0.47	-0.46	0.40	-0.50
	INDB4	50 - 75E	20 - 10N	0.03	-0.54	-0.05	-0.64
North Indian	NIND1	60 - 70E	15 - 20N	0.12	-0.60	0.11	-0.65
	NIND2	80 - 90E	10 - 20N	0.24	-0.68	0.28	-0.72
	NIND3	70 - 80E	5 - 15N	0.14	-0.51	-0.09	-0.62
South Indian	SIND1	45 - 55E	25 - 15S	0.51	-0.43	0.44	-0.47
	SIND2	80 - 90E	20 - 10S	0.47	-0.47	0.41	-0.49
	SIND4	120 - 130E	15 - 5S	0.41	-0.62	0.46	-0.60
	SIND7	70 - 80E	15 - 5S	0.40	-0.49	0.35	-0.52
East Indian	EIND	90 - 110E	5N - 5S	0.20	-0.48	0.21	-0.56
East Pacific	EPAC	100 - 80W	5N - 5S	0.28	-0.28	0.20	-0.36
Equatorial Pacific	EQPA1	150 - 140W	5S - 5N	0.06	-0.28	0.03	-0.36
	EQPA2	120 - 110W	5S - 5N	0.04	-0.24	0.01	-0.30

Table 5.2: MDS and TDD predictors for locations in MDB and the corresponding highest correlation coefficients using monthly SST

Ocean Region	Predictors	Longitude	Latitude	Pearson Correlation Coefficient (r)			
				MDS		TDD	
Atlantic	ATB1	20W - 15E	10 - 20S	0.44	-0.10	0.47	-0.14
	ATB2	20W - 15E	20 - 30S	0.52	-0.09	0.57	-0.24
	ATB3	40 - 15W	20 - 10N	0.00	-0.42	0.14	-0.44
	ATB4	40 - 10W	30 - 20N	0.06	-0.44	0.19	-0.49
	ATB5	40 - 10W	40 - 30N	0.13	-0.51	0.25	-0.60
Equatorial Atlantic	EQAT1	25 - 15W	5S - 5N	0.39	-0.10	0.44	-0.12
	EQAT2	40 - 30W	5S - 5N	0.28	-0.06	0.27	-0.10
North Atlantic	NAT1	20 - 10W	30 - 40N	0.11	-0.50	0.24	-0.58
	NAT2	50 - 40W	25 - 35N	0.13	-0.51	0.26	-0.62
	NAT3	80 - 70W	35 - 40N	0.20	-0.59	0.32	-0.70
South Atlantic	SAT1	25 - 15W	40 - 30S	0.52	-0.12	0.60	-0.29
	SAT2	5 - 15E	20 - 10S	0.50	-0.11	0.58	-0.24
	SAT4	40 - 30W	15 - 5S	0.41	-0.03	0.47	-0.16
East Atlantic	EATL	10W - 10E	5N - 5S	0.48	-0.10	0.59	-0.23
Equatorial Pacific	EQPA1	150 - 140W	5S - 5N	0.28	-0.06	0.25	-0.11
	EQPA2	120 - 110W	5S - 5N	0.30	0.04	0.32	0.04
North Pacific	NPA1	150 - 160E	25 - 35N	0.11	-0.52	0.25	-0.61
	NPA2	140 - 150E	10 - 20N	0.14	-0.55	0.27	-0.61
	NPA7	170 - 160W	30 - 35N	0.13	-0.52	0.26	-0.62
South Pacific	SPA1	179 - 170W	20 - 10S	0.50	-0.13	0.60	-0.23
	SPA2	160 - 170E	30 - 20S	0.55	-0.21	0.63	-0.33
	SPA3	100 - 80W	40 - 30S	0.54	-0.14	0.61	-0.29
	SPA4	150 - 160E	25 - 15S	0.57	-0.27	0.66	-0.38
Equatorial Indian	EQIND1	50 - 60E	5S - 5N	0.32	0.02	0.37	-0.05
Indian Ocean	INDB1	35 -70E	20 - 30S	0.56	-0.18	0.65	-0.33
	INDB2	40 - 70E	10 - 20S	0.55	-0.14	0.65	-0.28
	INDB4	50 - 75E	20 - 10N	0.22	-0.20	0.24	-0.23
North Indian	NIND1	60 - 70E	15 - 20N	0.23	-0.36	0.32	-0.40
	NIND2	80 - 90E	10 - 20N	0.32	-0.46	0.41	-0.55
	NIND3	70 - 80E	5 - 15N	0.27	0.01	0.23	0.03
South Indian	SIND1	45 - 55E	25 - 15S	0.55	-0.16	0.65	-0.31
	SIND2	80 - 90E	20 - 10S	0.57	-0.14	0.67	-0.27
	SIND4	120 - 130E	15 - 5S	0.48	-0.30	0.59	-0.39
	SIND7	70 - 80E	15 - 5S	0.55	-0.13	0.65	-0.25
East Indian	EIND	90 - 110E	5N - 5S	0.28	-0.31	0.29	-0.42
East Pacific	EPAC	100 - 80W	5N - 5S	0.39	0.03	0.40	-0.07
Equatorial Pacific	EQPA1	150 - 140W	5S - 5N	0.28	-0.06	0.25	-0.11
	EQPA2	120 - 110W	5S - 5N	0.30	0.04	0.32	0.04

5.2.3. Binary forecast

A generalized additive model (GAM) for logistic regression is used to develop binary forecasts using 1, 3 and 6 months lagged SOI phases. A logistic regression model allows for development of linear relationships between binary outcome variables, for example above or below median TDD or MDS, and a set of covariates, lagged SOI phases. The advantage of a GAM is that it can model both linear and non-linear relationships between a binary outcome and the covariates. The parameters of the model are estimated via maximum likelihood method. The logistic regression model is of the form:

$$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + f(Month) + \sum_{j=1}^{5} \beta_j lagSOIPhase_j \qquad \textbf{[5.1a]}$$

$$\ln 1\left(\frac{\pi}{1-\pi}\right) = \beta_0 + f(Month) + \sum_{k=1}^{n} g_k(lagSST_k) \qquad \textbf{[5.1b]}$$

Where, ln/ln1 () represents the log odds of the response variable (above or below median TDD or MDS) with π being the probability of occurrence and $1-\pi$, the probability of non-occurrence of above or below median TDD or MDS. The *f ()* is a smooth function that smoothes the *Month* term to represent the seasonal behavior of TDD and MDS. There are 5, *j*=1:5, SOI phases (*lagSOI*Phase), the β_j*'s* are the estimated model coefficients for each phase. The *lagSOIPhase* covariate can only take on a value of 0 or 1 and only one phase will have a value one and the other four zero, depending on which phase the lagged SOI is in at any model run. The g *()* is a smooth function or a thin plate spline while, *i* is the i^{th} selected SST predictor with *n* being the total number of SST predictors used.

Split calibration/validation was used to evaluate model performance. This involved training the model on the first 70% of the data, then running the model on the last 30% of the data and calculating forecast skill.

5.2.4. Forecast Accuracy

For a two-category forecast of above/below median rainfall, the contingency table (Table 5.3) can be used to determine the accuracy of the forecasts. A forecast where the probability of above median rainfall is greater than 50 per cent is categorised as a 'yes', and where it is less than 50 per cent is categorised as a 'no'.

To evaluate binary forecast skill, a total of 5 measures or scores were used. The scores used are mostly based on the results of a 2 x 2 contingency table such as shown in table 5.3 where the cell (**i**) represents a <u>Hit</u> (Forecast = below, Observed = below), (**ii**) <u>False Alarm</u> (Forecast = below, Observed = above), (**iii**) <u>Miss</u> (Forecast = above, Observed = below), and (**iv**) <u>Correct rejections</u> (Forecast = above, Observed = above). When the contingency table uses a two-category forecast of above/below median dry spell/days to establish the skill of the forecasts, a forecast with a probability of the above median event or observation of above median event >50% is categorised as a 'yes' and a forecast or observation of median dry spell < 50% as a 'no'. A forecast therefore can only be accurate or correct if it is either a Hit or Correct rejections or inaccurate/incorrect if the score is either a False Alarm or a Miss.

Table 5.3: Example of contingency table and related skill scores

	Observed				
Forecast		**Below**		**Above**	**Marginal Total**
Below	(i)	73	(ii)	79	152
Above	(iii)	7	(iv)	81	88
Marginal Total		80		160	240

The Hit Rate (H) (also known as the probability of detection –POD) is the fraction of occurrences of an event that were correctly forecast or the estimated frequency of an event that is forecast happening assuming that the observed event have occurred. The score for correctly forecasted events range from 0 (no skill) – 1 (highest skill). The hit rate alone may however not be enough to measure forecast skill of a system since it relies on the highest number of hits and minimal number of false alarms which may not necessarily be easy to achieve. The Hit rate can be calculated from the contingency table (Mason 1982) as;

$$H = \frac{i}{(i + iii)} \qquad \textbf{[5.2]}$$

In contrast to the Hit Rate, False Alarm Rate (F), also known as probability of false detection is the fraction of non-occurrences of an event that were inaccurately forecast. From the contingency table, the False Alarm Rate can be derived as;

$$F = \frac{ii}{(ii + iv)} \qquad \textbf{[5.3]}$$

The Proportion Correct (PC) on the other hand represents the proportion (%) of correct forecasts in given forecast samples (n). It is a measure that can directly examine the quality of non-probabilistic forecasts for discrete events and penalizes forecast errors (false alarms and misses) (Wilks 2011). The PC provides the probability of a "yes" or "no" forecast occurrence with scores ranging from 0 for poor score to 1 for perfect score. It is given by;

$$PC = \frac{i + iv}{n} \qquad \textbf{[5.4]}$$

Heidke skill score (HSS) is based on Proportion Correct (PC) score modified to take into consideration the proportion of forecasts perceived to be correct by chance assuming there is no skill. It is formulated for forecasts with more than two (binary) categories in the contingency table (Jolliffe & Stephenson 2012). The value for HSS ranges from ∞ to 1 and represents the standardized number of correct hits and rejections when randomized forecasts have no skill. A score of 1 indicates perfect skill and a zero (0) indicates no skill. The HSS is defined as;

$$HSS = \frac{2(B - H)(H - F)}{F - H + B(1 + B - H - F)} \qquad \textbf{[5.5]}$$

The Brier Score (BS) a popular measure of forecast quality (Pappenberger et al. 2011, Ferro & Fricker 2012, Weisheimer & Palmer 2014). The Brier Score (BS) measures the magnitude of the forecast errors (Murphy 1973) and ranges from 0 (perfect score) to 1 (no skill). The BS can further be broken into 3 main components measuring; resolution, reliability and uncertainty. For instance, uncertainty measures the expected value of the score if climatology is used as the baseline strategy.

$$B = \frac{1}{m} \sum_{q=1}^{m} (\hat{p}_q - x_q)^2 \qquad \textbf{[5.6]}$$

Where, $\hat{p}_q$ is the estimated probability of occurrence for the first of the two forecast outcomes at verification point *q*, and x_q is the outcome for the first binary [1] or second [0] event.

All verification scores were calculated using the verification package in R (NCAR - Research Application Program, 2012). A detailed guide to verification principles can be found in Jolliffe and Stephenson (2012).

5.2.5. Continuous Forecasts

Continuous forecasts were developed using the following GAM models

$$h(x) = \beta_0 + f(Month) + \sum_{j=1}^{5} \beta_j lagSOIPhase_j \qquad \textbf{[5.7a]}$$

$$h1(x) = \beta_0 + f(Month) + \sum_{k=1}^{n} g_k(lagSST_k) \qquad \textbf{[5.7b]}$$

Where *h/h*1 is a link function of the mean μ [the expected value of dry spell length (***y***)] and the *Month*, *lagSOIPhase* and *lagSST* terms are as described in the binary model (Equation 5.1). The data was assumed to be normally distributed and an identity link function was used.

Two forms of forecast evaluation were used, 1) as in the binary forecast a 70/30% split calibration/validation was used and 2) a one step-ahead validation was used, where the model was trained on all data up to a time point and then the next relevant time point was forecast and model skill of the forecasts were evaluated.

5.2.6. Quality of continuous forecasts

Formal inferences on quality of the gam models were through checking normality in the model error residuals and adjusted r^2 (Wood 2006). Absolute diagnostic measures of accuracy used are the root mean square errors (RMSE), the coefficient of determination (R^2) and the 95% prediction confidence intervals (CI) (Wilks 2011, Jolliffe & Stephenson 2012). The lower the RMSE and the higher the R^2 scores, the better the skill of the forecast (model).

5.2.7. Further model diagnostics

Model residuals were tested for serial correlation using the Ljung-box test. Furthermore, the model residuals were checked for normality using a normal quantile- quantile plot.

5.3. Results

5.3.1. Results of Varimax – PCA analysis of dry spell statistics

After subjecting the predictors (SST/SOI-Phases) to PCA, the first 3 dominant VARIMAX rotated principal components explained 85.3% of the variance in the SSTs and SOI-Phases data (Table 5.4). Figure 5.1 shows scree plots of the dominant factors and Eigen values from the Varimax – PCA analysis of MDS, TDD and the selected SST/SOI–Phases predictors for the study locations in Kenya and the MDB.

In Kenya, the first 5 modes accounting for 64.6% of the explained variance in the MDS and 4 modes accounting for 71% of the variance in the TDD were statistically significant with eigen values greater than 1.0 (Sass & Schmitt 2010) (Table 5.1). In the MDB, the first four modes explained 66.7% of the total variance in the MDS and 75.1% of the variance in the TDD. For the SST and SOI-Phases data sets, only 3 of the dominant factors accounting for 85.3% of the variance were significant (eigen values > 1) for both Kenya and the MDB. For example, factor 1 with 11 variables comprising the climatic predictors' characteristics explained 62.4% of the total variance with eigen value of 6.9.

Table 5.4: Total (cumulated) variance explained by selected mode of the monthly MDS and TDD in Kenya (K) and Murray Darling Basin (M).

Factor	Eigen values				Variance extracted (%)				Cumulative variance (%)				
	MDS		TDD		MDS		TDD		MDD		TDD		SST/ SOI-phases
	Ken	MDB	Ken	MDB	Ken	MDB	Ken	MDB	Ken	MDB	Ken	MDB	K/M
1	10.6	18.8	12.4	19.9	35.2	40.0	41.5	43.2	35.2	40.0	41.5	43.2	62.4
2	5.1	8.8	6.0	11.2	17.1	18.7	20.0	24.3	52.3	58.7	61.5	67.5	74.2
3	1.6	1.9	1.7	2.0	5.2	4.1	5.7	4.4	57.5	62.8	67.2	71.9	85.3
4	1.1	1.8	1.2	1.5	3.7	3.9	3.8	3.2	61.2	66.7	71.0	75.1	-
5	1.0	-	-	-	3.4	-	-	-	64.6	-	-	-	-

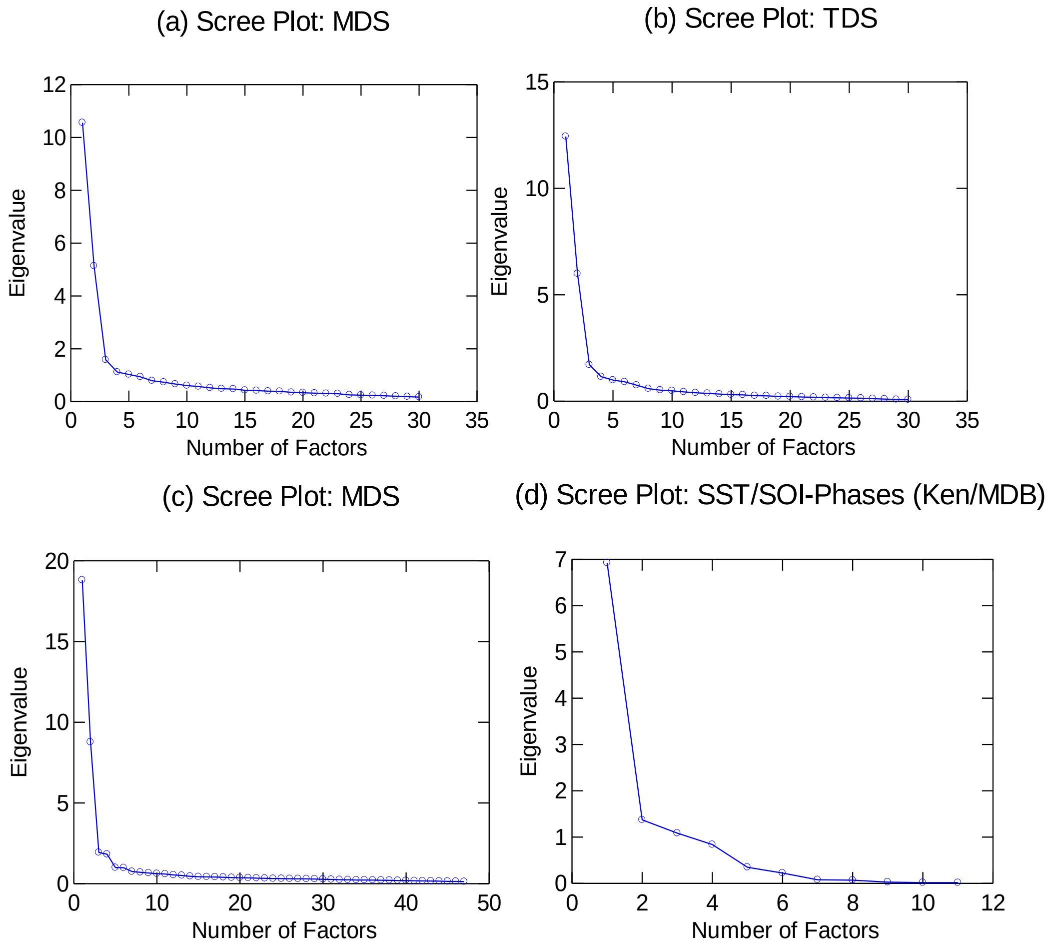


Figure 5.1: Scree's test selection of dominant principal components for (a) MDS and (b) TDD in a month in Kenya and (c) MDS in MDB and dominant PC modes for SST and SOI – Phases

5.3.2. Binary forecasts

Figure 5.2 shows the smoothed seasonal term in the logistic model for the median monthly dry spell lengths at Isiolo at 1 month lagged SOI phases. Importantly it shows that the seasonal term captures the two wet seasons (the short and long wet seasons). No strong evidence of serial correlation in model residuals was found in most of the locations in Kenya and the MDB. Furthermore, the standardized model residuals for the binary models, such as for Isiolo in Kenya, generally follow a 45 degree line indicating they are normally distributed (Figure 5.2b).

The quality of categorical forecasts for TDD in Kenya and MDB are given in Figure 5.3. The PC and Hit scores are slightly lower in all lags in Kenya (PC=0.41 - 0.66) than in the MDB (PC = 0.42 - 0.67). However, the forecast bias for TDD is larger in the MDB (max>2) than in Kenya (max < 2), suggesting a tendency to over-predict the frequency of dry days in the MDB. This might probably be the reason why the False alarms (F) are again higher in the MDB than in Kenya. Moreover, the brier scores (BS) are slightly lower 0.5 and appear to increase with the lag in Kenya topping 0.45 in lag 6 and 0.43 in the MDB.

Overall, the skill of binary forecasts averages 52% in both regions but appear to be slightly better in Kenya than in the MDB. The binary forecasts appear to show better skill at 1 and 3 month lead times in Kenya. At 6 months, the HSS shows no skill for most locations in Kenya. In contrast, the 6 months lead time shows marginally better skill in the MDB, in particular, the false alarm rate has decreased slightly.

In addition, for the binary forecasts in Kenya, the SOI-phase term was significant in lag 3 for the MDS (33% of locations) and TDD (40% of locations). Similarly, the SOI-phase was significant in the MDB in lag 3 for the MDS (28% of locations) and TDD (32% of locations). In other words, the SOI-phase is important in the 3 month lead time prediction in these regions. Even when SOI was not significant, it was found that including it in the model generally slightly improved the adjusted r^2.

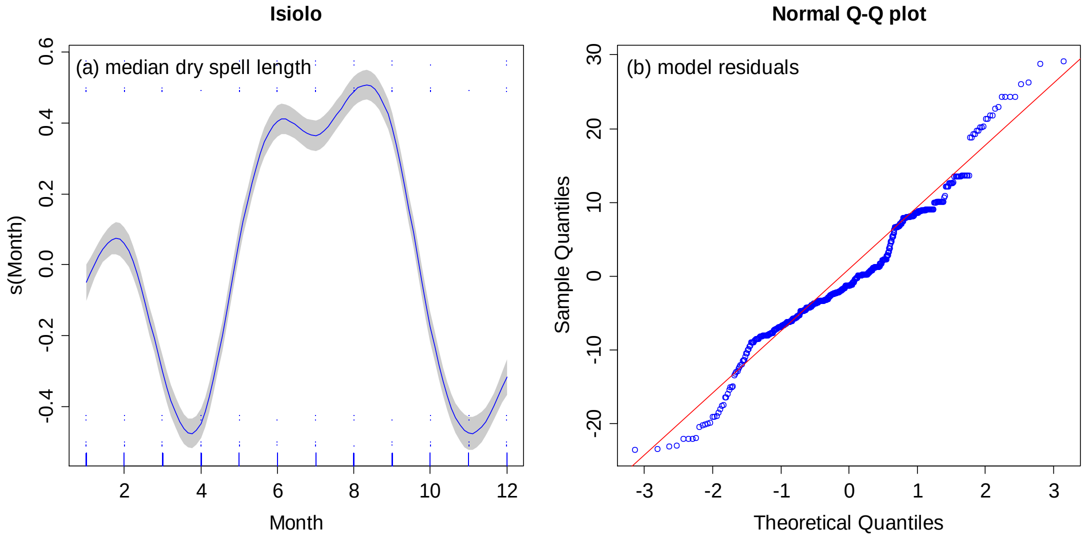


Figure 5.2: Effects of (a) Month (seasonal term) on the median monthly dry spell lengths for binary forecast for Isiolo at one month lagged SOI phases and (b) normal Q-Q plot of the residuals. The blue dots in (a) are the partial residuals and the grey shade is the GAM estimate for upper and lower 95% confidence limits.

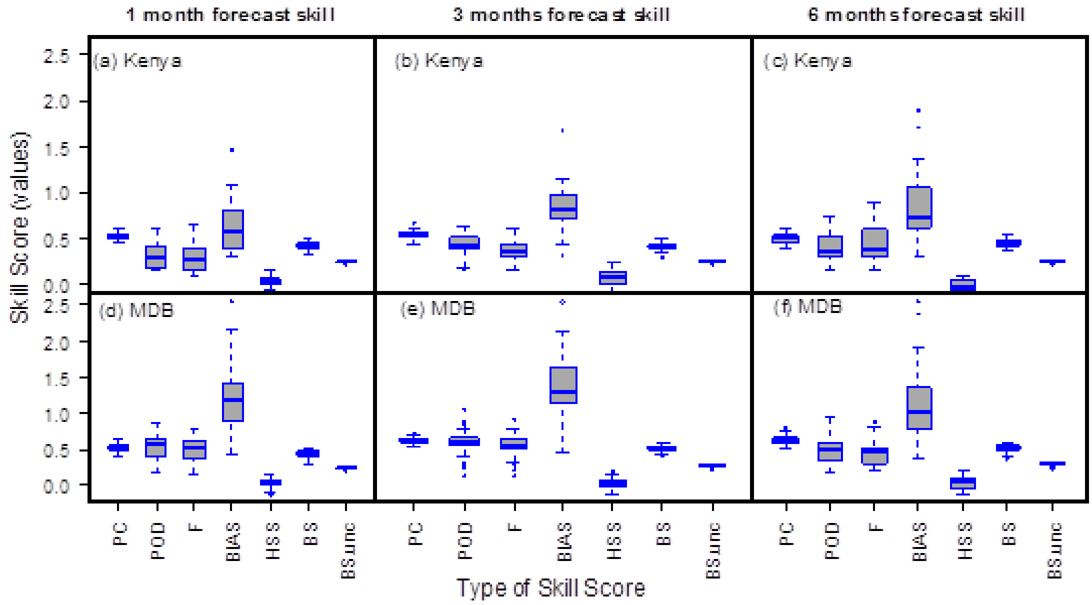


Figure 5.3: Skill scores for total dry days (TDD) by 1, 3 and 6 months lagged SOI phases in Kenya (top panel) and MDB (bottom panel). BS.unc is the uncertainty component of the brier score (BS). A perfect score for H, POD and HSS is 1. A perfect score for F and BS is 0 and for BIAS is 1 but ranges from 0 to infinity.

5.3.3. Continuous forecasts

An example for the results for 1-month lead time forecasts using lagged SOI-phases for Isiolo in Kenya is given in Figure 5.4 and Figure 5.5. The 3-month lead time forecasts for Lake Eildon in the MDB are appended in Figure 5.6. Both model evaluations methods yielded similar results with the one-step ahead yielding a R^2 = 56% and a RMSE=6.3 (Figure 5.4b). For TDD (Figure 5.5b) the R^2 is 57% and

RMSE=6.3. The observed MDS is higher than the forecasted upper bounds (95% CI) for most of the periods. In contrast, the skill of lagged SST models for Isiolo improved slightly over those of the lagged SOI-phases (R^2 = 57.5%, RMSE=6.0 (MDS)) while the skill for TDD forecasts reduced slightly (R^2 = 54%, RMSE=6.6). Similarly, for Lake Eildon, the forecast skill (TDD) improved from R^2 = 66.1% (lagged SOI-phases (3-Month lead)) to R^2 = 71% (lagged SST).

A summary of the results for all locations in Kenya and MDB are displayed in Figure 5.7 and Figure 5.8 respectively. In Kenya and the MDB, the distribution of the R^2 and RMSE was similar for all three lead times for the lagged SOI-phases forecasts but tended to improve for some locations for lagged SST forecasts. In Kenya (Figure 5.7) for example, skill for lagged SST forecasts for MDS ranged from R^2 = 21.9% - 68% (lag 1), R^2 = 20.6% - 68.3% (lag3) and R^2 = 22.3% - 66.7% (lag6). For TDD, the skill varied from R^2 = 30.5% – 68% for lag1, R^2 = 27.2% – 69.3% for lag3 and R^2 = 28% - 64.7% for lag6. In the MDB (Figure 5.8), the skill (R^2) of lagged SST forecasts ranged from 3% - 49.1% (lag1), 5.4% - 46% (lag1) and 8.5% - 45.3% (lag6) while those for TDD ranged between 14% and 71% (lag1), 10.1% and 68.4% for lag3 and R^2 = 5.7% - 72% for lag6. Overall, forecasts for TDD tended to be better than those for MDS for both Kenya and MDB in both cases. In general, forecasts skill tended to be higher in Kenya than in MDB indicated by the central mass of the box plots having higher R^2 in Kenya than in MDB as well as the differences In the RMSE values between the 2 areas (Figures 5.7 and 5.8)

For continuous forecasts, the SOI-phase in Kenya was most significant in lag 6 for the MDS and TDD (40% of locations in each case). Similar to the binary forecasts, the SOI-phase in the continuous forecasts in the MDB was most significant in lag 3 for the MDS (21% of locations) and TDD (28% of locations). In the case of lagged SST, the highest forecast skill (R^2~70 %) occur in lag 3 in Kenya and in lag 6 in the MDB suggesting the potential for higher skill in longer lead times in the regions.

Comparing this with climatology in these regions (R^2 = 32% (Kenya) and R^2 = 34%) the skill of the forecasts at the 3 lead times improved by about 25% in Kenya and 22% in the MDB.

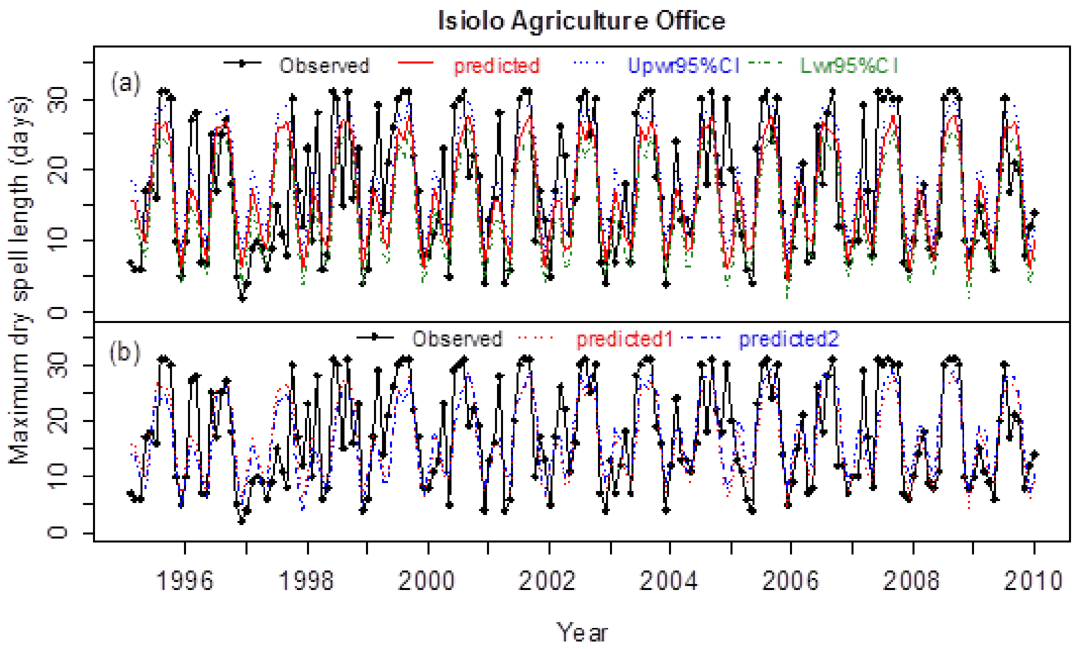


Figure 5.4: (a) Numerical forecast of MDS versus the observed for Isiolo in Kenya by 1 month lagged SOI phase. The plain solid line indicates the predictions calibrated from the 1961-1995 dry spell data sets. The dotted and dashed lines indicate the upper and lower 95% confidence intervals respectively. (b) Numerical forecast of MDS (bottom panel) based on the one-step procedure and 1 month lagged SOI phase. The dotted (predicted1) and dashed (predicted2) lines represent the predictions from the procedure in (a) and in the one step respectively.

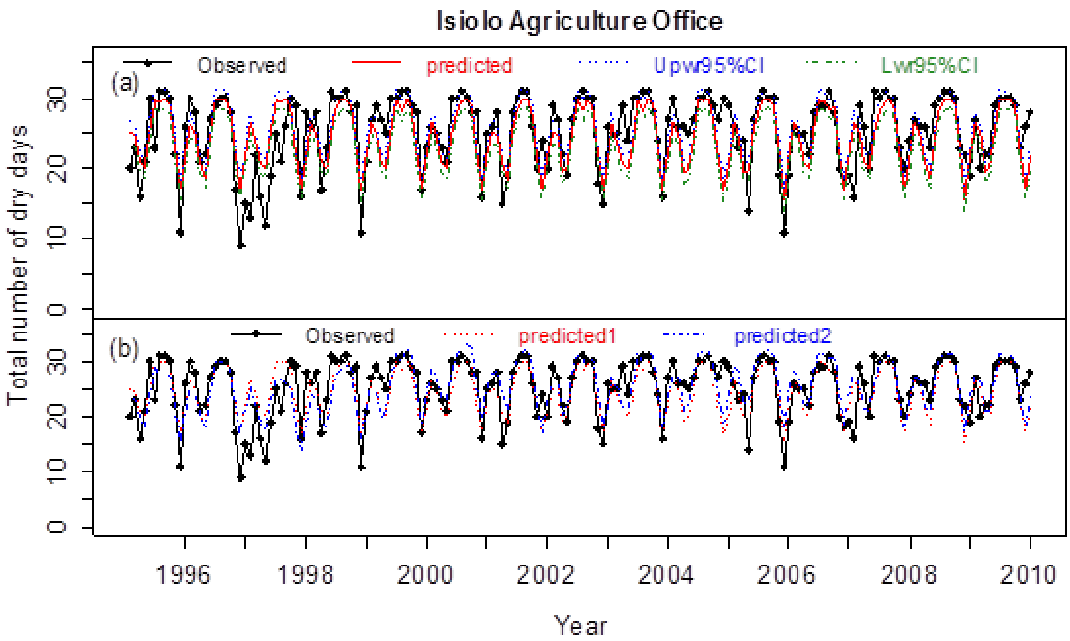


Figure 5.5: (a) Numerical forecast of TDD (top panel) versus the observed for Isiolo in Kenya based on 1961-1995 calibration periods and by 1 month lagged SOI phase. As in Figure 5.4, the dotted and dashed lines indicate the upper and lower 95% confidence intervals respectively. (b) Numerical forecast of TDD (bottom panel) for Isiolo from the one-step procedure and by 1 month lagged SOI phase. The dotted (predicted1) and dashed (predicted2) lines represent the predictions using the procedure in (a) and in the one step respectively.

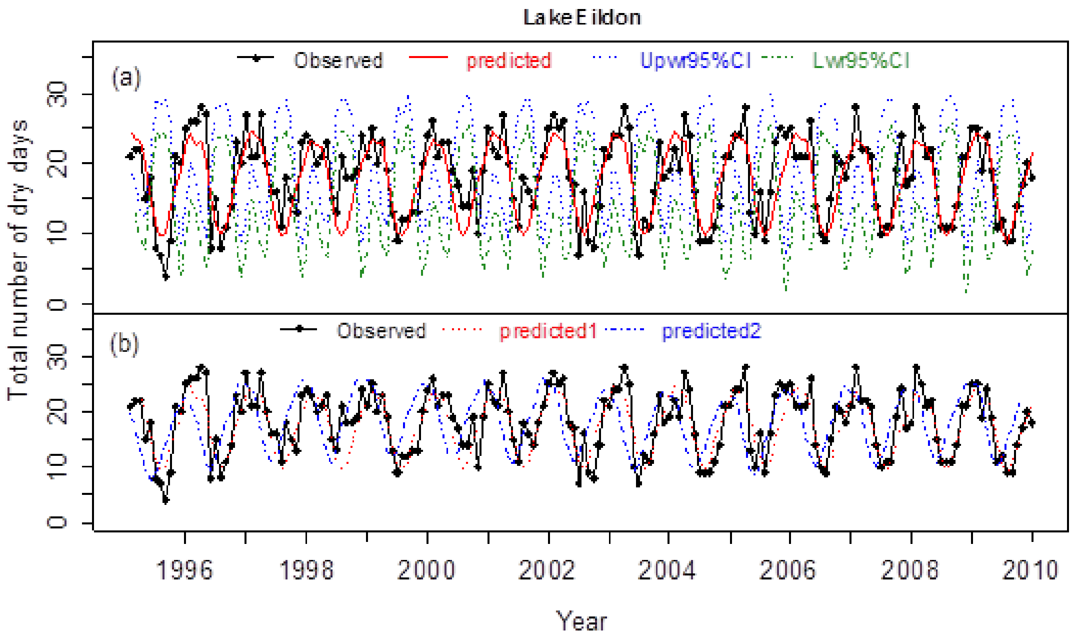


Figure 5.6: (a) Numerical forecast of TDD (top panel) versus the observed for Lake Eildon in MDB based on the 1961-1995 calibration periods and by 3 month lagged SOI phase. The dotted and dashed lines indicate the upper and lower 95% confidence intervals respectively. (b) Numerical forecast of TDD (bottom panel) for Lake Eildon from the one-step procedure and by 3 month lagged SOI phase. The dotted (predicted1) and dashed (predicted2) lines represent the predictions from the methods in (a) and one step respectively.

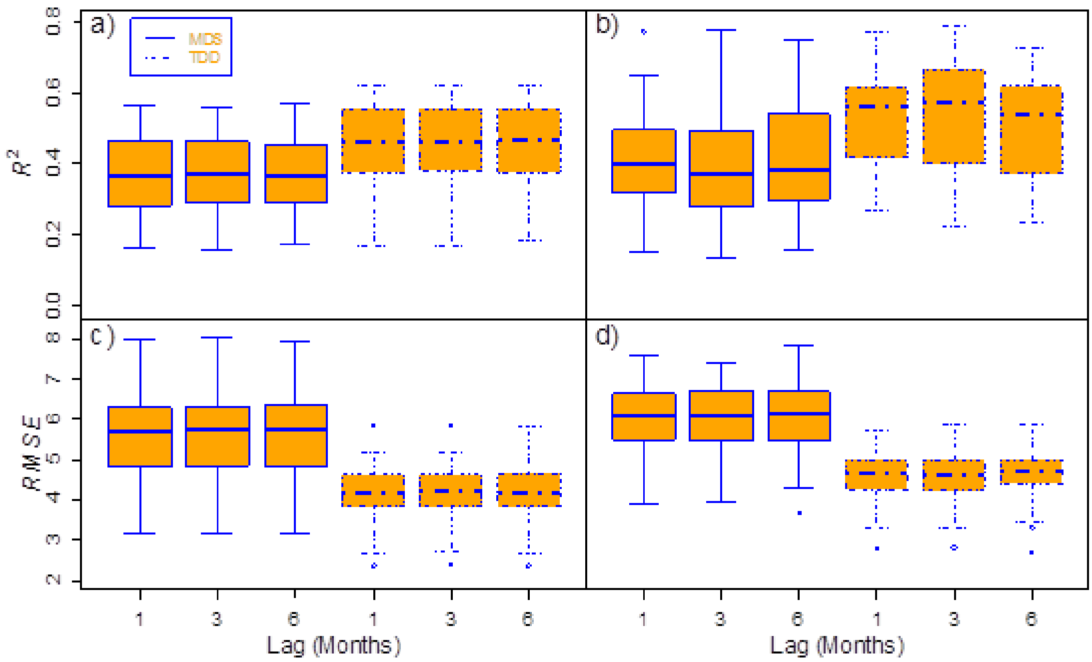


Figure 5.7: Box and whisker plots for R^2 and RMSE values for numerical forecasts of MDS (solid lines) and TDD (dashed lines) based on (a & c) lagged SOI-Phases and (b & d) SST predictors in Kenya validated at one-step ahead.

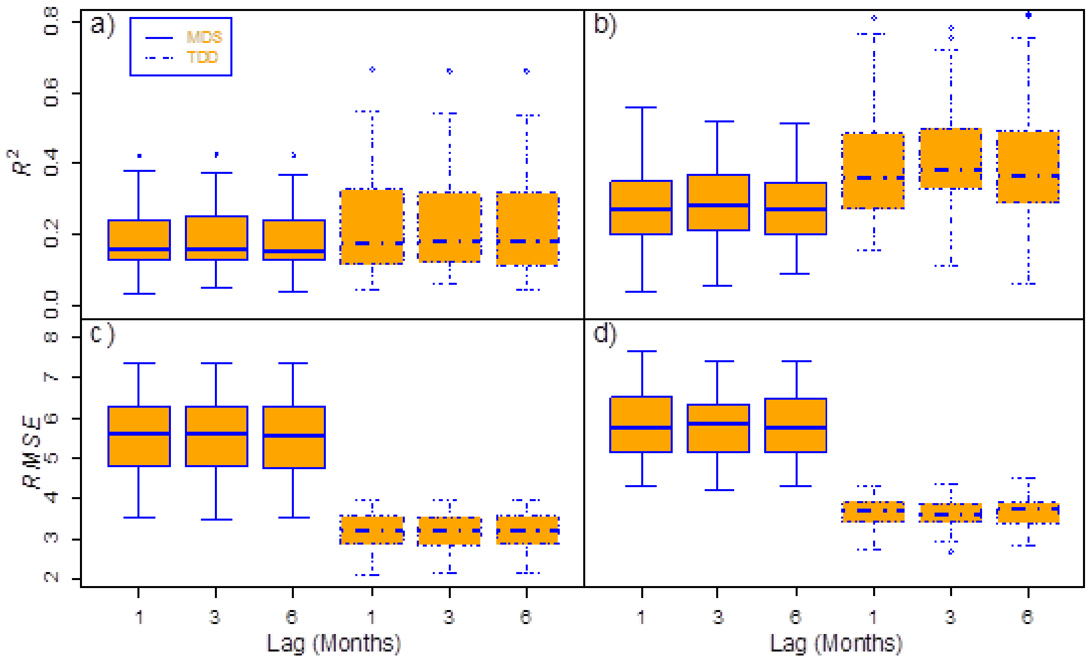


Figure 5.8: Box and whisker plots for R^2 and RMSE values for numerical forecasts of MDS (solid lines) and TDD (dashed lines) based on (a & c) lagged SOI-Phases and (b & d) SST predictors in MDB validated at one-step ahead.

5.3.4. Variation of forecasts skill by location

Forecast skill can vary from one location to another. To find out, the skill of continuous forecasts are plotted for each location by latitude and presented in Figure 5.9 and Figure 5.10. Figure 5.9, shows that higher forecast skill, occur mostly in locations near the equator (-2^0S – 2^0N) in Kenya and in locations in southern higher latitudes in the MDB (Figure 5.10). Forecast skill in Kenya seems to gradually increase from southern locations to near 2^0N and increase with increasing southerly latitude in the MDB at least for locations > 33^0S .

In contrast to the spatial variation in forecast skill of lagged SOI-phases (Figure 5.9a), the skill for lagged SST tend to be highest in locations around 2^0S and 3^0S with a tendency to declining trend northwards. In the MDB, forecasts skill tend to increase southwards for lagged SSTs (Figure 5.10b) with an average of 5% difference relative to forecast skill for lagged SOI phases (Figure 510a).

Overall, the skill in the MDB is lower (lower R^2) than in Kenya. The low performance in forecasts skill in locations north of the MDB may be due to weak relationship of SOI with drought in these regions. Moreover, 20% of locations in Kenya had skill (R^2) ≥50% for MDS forecasts and 57% of locations, had skill ≥50% for TDD forecasts. In contrast, only 11% of locations indicated skill exceeding 50%

in the TDD forecasts and none of the locations had skill exceeding 41% for MDS dry spells in the MDB. This however was different for SST based forecasts for locations in the south of 34^0 in which the forecast skill exceeded 44% with the maximum reaching 72% at about 38% of the locations.

Again, the spatial variation in skill of forecasts for lagged SSTs was dominant in the 3-month lead time in Kenya and the 6-month lead time in the MDB.

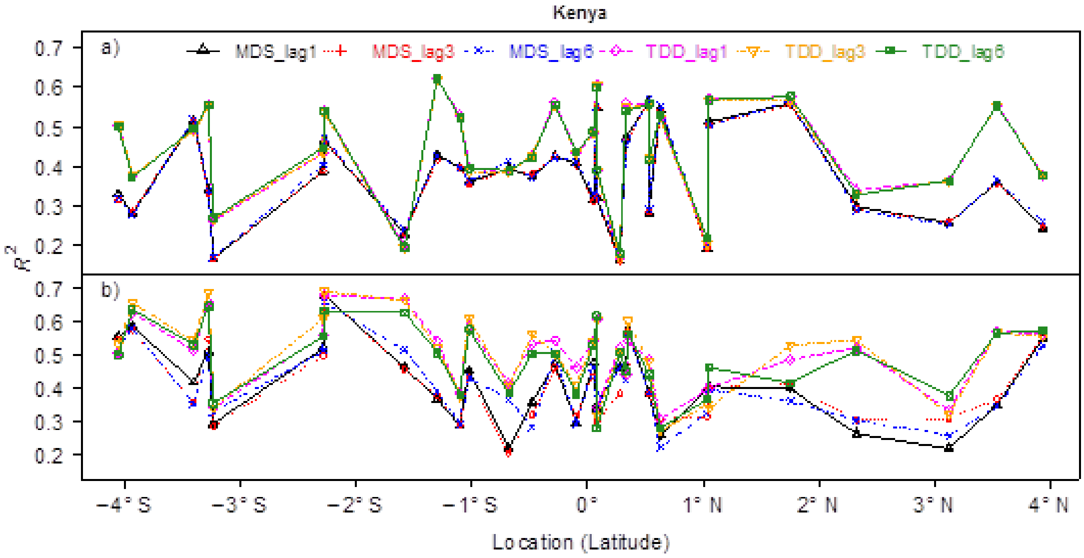


Figure 5.9: Variation of R^2 scores by location (latitude) for (a) lagged SOI and (b) lagged SST based forecasts at 1-, 3-, and 6- month lead times in Kenya.

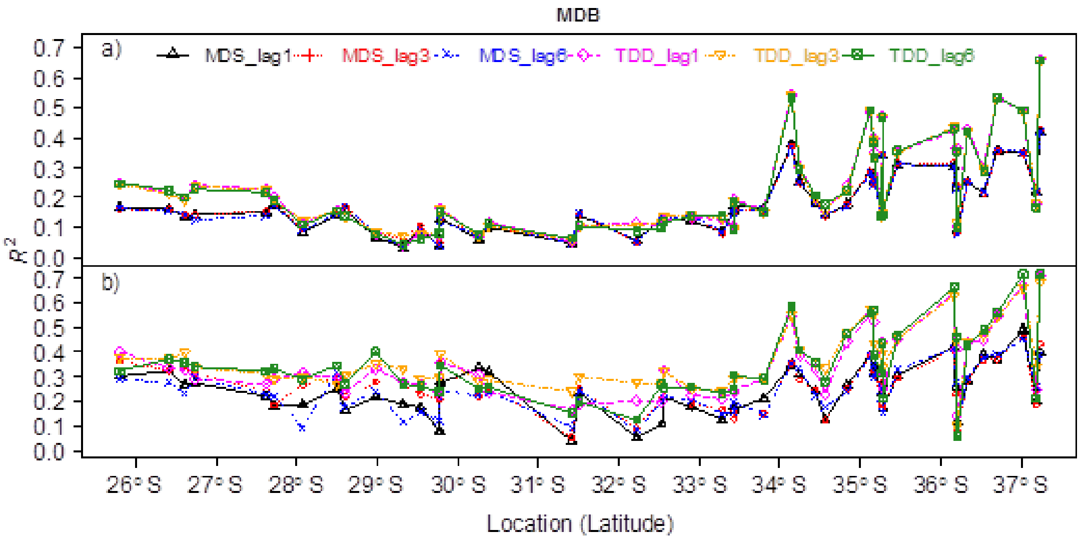


Figure 5.10: Variation of R^2 scores by location (latitude) for (a) lagged SOI and (b) lagged SST based forecasts at 1-, 3-, and 6- month lead times in the MDB.

5.4. Discussion

Drought forecasting at the monthly time step has received less attention compared to seasonal or longer time scale forecasting (e.g. Barnston et al. 1994, Mishra & Desai 2005, Fernández et al. 2009). Forecasting of dry spell length at a monthly time scale can be important for agriculture planning particularly in Kenya and the MDB. One particular motivation from the present findings is that in some locations, 1-, 3- and 6-month lead time forecasts captured some of the seasonal to inter-annual variability and turning points in the observed dry spell data series in Kenya and MDB (e.g. Figure 5.11).

This study found that monthly forecasts of dry spells over these regions have some skill which range between 10% and 66% using lagged SOI-phases and up to skill of 72% using SST based forecasts. In contrast to our findings, there is a lack or no clear information regarding accuracy of drought forecasts in these regions. A study by Krishnamurti et al. (1995) for example, examined the predictability of wet and dry spells in Northern Australia in only the 30-60 day oscillation monsoon and for March 1992 period. They observed that SSTs indicated low skill of about 25days in the 30-60 circulation. Even with formal tests of accuracy of rainfall forecasts, studies concentrate on the value of using forecasts rather than the nominal skill of forecasts (de Jager et al. 1998).

The current forecasts skill was obtained based on the 1996-2010 validation period, which coincidentally, corresponds to a period when severe droughts and some extremely wet conditions were experienced in these regions (e.g. Botterill 2003, Speranza et al. 2008). Goddard et al. (2003) cites a lack of knowledge about most real-time operational skill of forecasts as the greatest obstacle to use of forecasts which means the validity of forecasts remain questionable. For example, despite numerous studies on regional crop yields suggesting skill in rainfall forecasts in Australia (MDB) (e.g. Hammer et al. 1996, Meinke & Stone 2005), these studies do not objectively verify the forecasts accuracy. One exception is the work of Barros & Bowden (2008) in which drought forecasts 12-month in advance were predicted for the MDB with variances reaching up to 60%.

In light of the above, it appears that accurately forecasting dry spells can be of benefit where the rainfall forecasts have failed. In these regions, modest skill of dry spells at the - 1, -3 and 6 months lead times can open a new avenue for farmers to cushion against drought risk by integrating the forecasts information in farm plans to complement other risk management measures. Considering that drought is a key threat to agriculture production in Kenya and the MDB, rainfall forecasts or cumulative rainfall may not be so useful in detecting consecutive occurrences of water deficiency (dry days) particularly if heavy rainfall events occur in 2 different days separated by long dry periods (e.g. 1 June and 18 July). In this case, a dry spell forecast may be more appropriate for agriculture management of risk. Moreover, in agriculture terms, the most suitable time to make a decision for the forthcoming season in response to a dry spell forecast is during the wet or transitional season such as in January – February in Kenya and in summer in the MDB. However, even where dry spell or rainfall forecasts are of reasonable skill, they can only be valuable if they can be integrated in agriculture management plans (Ash et al. 2007).

In Kenya, no study as yet has formally tested the skill of drought forecasts based on the SST or SOI-phase regime and dry spells. However, one study (Farmer 1988) indicated a skill no better than climatology in the prediction of seasonal rainfall based on lagged SOI relationships while Mwangi et al. (2013) evaluated the probability of drought using the European Centre for Medium-Range Weather Forecasts (ECMWF) products in East Africa and showed that precipitation indicated better skill for the short (October–December) rain season compared to the long (March–May) rain season.

Climatology is the proxy used to define forecast probabilities for 2 category forecast i.e. below a normal category (e.g. median) or above a normal category, generally indicates the assumed average climate of a location or region (Gigerenzer et al. 2005).

This study, found teleconnections between the observed dry spell statistics variability patterns and SOI phases and SST variability modes over the Atlantic, Indian and Pacific oceans from which, the highest (significant) correlations between MDS and TDD and the 2 predictors provided useful indices to forecast dry spells at the monthly scale in these regions. In contrast to this study, relationships between precipitation and global Oceanic SST derived indices have been documented in these regions with a greater emphasis on the linkage with the ENSO phenomena and other climate drivers such as the Indian Ocean Dipole (Black et al. 2003, Wang & Hendon 2007, Ummenhofer et al. 2011, Smith & Timbal 2012, Mwangi et al. 2014).

In the current study, binary forecasts demonstrated modest skills ranging from 40-67% which is better than climatology. Comparing with skill of a climatology forecast

is useful in assessing the overall performance of a new forecast (Piechota et al. 1998). Binary forecasts have been used by Chifurira and Chikobvu (2010) to predict inter-annual droughts in Zimbabwe. They found that a 10% and 90% probability of current drought was predicted if a -ve and a +ve SOI value respectively from the previous year was used. Moreover, skill >70% for drought forecasts utilizing past drought indices (values) have been reported for longer lead times (Özger et al. 2012).
As well as obtaining some skill for continuous forecasts in this study; the predictability of dry spells using SOI-Phases seems to be more viable in Kenya than in the MDB while using SSTs to predict dry spells improved the skill substantially in some locations in both regions. The SOI phases were found to be significant in the 3 and 6 month lead times in over 1/3 of the locations in Kenya whereas this was found in lag 3 for locations in the MDB. There has been suggestions that the lower predictive power of SOI in the latter region might be due to the high sensitivity of Australian rainfall to the spatial structure of the SST anomalies during El Niño in the Pacific (Troccoli et al. 2008, Lim et al. 2009). Furthermore, while some skill was obtained with the SOI phases, this research did not examine whether forecasts can indicate better skill in certain seasons or months or whether they can also be tailored to suite specific cropping stages in these regions. The dependence on the past observations of the climate tend to occur most strongly at various underlying seasonal lags (e.g. Chiew et al. 1998, Kim & Valdés 2003). However, results obtained using lagged SSTs in these regions suggest that improvement in dry spell forecasts can be achieved if Oceanic SST areas with stronger correlations with the localized climate can be identified.
This study considers the SOI phases as a predictor of dry spell as it is a reasonably well understood climate index whereas SSTs have extensively been used to develop relations with rainfall in these regions. Ogallo et al. (1988) showed that the SOI was strongly related with rainfall over eastern Africa but in contrast Ropelewski & Halpert (1987) suggests that the SOI is weakly related to rainfall in the region but can cause enhanced precipitation during the El Niño events. The impact of ENSO differs between Kenya and the MDB. The magnitude of drought is enhanced in eastern Australia (MDB) and in Kenya during El Niño and La Niña periods respectively (Usman & Reason 2004, Ummenhofer et al. 2009).
The skill associated with SOI phase suggests that there may be prospects of skillful drought forecasts in these regions. However, there are more potential predictors of

drought as indicated from the results using SSTs in these regions. In Australia, SST-based skill for seasonal rainfall has the potential to exceed 60% (Lim et al. 2009) whereas in Kenya this ranges between 30% and 60% (Mutai et al. 1998). These studies seem to be in agreement with this study and also reflect the potential skill for seasonal drought forecasts in these regions. Some studies have suggested that the Inter-decadal Pacific Oscillation (IPO) may indicate some skill in long lead drought forecasts over Australia (e.g.Kiem & Franks 2004) although others (e.g. Verdon-Kidd & Kiem 2009) suggest that the predictability of drought may be related to different climatic patterns in the Pacific, Indian and Southern Oceans. Furthermore, there is evidence that NIÑO4 (region 5^0 S to 5^0 N, 150^0 E to 160^0W), and the Pacific Ocean thermocline may be better predictors of precipitation (drought) in Australia (Kirono et al. 2010). Similarly, the tropospheric wind anomalies and tropical cyclones activities in Indian Ocean may also provide better predictors of drought in Kenya (Ambenje 2000, Camberlin & Philippon 2002). Finally, dynamical models such as the Predictive Oceanic and Atmospheric Model of Australia (POAMA) currently used by the Australian Bureau of meteorology have been shown to predict drought 3 months in advance but tends to underestimate the magnitude of drought in the region (Lim et al. 2009).

Better skill indicated for the total number of dry days compared to maximum dry spell length maybe of some benefit for agriculture in these regions. Whereas, the occurrence of dry days during the growth stages of crops is one of the main causes of crop failures (Mishra & Desai 2005), forecasting the number of dry days or the maximum dry spell can increase the level of preparedness and influence better agriculture management. In other words, dry spell forecasts can be used to advice on water conservation where agriculture management measures designed during wetter seasons may fail if drier conditions are predicted in the following season. For instance, dry land winter and summer cropping in north eastern parts of MDB benefits from water stored in heavy clay soils across fallows, which is used to and act as cushion for the next crop against likely low seasonal rains are very low (Meinke & Stone 2005). In addition, forecasts can be used to advice farmers on food security such as the case of the forecast of the 1986 -1987 drought in Ethiopia where the government advice to farmers enable significant saving on the amount of relief food required. However, this alone may be insufficient where the ability of the farmer to respond to the forecasts is constrained by other operational or long term factors.

Whereas drought prediction remains a major challenge, this study has demonstrated that using SOI phase and SST; it is possible to obtain some skilful forecasts.

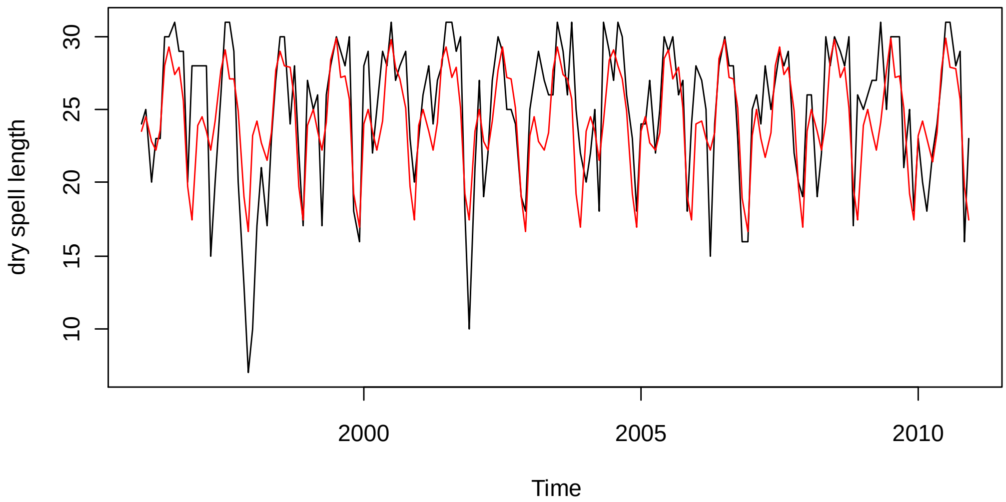


Figure 5.11: Predicted versus observed TDD for Voi in Kenya at the 3 month lead time using lagged SOI-phases.

5.5. Conclusions

This study shows that the skill of SOI phases in predicting monthly total number of dry days and the maximum dry spell length in Kenya and the MDB ranges from <20% – 67% while the skill extends to a maximum of 72% using SSTs. The skill of TDD supersedes that of MDS in both regions but skill for both MDS and TDD is better in Kenya than in the MDB.

In addition, impact of SOI-phase for binary and continuous forecasts was found to be better in the 3 and 6 month lead time in Kenya but in the 3-month lead time in the MDB. Nevertheless, better forecast skill was indicated in locations near the equator (2^0S – 2^0N) in Kenya with the SOI phases and around 2^0S - 3^0S for SST and in locations in southern higher latitudes (>34^0S) in the MDB and skill appears to increase from southern locations (SOI phase) and from northern locations (SST) in Kenya and increasing southerly latitude in the MDB in both cases.

The challenge still remaining is to find a way to capture all the inter-intra annual variability in the observed time series both at the monthly and seasonal time frames. Some prospects may be the inclusion of other predictors in the model such as NIÑO4, Pacific Ocean thermocline, tropospheric wind anomalies and tropical cyclone activities in the Indian and Pacific Ocean or the principal components derived from the relationships with SSTs. The current findings can have implications for agriculture in these regions.

CHAPTER 6

MANAGING THE WATER CYCLE IN KENYAN SMALL-SCALE MAIZE FARMING SYSTEMS (PART 1): FARMER PERCEPTIONS OF DROUGHT AND CLIMATE VARIABILITY

Abstract

Examining 'dryness'/drought variability in Kenya, is motivated by farmers perceptions that there has been decline in rainfall and yields in recent years. In recognition, farmer's perceptions of climate variability were examined in the 2 agro-ecological regions of Kenya: Laikipia west (semi-arid) and Vihiga district and compared with observed meteorological data.

Data was obtained through a questionnaire and semi-structured interviews and the results were analysed using both descriptive and inferential statistical methods. A total of 133 and 111 farmers were sampled from the 2 regions, respectively.

Most farmers perceived changes in the seasonal and long term patterns of rainfall and dry conditions in both areas, with significant changes occurring after the 1980's. Actual records indicated that rainfall and drought conditions varied more in the short rain season than in the long rain season in Laikipia compared to Vihiga. Rainfall patterns in the two regions showed no significant trends in the overall period, while farmers reported that the onset of rains and the planting times are later. Interestingly, farmers managed climate variability on their farms mainly through short term actions; changing planting times, crop diversification, water conservation and replanting in response to factors such as delay or early rainfall onset.

This study recommends that more research should establish why farmer's perceptions are opposite to observed climatic patterns and whether this could be related to climate change. This can improve advice to farmers to monitor and manage climate variability.

6.1. Introduction

Climate change and variability (CCV) is a major global debate (Akong'a et al. 1988, IPCC 1996, Handmer et al. 1999, Griggs & Noguer 2002, Blanc 2009, Bulkeley 2013). Scientific analyses point at human activities as the cause of CCV and global warming (Stocker et al. 2013) which in turn is affecting climatic patterns globally (Parry et al. 2004, Lobell et al. 2011). More specifically, temperature increases due to global warming have altered the distribution and quantity of rainfall in many places and affected agriculture production and other activities (Rosenzweig et al. 2001, Schmittner et al. 2008, Kurukulasuriya & Rosenthal 2013).

In the Sub-Saharan Africa (SSA), agriculture is mainly rain-fed and farmers recognise that erratic rainfall patterns affect their farming (Ngigi et al. 2005) and this makes the SSA one of the most vulnerable regions to climate impacts (Kotir 2011). Climate analysis by Ferede et al. (2013) show that a 3^0C rise in temperature and a 12.0 mm decline in precipitation will result in a 10% loss in crop production in the SSA region. Overall, these have far reaching implications for food security in the region since agriculture covers most of the cultivated land and about ¾ of the population depends on it for their livelihoods (Calzadilla et al. 2013). In this regard, some studies have assessed the impacts of CCV on agriculture in Africa with a view to understand and manage climate variability (e.g. Downing et al. 1997, Mendelsohn et al. 2000, Jones & Thornton 2003, Schlenker & Lobell 2010, Ferede et al. 2013).

Cropping is tightly intertwined with the seasonal rainfall in Eastern Africa (EA). Rainfall in EA emenates from complex interactions between sea surface temperatures (SST) and other global or local climate patterns (Ogallo et al. 1988, Mutai & Ward 2000, Gitau et al. 2013). As such, much of the interannual climate variability in Kenya and the region can be described using rainfall patterns (e.g. Ogallo 1989, Camberlin et al. 2009).

Of all climate variability in Kenya, dry spells and droughts are significant factors that can affect agriculture and often have been linked with crop losses (Huho et al. 2011). Since Kenyais an agricultural economy (Hassan & Karanja 1997), understanding theseasonal variability in 'dryness' (drought) becomes very important because planting corresponds with the rainfall seasons. The country experiences about 1 to 2 major droughts every 5-7 years and normally lead to severe food crisis (Herrero et al. 2010).

Examining 'dryness'/drought variability in Kenya, is motivated by the fact that farmers in Kenya and the region, perceive that there has been decline in rainfall and yields in recent years (Ovuka & Lindqvist 2000, Gbetibouo 2009, Mertz et al. 2009, Moyo et al. 2012, Yaro 2013). This notwithstanding that agriculture in most semi-arid tropical regions is found to be mostly characterized by relatively low yields associated with dry spells or low rainfall (e.g. Rockström et al. 2003).

Drought impacts and variability and how farmers perceive and respond to climate variability in maize farming systems in Kenya has been examined (Campbell 1999, Speranza et al. 2008, Calzadilla et al. 2013), with participatory methods most frequently used (e.g. Roncoli et al. 2010, Ogalleh et al. 2012). A recent survey across several agroecological zones of Kenya, revealed that over 80% of farming households had experienced drought over the last 5 years while drought and erratic rains were mentioned to be the most critical climate-related shocks (Bryan et al. 2011). Most farmers observed that the average rainfall had declinedand temperature increased in the last 20 years although the observed actual rainfall and temperature showed no significant trends in most of the locations. Esperanza et al. (2008)had looked at the linkage between farmers actions (farm practices) and vulnerability to drought and food insecurity in semi-arid areas of Kenya. Characteristic of most semi-arid areas, the study revealed presence of high temporal rainfall variability in both long and short rain seasons and significant variation in the onset in contrast to farmers' perception that onsets were later than expected. High temporal variability of rainfall in semi-arid areas is probably due to few rainfall events which account for most of the total rainfall in the season. The study concluded that other than drought and rainfall variability, lack of inputs and other constraints also contibute to vulnerability of farmers to food insecurity, a view shared by others in the region (e.g. Carter & Wiebe 1990, Barron 2004, Thornton et al. 2011).

Ovuka & Lindqvist (2000) showed that rainfall in central highland of Kenya (humid) exhibited high interannual variability, which seems counterintuitive. Whereas declining trends in rainfall were indicated in both rain seasons and dry spells tended to be more frequent in the short rains season than in the long rains seasons, it was consistent with farmers perceptions in the region. As would be expected, the occurrence of dry spells during the short rain season contributed to reduced yields. This contrasts with semi arid areas, where the short rains are deemed more reliable for cropping than the long rains. In most areas of Kenya, food shortages are often related with occurrence ofdrought or insufficient rainfall (Rockström et al. 2003, Bryan et al. 2011).

To analyse drought, stochastic and water balance models and other indices such as; standardized rainfall anomalies, the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI) (Ntale & Gan 2003, Speranza et al. 2008, Chumo et al. 2011). Detailed reviews on drought indices can be found in many studies (e.g. Alley 1984, Hayes 2000, Heim 2002, Tsakiris & Vangelis 2005).

While drought and rainfall patterns in Kenya appear to change, farmers perceptions either match or are opposite of actual climate observations in different areas. In addition,clear quantitative analysis of actual crop yields relative to drought variability is lacking. Understanding the relationship between true climate variability (degree of dryness or wetness) and maize yields in different seasons would allow farmers to adjust management.

Few studies focussed on recent years (seasons) even though a number of significant droughts have occurred in recent years. Most of the previous analyses have been based on rainfall, mainly at the seasonal or annual timescales. Dry spell lengths might offer another view on drought as it describes both the intensity and the occurrence of drought.

The objective of this study therefore is to analyse meteorological data for Laikipia (semi-arid) and Vihiga (humid) districts of Kenya and specifically to:

i. Explore intra-seasonal to seasonal variability in 'dryness' using the indicators 'dry spell' and 'Aridity index'
ii. Explore relationships between actual climatic observations (climatic indicators) and farmer perception of climatic variability
iii. Establish and provide an inventory of management options farmers use in response to climate variability

6.2. Research methods

6.2.1. Study area

Laikipia west district lies in the central region of Kenya (Figure 6.1), near the equator and covers 9322.9 Km^2. It has a warm, temperate climate and a bimodal rainfall distribution ranging between 400mm - 1200mm per annum. The agro-climate ranges from semi-arid to high potential and 20.5% is classified as medium or high potential (ROK 2011). The main economic activity is rain-fed agriculture and ranching (Karanja 2006). The main subsistence crops consist of maize, beans, potatoes, millet and wheat. Maize is the main food crop and covers an area of 32560 ha. Farms range between 3.5 Ha (small scale) to 16 Ha (large scale). The soils are fairly fertile, but increased production is constrained by soil moisture deficit and frequent dry spells due to poorly distributed rainfall (Ngigi et al. 2006, ROK 2011).

Vihiga district is located in western Kenya, about 5 km north of the equator. Western Kenya is the major producer of maize in the country (Salasya et al. 1998). Vihiga is one of the most densely populated rural areas in Kenya and is a high agricultural potential area at an altitude of 1300 to 1800 metres above sea level. It receives between 1,800 mm - 2,000 mm of rainfall annually (Ongadi et al. 2007). It has two main agro-ecological zones which are used to grow both cash and subsistence crops (Karanja 2006). Maize is the major staple food grown for average farm sizes between 0.5 Ha - 8.0 Ha (Salasya et al. 1998).

According to the 2009 census, the population of Vihigaand Laikipia was 554,622 and 399,227, respectively (ROK 2010).

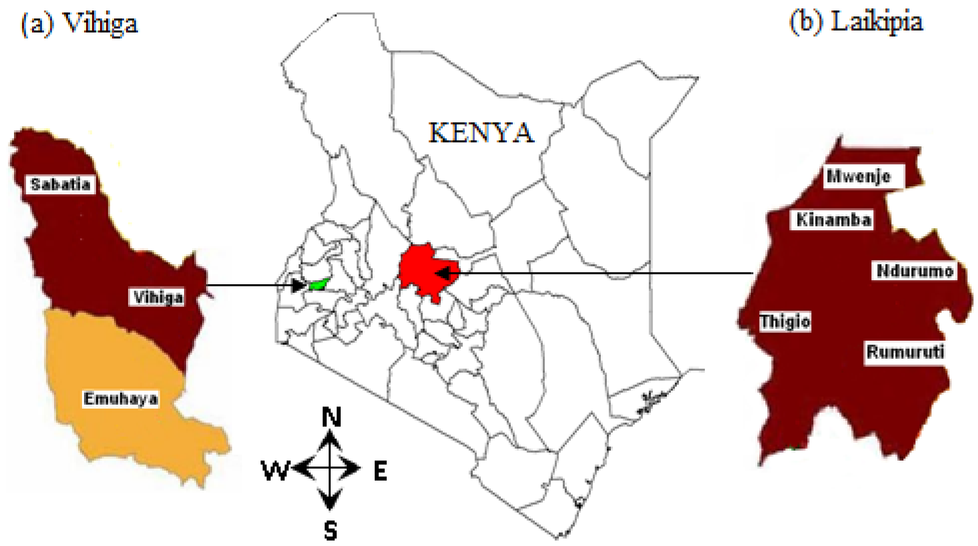


Figure 6.1: Map of Kenya (centre) showing (a) Vihiga district (left) and (b) Laikipia district (right). (Map sources: http://mapsof.net/map/kenya-districts/; http://unjobs.org/duty_stations/kenya/western-province/vihiga/photos/; http://www.kenyampya.com/index.php?county=Laikipia)

6.2.2. Data collection

6.2.2.1. Sample size estimation

Both quantitative and qualitative methods were used for the data collection in the 2 locations. Quantitative methods are based on data from structured questions within the semi structured interviews and the questionnaire was used as a qualitative (unstructured) follow up. The sample population (farmers) was first estimated using empirical methods and using agro-ecological zone, farm sizes and population census. For example, the total population of the farmers in the two areas estimated using the agro ecological zone crop area divided by the average farm size is shown in Table

6.1 and was about 2.4% of the population in Vihiga district and 2.3% in Laikipia west district. The actual sample size was 111 farmers in Vihiga and 133 farmers in Laikipia.

Sample size determination is a key question in a survey (Lenth 2001) as it limits errors caused by incomplete sampling and other statistical problems (e.g. Sackett et al. 1986, Ruggles 1995, Whitley & Ball 2002).

Table 6.1: Estimated population of farmers in Vihiga and Laikipia districts

Zone (District)	Total population	Cropping area (Ha)	Average arm size (Ha)	Estimated population
Vihiga	554,622	54100	4.0	13,525
Laikipia	399,227	32560	3.5	9,302

In addition, the Cochran (1963, 1977) formula, which utilises 3 sampling criteria (Miaoulis & Michener 1976) was used to estimate the sample population:

$$n_o = \frac{Z^2(p)(q)}{e^2} \qquad [6.1]$$

Where n_o is the sample size, Z is the value of the alpha (α) level, p and q are guessed/estimated variances and e is the margin of error for the proportion being estimated. By applying equation [6.1] we can be certain that the outcomes of the survey represent the best guess of the "true" values within the population.

A precision/sampling error of ±5% at 95% confidence level was selected which is the standard margin of precision commonly used (e.g. Kalton 1983, Kotrlik & Higgins 2001). As it was difficult to know the variability of the sample size that was to undertake the survey, a maximum variability for p = q = 0.5 was assumed as is used in similar surveys (e.g. Pons & Petit 1995, Deaton 1997, Israel 2003). This was likely to enable detecting a meaningful scientific difference at the given sampling error (Chow et al. 2007).

By applying the assumptions in [1], and choosing the 3 criteria indices at maximum values of; Z (α) = ±0.05 or 95% confidence level, p = 0.5, q = 0.5 and e = 0.05, the estimated sample size of farmers arrived at was;

$$n_o = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 384 \quad \textit{farmers}$$

Whereas the survey had several questions, the current analysis used data extracted from farmers' comments in regard to their experiences of rainfall and drought patterns and based on 3 main questions. Firstly, farmers were asked to rate their maize yields in the last 5 years and give explanations in terms of climate variability and impacts. In this regard, farmers (interviews) provided extra information on historical climatic patterns in the study areas. For example, one farmer aged 79 years gave a chronology of more than 15 droughts (and floods) that impacted western Kenya and other parts of the country since 1954 and narrated how on one occasion, the president visited the region to plead with the popularly known rainmakers to end a severe drought that had caused widespread hunger and livestock losses in the country. The second question sought to know the source of climate information that farmers used in which >70% of the farmers indicated that they obtained through long term personal experiences and observations. Some of the information (notes) highlighted the years when yields were low or completely lost to drought. This was translated to mean that farmers' remember climatic occurrences from the past which could form a basis for probing climate variability. The last question regarded absence or occurrence of dry spells (dry periods) during the planting seasons. This question was generally aimed at understanding the occurrence of dry spells and drought and how farmers coped with impacts of drought.

In addition, a Focus Discussion Group (FDG) from each of the study areas was used to validate the earlier results. Some of the additional questions guiding the FDGs included: (1) what impact did the severe drought in 2011 had on maize crop in the study areas? (2) Do you remember any other similar drought or extreme events like floods in your area? Please list as much as you can remember and explain how droughts affected your crop (maize). (3) In your opinion, has rainfall increased or declined in your area in the last 10 years or more years? (4) Are there any climatic or others factors you think have influenced maize production / yields in your area in the last 5 or more years?

6.2.3. Selection criteria, size and questionnaire administration

The farmers were sampled from 8 zones in Vihiga which were sub-divided into north, south, east or west and comprised a total of 72 villages. In Laikipia, farmers from 17 zones (areas) were sampled, consisting of a total of 32 villages. Vihiga was selected because it represents a region of high rainfall potential and population density and comprises a large number of the popular traditional rainmakers from Western Kenya. In contrast, Laikipia district is mostly semi-arid with low rainfall and its farmers are suggested to be less reliant on traditional forecasters. However, both study areas produce maize in large quantities during abundant rainfall seasons. Firstly, the local (district) agriculture officers (Vihiga office based in Mbale town and Laikipia offices based in both Rumuruti and Nyahururu town) were visited to obtain some background information and area maps on the status of agriculture and farming practices in the 2 areas.

The questionnaire used in the survey and containing 2 sections and a total of 27 questions (Appendix A4), was given to each farmer in the 2 areas. The 2 sections were designed to collect: 1) farming or farmer information; and 2) usage of forecasts in decision making. Two questions (9a & b and 9c & d) originally not included in the questionnaire were added after a pre-survey was conducted in the first week using a small sample of 24 randomly selected farmers from Emuhaya division in Vihiga. To assist in the exercise, two field enumerators were hired from each of the two areas. After the first 2 days of the survey, it was clear that most farmers preferred to answer the questions on “a face to face” or on the spot basis (“interview”). In other words, one had to be physically present as the farmer completed the process. Farmers who could not read or write preferred the interviewer to fill out their responses. Moreover, the questions were both in English and Kiswahili (national language) but where a farmer had difficulties and prefered to use the local language, a field assistant acted as an interpreter.

The survey started in Vihiga in February 2012 and ended in April. The survey in Laikipia started in May and ended in June 2012. Selection of a farm was random with at least 4 farms being skipped after the selection of a farmer, to avoid bias in the results. Towards the end of each survey a group discussion with about 24 farmers was held in each of the two areas to validate some of the issues raised in the questionnaires (Appendix A5). Overall, there were a total of 111 responses and one discussion group response from Vihiga, while a total of 133 questionnaires and one discussion group response were collected in Laikipia. This means that the overall number of respondents was lower than the estimated sample size but still large enough to have confidence in the results.

A summary of the conceptual sampling design modified from Dillman (2007) for the entire selection process from desk top review to field survey is shown in Figure 6.2.

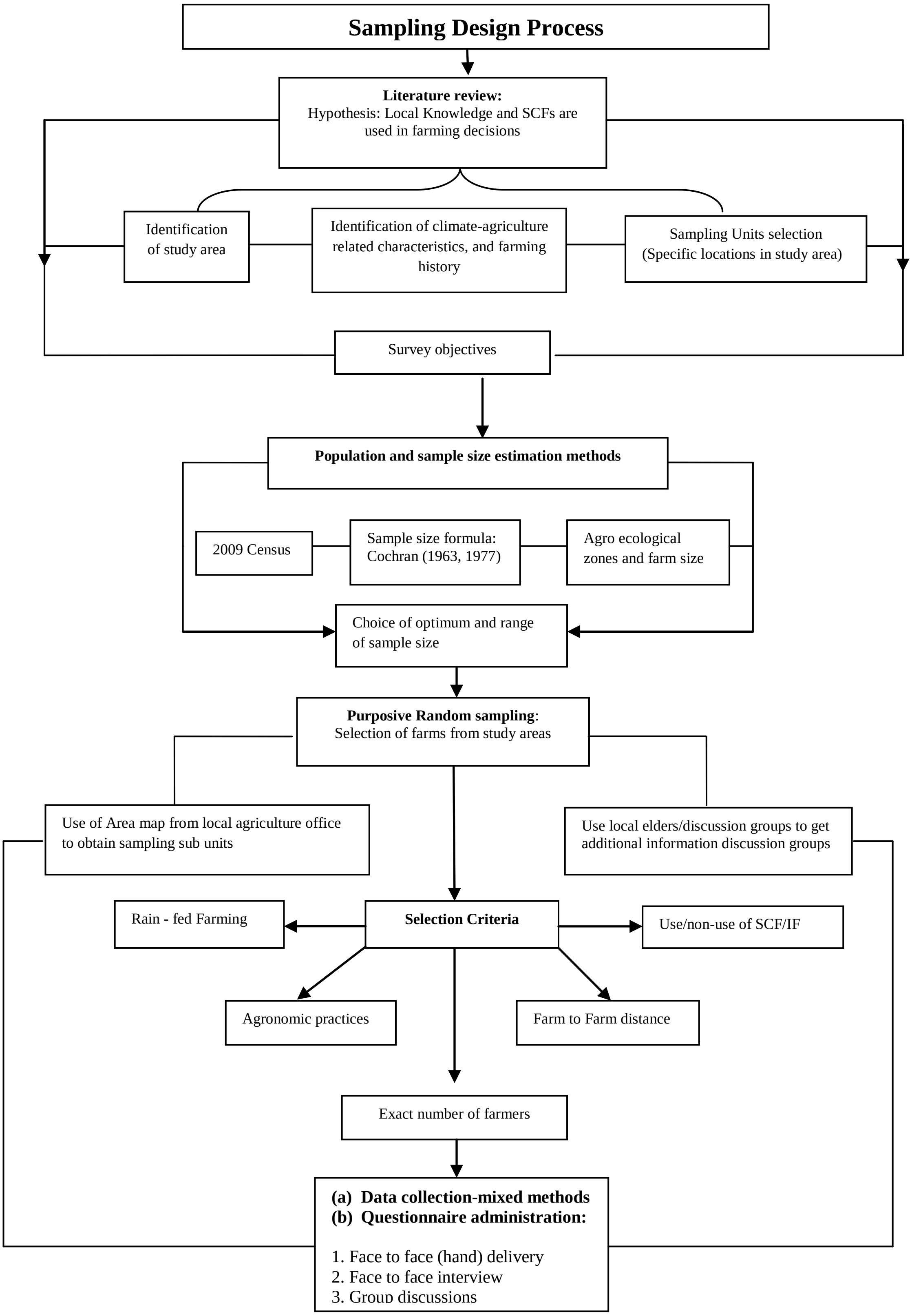


Figure 6.2: Sampling design process for the survey of farmers in Vihiga and Laikipia districts of Kenya

6.2.4. Climate data collection and analysis

a) Precipitation and dry conditions characteristics

The long term characteristics of rainfall and dryness patterns in the 2 study areas were analysed using historical rainfall, minimum and maximum temperature, wind speed, sunshine hours, relative humidity and cloud cover data for periods between 1961 and 2012. This data was obtained from the Kenya Meteorological Department. Apart from rainfall, the rest of the data was only available from 1980. Missing data were minimal and were filled with the long term average, apart from the rainfall for 1998 (a strong El Niño year), which was missing from all the locations selected. This might have resulted in an overall underestimation of the monthly drought extremes.

b) Dry spell analysis and Aridity Index (AI) calculation and their characteristics

Dry conditions ('dry spell') were calculated using the methods in chapter 3 and 4. A dry day is considered to be any day with rainfall amount not exceeding 0.1 mm and a dry spell the sum of consecutive dry days in a month. To see if there are trends in dry spells, a generalized linear model (GLM) was used.

To answer the question 'how dry is dry" both rainfall and evapo-transpiration need to be considered (Tsakiris & Vangelis 2005). To complement method (b), Aridity Index (UNEP 1992) was used assess the degree of dryness. The Aridity Index (AI) is calculated as a numerical indicator using the ratio:

$$AI = \frac{P}{PET} \qquad [6.2]$$

where P (mm) is the average monthly rainfall and PET is the Potential evapo-transpiration expressed as average monthly PET (mm).

To estimate PET, the FAO Penman-Monteith method described in Allen et al. (1994, 1998) was used. The FAO Penman-Monteith method require minimum and maximum temperatures (°C), radiation/sunshine hours (h), relative humidity (%), wind speed (meters per hour) and precipitation (mm). The Penman-Monteith method to estimate PET/ET_o is expressed in mm per month and can be given as:

$$ET_O = \frac{0.408\Delta(R_n - G) + y\dfrac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad [6.3]$$

Where ET_o/PET is reference evapotranspiration (mm per day), Rn net radiation at the crop surface (MJ m^2 per day), G soil heat flux density (MJ m^{-2} per day), T mean daily air temperature at 2 m height (°C), u_2 wind speed at 2 m height (m/h), e_s saturation vapour pressure (kPa), e_a actual vapour pressure (kPa), e_s - e_a saturation vapour pressure deficit (kPa), Δ slope vapour pressure curve (kPa /°C), and γ psychrometric constant (kPa/°C).

Table 6.2 shows the classification of climates (aridity indices) according to the UNESCO (Penman) and UNEP (Thornthwaite) methods.

Table 6.2: Degree of aridity according to UNESCO (1979) and UNEP (1992)

Zone	UNESCO (1979) P/PET(Penman method)	UNEP (1992) P/PET(Thornthwaite method)
Hyper-arid	<0.03	<0.05
Arid	0.02 – 0.20	0.05 – 0.20
Semi-arid	0.20 – 0.50	0.20 – 0.50
Sub-humid	0.50 – 0.75	0.50 – 0.65
Humid	>0.75	>0.65

c) Standardized Precipitation Index

Due to difficulties in obtaining daily data sets in the study areas, the analysis of daily rainfall from neighbouring areas (GLM) was used to strengthen the monthly analysis (dry spells and AI calculations) using the standardized precipitation index [SPI] (McKee et al. 1993). The SPI is simple to apply and only requires monthly rainfall totals which may be easier to obtain compared to daily data and other climatic factors such as temperature. Positive [SPI] values indicate wet periods and negative [SPI] values indicate drought periods.

6.2. 5. Analysis of farmer based information

(a) Questionnaire data analysis

Responses in regard to climate information were organised using MS excel spread sheets and qualitative and quantitative responses analysed using both descriptive and inferential statistical approaches such as; correlations and cross tabulations in R statistical program (R Development Core Team 2011).

(b) Associations between climate observations and farmers' perceptions

To explore relationships between different observations (indicators), a generalized linear model (GLM) was used within the frame work of the survey package in R (R Development Core Team 2013).

6.3. Results

6.3.1. Monthly and seasonal rainfall patterns in Laikipia and Vihiga

Variable rainfall patterns occur in the study locations (Figure 6.3 and Figure 6.4). In Laikipia (Rumuruti & Marmanet), the highest monthly total rainfall between 1961 and 2011 was 354 mm with peaks occurring in April, July/August and November (Figure 6.4) whereas in Vihiga the highest rainfall was > 600 mm in the same period. The highest peaks in Vihiga were in March/April and November. Rainfall seems to be tri-modal in Laikipia and bimodal in Vihiga. In these regions, the long rain season is from March - May (MAM) and the short growing season from October - December (OND).

The seasonal variability in the long and short growing seasons varied between the 2 study areas. In Laikipia, the coefficient of variation (CV) of the mean seasonal rainfall was higher in the OND season (CV= 54.3% - 61.9%) compared to the MAM season (CV = 48% - 52.4%). Similarly, the CV of the mean seasonal rainfall in Vihiga was higher in OND (CV = 26.9% – 38.6%) than in MAM (CV = 19.2% - 22.1%) season, but overall it was lower than in Laikipia.

Across and within the seasons, there is a significant declining trend in rainfall for Marmanet (p=0.01) in MAM, an insignificant increasing trend in Rumuruti in both seasons and insignificant declining trends in both seasons in Vihiga and Sabatia, respectively. For individual months, no trends were indicated in most of the months, apart from significant trends in January and February in Vihiga.

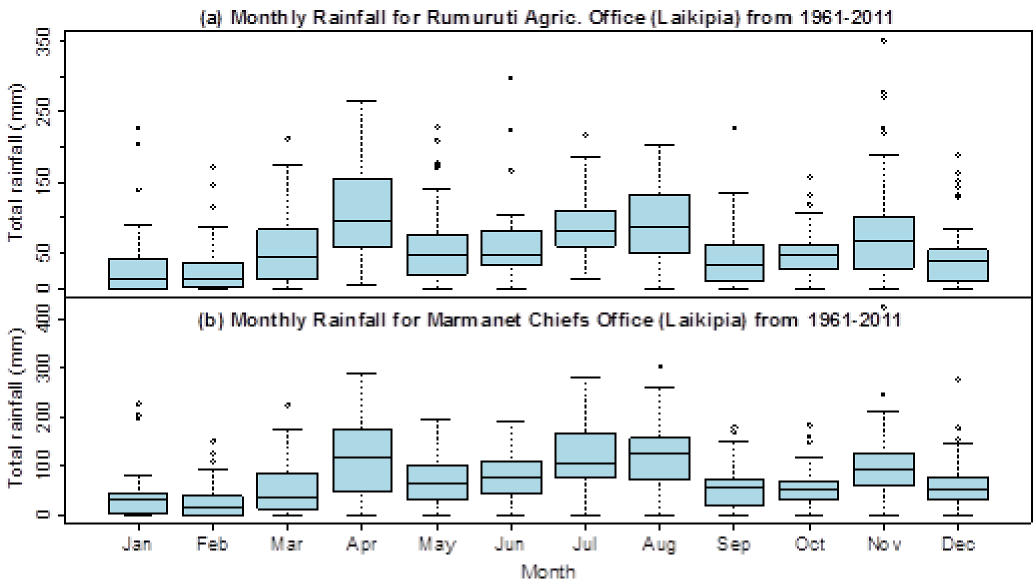


Figure 6.3: Monthly total rainfall for Laikipia west district between 1961 and 2011

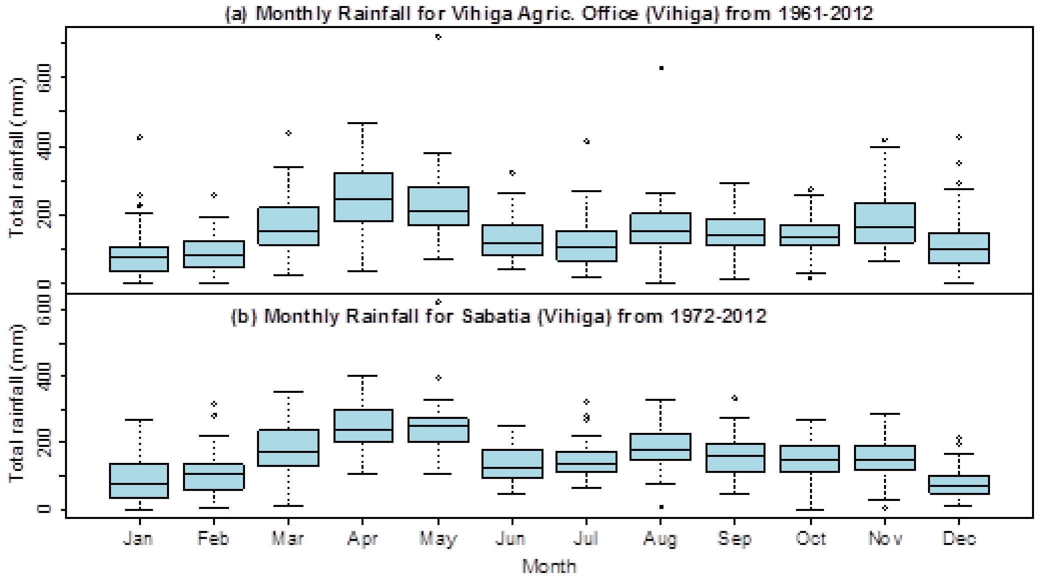


Figure 6.4: Monthly total rainfall for Vihiga between 1961 and 2011

6.3.2. Monthly and seasonal variability using dry spells and aridity index

Figure 6.5 and 6.6 give the dry spell lengths (DSL) for locations in Laikipia and Vihiga from 1961-2012. The DSL increased from January - March/April at Colcheccio and Nyahururu (Laikipia) and again from June – October (Figure 6.5). Increases in DSL in Kakamega and Kisumu (Vihiga) occur from May - February (Figure 6.6). These patterns match those of the SPI results (ranging between -2.0 (extreme dryness) and +2.0 (extreme wetness)). Negative SPI values occur in most of the months apart from April-May and July-August in Laikipia. This means that wet periods occur in the monsoon months and in July-August. In contrast negative SPI values occur in Vihiga in most of the months, apart from March-May and around November.

Dry spell lengths in Colcheccio declined significantly (p=0.01) by 0.1 days per year or by 5 days in the overall period but showed no trends in Nyahururu. In contrast, DSL increased by 0.01 days per year in Kisumu but showed no trend in Kakamega. This seems to concur with the rainfall patterns in these regions which suggested declines in drought conditions over Laikipia relative to Vihiga.

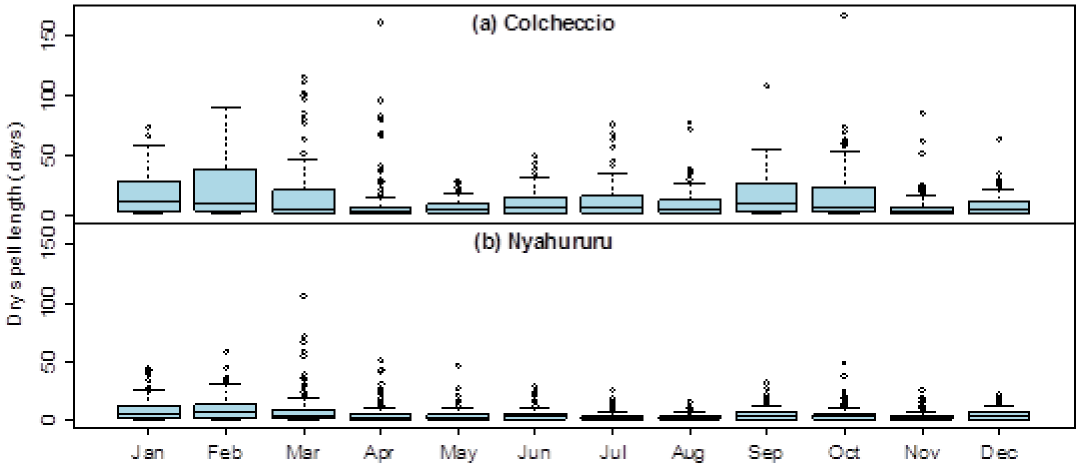


Figure 6.5: Dry spell lengths based on 1961-2012 period for Colcheccio and Nyahururu in Laikipia district

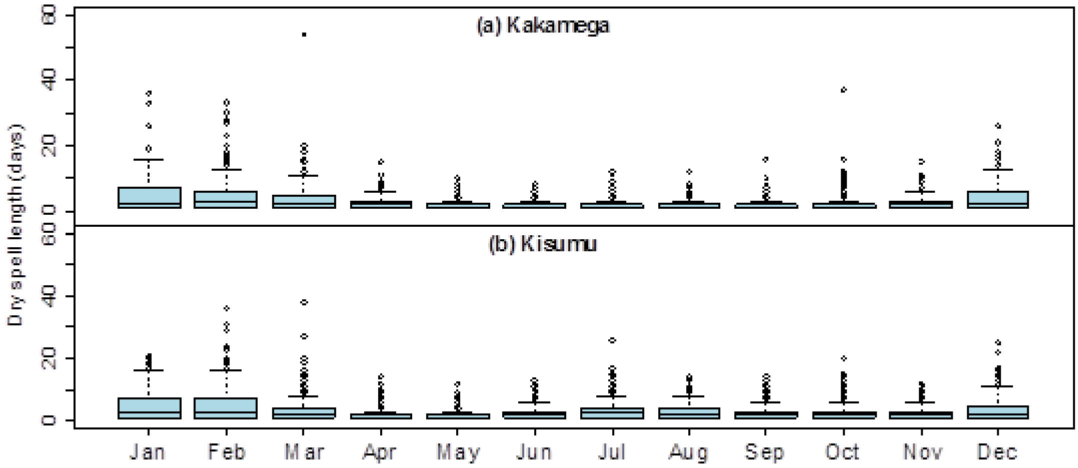


Figure 6.6: Dry spell lengths based on 1961-2012 period for Kakamega and Kisumu in western Kenya (Vihiga)

Figure 6.7 displays the degree of aridity (AI) using the Penman-Monteith (Pen) method and plotted alongside the mean dry spell length for Nyahururu (Laikipia) and Kakamega (Vihiga) from 1980 to 2012. According to the classification in Table 1, Nyahururu was drier (AI ≤ 0.50) in 77% of the time compared to 52% of the time over Kakamega between 1980 and 2012. In other words Nyahururu seems to have been drier than Kakamega.

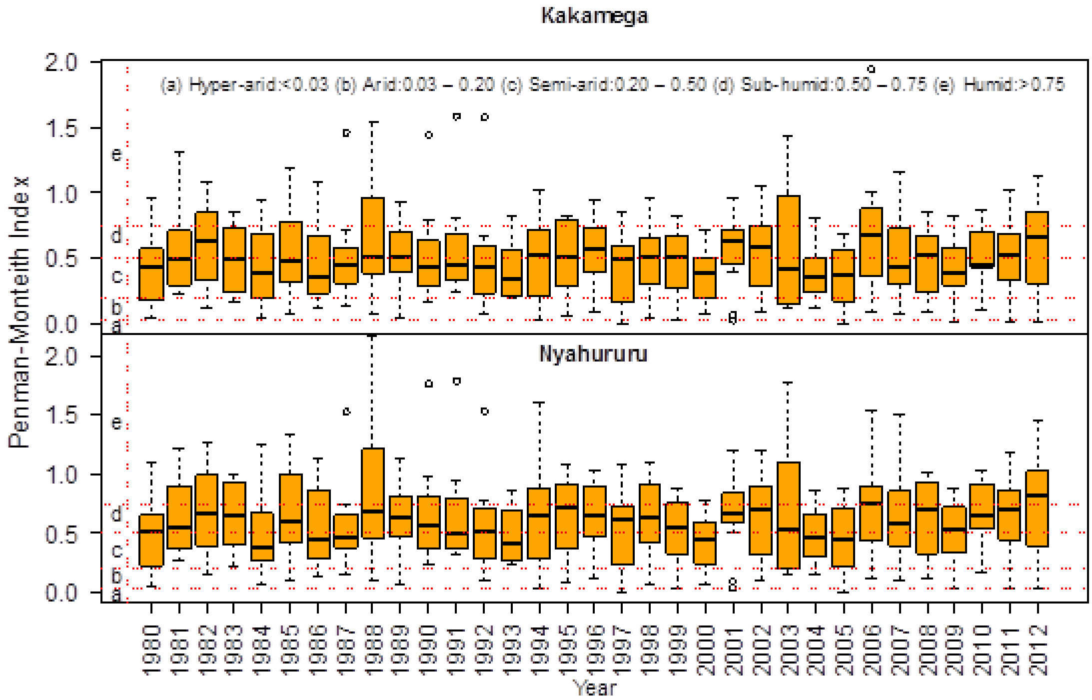


Figure 6.7: Aridity Index (AI) for Kakamega (top panel) and Nyahururu (bottom panel) for the period 1980-2012. The horizontal dashed lines bounding the letters marked 'a', 'b', 'c', 'd' and 'e' shows the AI values (y-axis) according to the FAO Penman-Monteith aridity classification described in Table 6.1.

In both the MAM and OND seasons, the degree of aridity tended to be similar to the monthly patterns (Figure 6.8). In Nyahururu, it was drier ($AI \leq 0.50$) in 77.7% of the time compared to 28.3% of the time over Kakamega in the MAM season. In contrast aridity was higher in the OND than during the MAM season where Nyahururu was dry ($AI \leq 0.50$) in 87.8% of the time compared to 65.7% of the period in Kakamega. A paired-test of the means between the monthly, MAM and OND patterns, indicate that, the AI for the 2 locations do not provide any evidence that means differ ($p < 0.05$). This results corroborate the earlier ones in which the rainfall was highly variable (CV) in OND season than in the MAM season for the period starting in 1961.

For both the monthly and seasonal analysis, no significant trends in aridity were indicated in both locations using the 2 indices. The lack of trends may be attributed to the short period (1980-2012) since analysis based on the 1961-2012 period (results not shown) had indicated some trends in both regions.

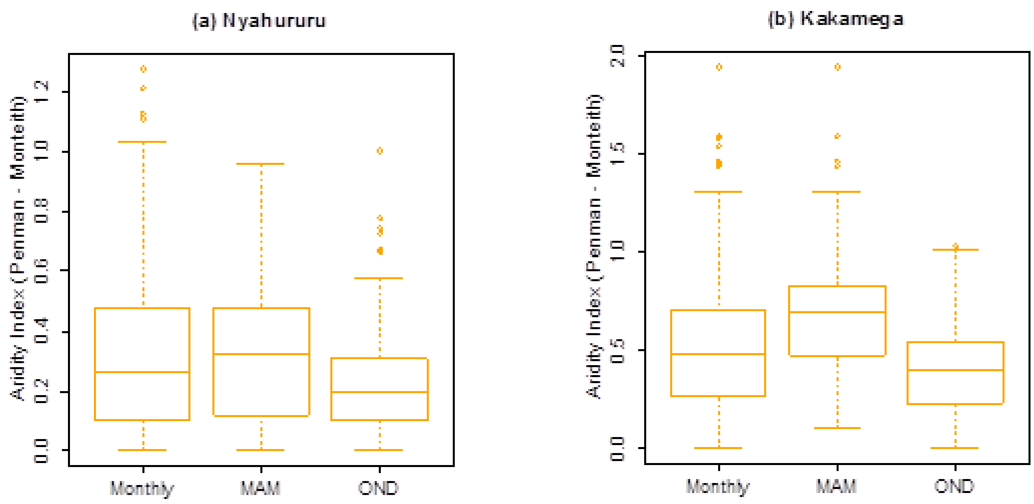


Figure 6.8: Comparison of Aridity Indices for the monthly, MAM season and OND seasons for (a) Nyahururu and (b) Kakamega for the period 1980-2012.

6.3.3. Farmers Perceptions of ClimateVariability

Perceptions obtained from the Focussed Discussion Groups (FDG) and individual farmers from both study areas indicate that the seasonal rainfall patterns have changed in the last 2 decades (Table 6.2). More than 50% of the farmers from the 2 study areas were aged at least 45 years meaning that their perceptions on local climate for the period under study was reasonably informed. This is consistent with the number of the farmers (>55%) who indicated having a good knowledge (memory) of the local climate. Most of the farmers had indicated that the local climate never used to “misbehave” before the 1980’s and therefore this year (1980) was used as proxy to assess climate patterns/variability over 2 periods (before and after 1980) as perceived by the farmers.

Most of the FDG/farmers perceive that the rainfall seasons were more regular and predictable before the 1980’s compared to later. For example, 75.4% of farmers in Laikipia believe that the seasonal rains were regular as were 78.7% of their counterparts in Vihiga before the 1980’s. In contrast, more than 79% of farmers in both study areas indicate that the rainfall patterns were not regular after the 1980’s.

Consistent with the rainfall patterns, most farmers considered that the rainfall amounts were more before the 1980’s compared to the latter period.This however is ironical because a substantial number of farmers (30% - Laikipia & 20% - Vihiga) had shown that they did not know whether the rainfall amounts had changed, a situation that appears to reflect the number of farmers who considered not having good knowledge of the local climate in both regions. Farmers’ sentiments on rainfall and drought characteristics was principally in relation to declining or increasing agricultural production in their areas (see Table 6.3).

Results from the analyses of seasonal patterns of dry conditions, show that about 80% of farmers noticed regular patterns in the dry spells in the past (1960's-1980's) but a slightly lower (70%) number of farmers reported the opposite patterns in the later period in both areas. These results were almost similar to those reported by farmers that dry spells were more frequent in the later period in Laikipia (68.9%) and Vihiga (77.3%) than in the first period. This is consistent with climate data showing frequent trends (peaks) in dry spells in Kakamega and Laikipia (Figure 6.7).

The views in regard to magnitude (duration) of dry conditions and change in the length of the growing season, was only limited to the FDG responses which were done after the overall survey (farmers) ended in each of the study areas. The majority of the discussants (FDG) from Laikipia (76.7%) and Vihiga (83.1%) felt that the duration of dry conditions have increased since the 1990s. Interesting however, was that, a large proportion of FDGs in Vihiga (>50%) reported that dry conditions declined in the first period compared to the proportion of those in Laikipia (2% & 9%) who felt that dry conditions had declined in both periods. The later case might be a reflection of the most of the majority of FDGs (90%) who reported they didn't know whether there were changes in the magnitude of dry conditions. Almost all the group indicated that the length of the growing season did not change in the first period in both areas. However, a substantial number of farmers (>47%) in both areas feel that the growing seasons have increased in the latter period. This might be due to the delay of the onset of the rains seasons.

Table 6.3. Farmers' perceptions of rainfall and 'dryness' patterns in Laikipia and Vihiga districts. The definition of the terms Good, Poor, Regular, Not regular, Don't know are used to mean the farmers' judgement of the climate pattern, More, Less,No change, Increase and Decrease as the farmer's perception of quantity or magnitude of climate variable (Rain and degree of dryness).

Variable		**Laikipia (N=133), FDG (N=24) % of N Before 1980s, after 1980s**		**Vihiga (N=111), FDG (N=26) % of N Before 1980s, after 1980s**	
Age (years)	**20-45**	33.1		43.2	
	>45	68.4		56.8	
Local knowledge of climate >20years	**Good**	55.4	89.2	58.9	96.5
	Poor	42.3	8.2	40.1	4.5

Rainfall (pattern)	**Regular**	75.4	9.2	78.7	7.5
	Not regular	12.3	85.4	8.4	79.2
	Don't know	10.4	5.4	12.1	12.7
Rainfall (amount)	**More**	65.2	49.8	73.1	14.0
	Less	2.2	30.3	2.7	63.5
	No change	2.3	13.7	3.6	12.6
	Don't know	30.1	5.8	20.1	9.3
Dryness (pattern)	**Regular**	78.3	11.3	80.1	17.3
	Not regular	3.4	70.8	5.3	68.9
	Don't know	18.2	17.1	13.6	12.2
Dryness (frequency)	**More**	9.3	68.9	8.4	77.3
	Less	84.1	2.9	81.2	7.7
	No change	5.6	11.1	1.4	3.3
	Don't know	<1	14.7	5.4	10.1
		% of N = 24 (FDG)	**% of N = 24 (FDG)**	**% of N = 26 (FDG)**	**% of N = 26 (FDG)**
Dryness (duration)	**Increase**	1.3	76.7	2.4	83.1
	Decrease	2.4	9.2	54.4	5.7
	No change	-	2.1	9.4	2.8
	Don't know	90	-	21.3	7.3
Growing season (length)	**Increase**	2.5	58.2	5.7	48.5
	Decrease	-	43.0	30.0	12.4
	No change	95.8	1	92.6	36.3

Comparing the results for the rainfall and 'dryness' patterns (Table 6.3), it seems that most farmers from both locations indicate that the rainfall and dryness patterns were consistent in the 1960-1980's period but more irregular in the following period. Farmers from both areas also appear to be concerned that the rainfall amounts were more in the first period but less in the second period consistent with the majority of farmers who felt that dry conditions have become more frequent and longer in the later period than in the previous period. However, a larger number of farmers in Laikipia relative to Vihiga report more rainfall and less dry conditions.

The perceptions between the climate patterns and the changes in the growing seasons are not clear cut but suggest that in both study areas farmers did not perceive any changes in the length of the growing season before the 1990's. This might be related to farmers' reports that there has been delay or changes in the start of the rains seasons which may have delayed/prolong planting/length of crop maturity. However, it might also have to do with the length of time that can be remembered accurately.

6.3.4. Relationships between climate variability and farmers' perceptions in Laikipia and Vihiga

In addition to probing farmers' perceptions on climate variability and change, Table 6.4 presents different ways in which farmers from the two study areas expressed the behaviour and variability of rainfall and dryness conditions in the past. The terms rainfall and dryness characteristics were mentioned by 56.3% and 44.0% of the farmers in Laikipia and 1/3 and 65.4% of the farmers in Vihiga respectively. While these do not directly indicate climate variability in temporal terms, they specify how farmers notice climate variability in varied ways. Moreover, these perceptions seem to match earlier reports by farmers on climate variability such that wetter than dry conditions occurred in Laikipia in the recent decades in contrast to opposite patterns in the past and the reverse patterns in Vihiga.

More specifically, whereas farmers in Laikipia and Vihiga perceived larger changes in rainfall amounts and dry conditions after the 1980's (Table 6.2) the analysis of the observed monthly and seasonal dry spell length in the 2 areas (Figure 6.4, Figure 6.5) over the period 1961-2011 only show trends in some months and locations and no significant trends in most of the months and seasons. However, rainfall indicated high variability (CV) in the short rain season compared to the long rain season in Laikipia and Vihiga (dry spell lengths tended to increase in some locations (Kakamega and Kisumu (Vihiga) and Colcheccio and Nyahururu (Laikipia)) which appears to reflect farmers perceptions that drought conditions have increased (more frequent) after 1980 in Laikipia (69%) and Vihiga (77%) (Table 6.3). This is also evident from Figure 6.6 whereby, longer dry periods (higher peaks and low AI values) are indicated in Nyahururu and Kakamega from around 1995 compared to the first period.

Farmers' perceptions may be influenced by recent trends in rainfall patterns where prolonged and severe dry periods have been witnessed, at least since 2006. For instance, a majority of farmers in both areas indicated that the rainfall patterns were more regular previously but have become more irregular since the 1980's. This maybe a reflection of the rainfall patterns across both study areas (not shown), which indicates distinct variations between the years and across seasons during the period. Analysis of rainfall showed the greatest variability in the short (OND) season. Claims of shortening of the growing seasons suggest that farmers perceive greater variability in the rainfall and drought patterns than may be highlighted in the actual observations. Whereas this concept is supported by farmers' perceptions of climate change (Laikipia (3.5%) and Vihiga (11.5%)), change in rainfall patterns (15.4%) in Vihiga and increased rainfall amounts (11.8%) in Laikipia and so on (Table 6.4), analysis of dry spell lengths (Figure 6.5 and 6.6) indicates that there are variations in the climate of the two areas. There were also reports of warmer night and day temperatures in Laikipia (6%) and Vihiga (4.5%) in the last recent decade which was consistent with analysis of the maximum (max) and minimum (min) temperatures in which a rise of 0.03^{0}C/year (max, p=0.001) and 0.02^{0}C/year (min, p<0.0001) occurred in Kakamega while an increase of 0.02^{0}C/year in the minimum temperature (p=0.01) was observed in Nyahururu. The farmers' perceptions are generally in agreement with other studies in the region that suggest that temperatures have substantially risen in the last several years (Kilavi 2008).

More specifically, farmers mentioned the occurrence of severe droughts in the years 2000, 2009 and 2011 which tend to be similar with patterns in Figure 6.7. The AI values for these years varied from 0 – 0.006 in Laikipia and from 0.02 – 0.08 in Vihiga. This indicates that farmers in Laikipia seem to have experienced harsher dry conditions than their counter parts in Vihiga during the 3 respective droughts.

Table 6.4: How farmers in Laikipia and Vihiga districts described climate variability. Terms used are indicators expressing how farmers perceive rainfall and dryness characteristics

Laikipia (% of N=133)		**Vihiga (% of N=111)**	
Rainfall related characteristics		**Rainfall related characteristics**	
High rainfall variability	3.5	Better rains	7.7
Better rains	10.5	Floods	3.8
Climate change	7.0	Good rains	3.8
Early rains	1.8	Hailstorms	7.7
Favorable rains	1.8	High rainfall	3.8
Good rains	7.0	Improved rains	3.8
Improved rains	5.3		
Increased rainfall amounts	11.8		
Rainfall sufficiency	1.8		
Timely rains	1.8		
Too much rains	3.5		
Dryness related characteristics		**Dryness related characteristics**	
Unreliable rains	1.8	No change in rainfall	3.8
Dry spells occurrence	1.8	Poor rains	3.8
Erratic rains	3.5	Wind destruction	7.7
Reduced rains	10.5	Dry spells	3.8
Less rainfall	3.5	Erratic rains	11.5
Low rainfall	5.3	Low rainfall	7.7
Poor rains	3.5	Climate change	11.5
Rainfall deficit	12.3	Change in rain patterns	15.4
Frost effect	1.8	Frost effect	3.8

6.4. Coping with climate variability in Laikipia and Vihiga

In Kenya, planting times correspond to the rainfall season, but at times, occurrence of dry periods may break this pattern and affect cropping decisions. All the farmers in Laikipia and 97% of those in Vihiga said they experience dry spells in some cropping seasons. The mean and variance of the DSL in these regions indicates that, the average DSL for Laikipia in the long March – May cropping season is about 5 – 10 days and 4 -10 days in the short October-December cropping season. For Vihiga, the average DSL is about 3 days in each of the two growing seasons. Between the 2 study areas and as indicated earlier, dry spells are more highly variable in Laikipia than in Vihiga consistent with the climates of the two areas.

Table 6.5: Mean and variance of dry spell length in Laikipia and Vihiga

Area	Location	Seasonal mean dry spell length (days)		Seasonal dry spell length variance (days)	
		MAM	OND	MAM	OND
Laikipia	Colcheccio	9.8	10.1	321.4	250.4
	Nyahururu	5.1	4.3	72.9	24.1
Vihiga	Kakamega	2.7	3.0	12.0	11.0
	Kisumu	2.6	3.0	8.4	8.8

To deal with climate variability, farmers in the 2 locations use varying coping mechanisms (Table 6.6). Comparatively, more farmers from Laikipia (62%) than in Vihiga (41%) indicated that their first option, to cope with dry periods, was to replant the same crop, or an alternative crop. However, a key difference between the two areas is that farmers in Laikipia said they experienced dry periods often, which in turn forced them to have more coping mechanisms in place compared to their counter parts in Vihiga. These results are consistent with the dry spells statistics (at most DSL = 10 days in Laikipia but DSL = 3 days in Vihiga) in these regions and what the farmers reported.

Multiple options were preferred as they ensured more resilience to drought and hence they were used in combination at the same time. In Laikipia, digging of trenches to conserve water, mixed cropping, short and fast maturing crops, alternative farming or businesses such as raising poultry, doing nothing and use of previous season's yields to get income, supplementary irrigation and prayers, all formed an integrated framework for coping with drought risk. Although less coping mechanisms were practiced by farmers in Vihiga, it is interesting that 15% of the farmers indicated that they uprooted their crops before replanting afresh. This is a strange strategy as one would expect crop residuals would act as a barrier against soil evaporation during a dry period.

In addition, farm households purchased food in response to drought conditions after their stocks (previous harvests) ran out. About 34% of farmers in Laikipia and 43% from Vihiga also reported purchasing subsidized fertilizer and seeds from the National Cereals and Produce Board before the planting seasons as a way of boosting agriculture production and food security. However most complained that there are often delays and forces them to purchase from private traders mostly at higher prices. Yet, some farmers mentioned selling assets and other things such as livestock and portions of their land to cope with climate extremes.

Table 6.6: Coping mechanisms and adaptation strategies to climate variability in Laikipia and Vihiga

Climate perception	Indication	Coping or adaptation strategy
Late rainfall onset	Seasonal rains come after mid-March or in April and late October	• Soaking of seeds over night • Planting of quick maturing crop varieties (Katumani or 511 maize breed etc.) • Digging of trenches to conserve rain water • Use of climate and indigenous forecasts
Early or normal rainfall onset	Seasonal rains come in February-very early March and late September to early October	• Planting of late/long maturing crop varieties and livestock feeds (Napier grass) • Mixed cropping (early & late maturing crop) Enhances food availability early in the season • Double ploughing before planting • Use of climate and indigenous forecasts
False start of the rains	Few days of heavy rainfall followed by long breaks of dry days.	• Delaying of planting (some farmers risk and hope the rains will resume shortly) • Replanting of same crops or alternative crop • Seek advice from local agriculture office
Increased rainfall amounts as the season progresses	Increased soil moisture due to continuous light to mild rainfall in the season	• Digging of trenches and small water pans • Mixed cropping and continuous weeding • Planting of trees • Planting of vegetables (e.g. Kales) • Use of treated seed fertilizer and manure
Erratic or poor rains as the season progresses	Poor patterns in distribution of rainfall and spacing and mostly characterized by little daily rainfalls amounts	• Planting of short maturing or drought tolerant crops e.g. millet, sorghum, cassava • Change to other types of enterprises such chicken, pigeon or rabbit rearing • Use of supplementary irrigation
Rainfall failure	The rains occur in few occasional storms or normal rainfall events and suddenly disappears throughout the season	• Shifting to other businesses or look for casual (temporary) jobs. • Planting and use of mulching to limit evaporation • Prayers and doing nothing • Uprooting of crops

Increase in occurrence of dry spells	Dry spells occur in the season after the crop development and around when maize crops are knee or waist high. Dry spells on some occasions occur earlier	• Mulching around the crop to limit evaporation • use of supplementary irrigation or water conserved in trenches or pans • Continuous weeding • Uprooting of crops
Increase in heavy rains e.g. 1997/1998, 2006	Continuous heavy rains lead to much flooding in the season and water logging of the soils as well as erosion in some areas	• Digging of trenches around farms to take water away • Planting of water resilient crops such as arrow roots and Kikuyu/Napier grass • Move to other areas
Other views: Prolonged droughts Rains in harvest times Increased temperatures	Continuous dry periods spanning several months/years or rains during harvest times Incidences of pests such as army worms, locusts and moths	• Purchase food, sale of assets (livestock etc.) • Premature harvesting • Migration to towns to look for employment • Application of pesticides • Consult agriculture extension officers

6.5. Discussion

The current study shows that, farmers discern and analyse climatic patterns through observation and experience. This study had > 90% response rate, a standard deemed good and therefore likely to give results that are representative of the entire population (Button et al. 2013).

Observed rainfall patterns in the study areas are generally consistent with the agro-climatology of these regions (Sombroek et al. 1982) which are humid (Vihiga) to semi-arid (Laikipia). Analysis of dry spells and degree of aridity from the historical rainfall records in these regions gave some interesting results. Considering that Laikipia is a dry region and Vihiga a humid region that are characterised by low and high rainfalls respectively, it was expected that these areas would exhibit drier and wetter patterns. However, the rainfall patterns in Laikipia showed that in the last 50 years, less dry periods occurred compared to Vihiga. This concurs with farmers reports which indicated better yields in Laikipia than in Vihiga Changes in rainfall distribution and amounts can affect crop production (Riha et al. 1996) and prolonged dry periods during the critical cropping periods cause crop failure or reduced yields (Sivakumar 1992). The above results contrasts with those of a recent study in eastern Laikipia where farmers indicated increased droughts in the last few decades (Huho et al. 2010, Ogalleh et al. 2012) while prevailing declining rainfall trends in western Kenya (Vihiga) are consistent with those reported recently (see, for example, Omondi et al. 2013).

Some key differences can be identified between the two areas. For example, farmers in Laikipia tended to adapt water conservation approaches to respond to the perennial problem of dry spells or drought in the region whilst farmers in Vihiga proactively adopted agronomic strategies (Table 6.7). The tendency to use several coping strategies in Laikipia is probably due to the frequency and increased occurrence of drought (Ayeri et al. 2012, Gitau 2014) whereas the need to ensure food availability relative to occurrence of drought drives the agronomical actions of farmers in Vihiga (Figueroa et al. 2008). Trends in aridity patterns between the 2 areas appear to occur at different times (Table 6.7). The degree of dryness and DSL tended to increase in prior to the monsoon season in Laikipia (January-March and June – October) whereas this occurred after the long rain season (May – February) in Vihiga. This might be due to the differences in the synoptic patterns controlling the local climate in these regions.

Table 6.7: Key differences between Laikipia and Vihiga

Attribute	Explanation	
	Laikipia	**Vihiga**
Seasonal rainfall pattern	Coefficient of variation is highest in OND compared to MAM, and monthly total rainfall averages <200mm – 350mm	Coefficient of variation highest in OND compared to MAM and monthly total rainfall averages 400mm – > 600mm
Average dry spell length (DSL)	DSL range from 5 days – 10 days in MAM and 3.5 days – 10 days in OND	DSL range from 2.5 days – 2.8 days in MAM and 2.7 days – 3 days in OND
Dry spell length/ Aridity trends	Between 1961 and 2012, DSL and degree of aridity increased from January – March and from June - October	Between 1961 and 2012, DSL and degree of aridity increased from May - February
Coping mechanisms	Strategies to cope with weather changes such as dry periods/drought occurrence are mostly related to water conservation and change of crop choices	Strategies to cope with weather changes such as dry periods/drought occurrence are more related to change in planting times and other agronomic decisions

Farmers' responses indicate that they are aware of the general climate patterns in their locations, which they said had changed. Similar claims from farmers, have been reported in central Kenya (Ovuka & Lindqvist 2000, 2010) and Uganda (Roncoli et al. 2010). While farmers perceived variability in the rainfall and drought patterns, the observed climatic data show no significant trends in most of the months and seasons with the exception of few locations where declining or increasing trends were indicated. Rainfall analysis of locations in ASAL areas in the north and north eastern parts of Kenya show declining trends in rainfall in the MAM season compared to the OND season since 1960. Although the current findings agree with those by Bryan et al. (2010) in which most farmers perceived that the long term average temperatures had increased while precipitation declined across several regions in Kenya, the results were limited to data for the period 1957-1996 and not specifically focused on intra-seasonal patterns. The current results might then question farmers' perceptions of changes in the climate when the actual data doesn't seem to support such notions. It is possible that farmers' perceptions are correct in qualitative terms but the differences with the observed historical data could be related to other factors not considered in the assessments. This might be related to the fact that climatic data is naturally non stationary. For instance, the actual minimum and maximum temperatures in the study areas increased (Funk et al. 2010) consistent with farmers' reports and might have had a significant effect on evaporation and water availability, and aggravated drought conditions. Currently, no study appears to have specifically examined the relationship between temperature and drought conditions in these regions. Dagg & Blackie (1970) had examined the variation of evaporation in eastern Africa and found that it was more dependent on solar radiation than on temperature and suggested a possible association between evaporation rates and cloud cover or sunshine hours rather than temperature. It is therefore likely that the use of several climatic data sets (rainfall, sunshine hours, cloud cover etc.) in this study gives a better picture of the drought patterns in the study regions.

Farmers in Kenya recounted that the timing of the monsoon which normally occurs between March and May (long season) and again in October - December (short season) appears to have changed since the 1980's. Specifically, planting and harvesting times occur late due to a delay in the monsoons. Consistent with the current results (see Table 6.3 and 6.5), farmers memory length may span several years back (Lundqvist 2001) and how far in the past farmers may remember is influenced by exceptional events which may have occurred, such as extreme precipitation and drought (Nazarea 2006). While farmers planted with the start of the monsoons, in Vihiga, they reported planting 3-5 days after the onset in contrast to their counter parts in Laikipia where planting occurred 2 days after the rainfall onset. This, on one hand, suggests that, planting occurred "late" not because of delayed monsoon, but rather because farmers choose to delay as a precaution against false start of the rains. On the other hand, planting came later, because the actual start of the monsoon often delays. Farmers said they used to plant towards the end of February or early March in the past but now they plant late in March or early April. Some farmers in Laikipia said the onset comes after rains occur in Nairobi (capital city), which means the highlands east of the rift valley.

Matching this views, some evidence of later onset of the monsoon season has been shown in central Kenya (Ovuka & Lindqvist 2000). Camberlin and Okoola (2003) suggest that the onset of the monsoon seasons in Kenya exhibits unexplained year-year variability. In contrast to perceptions of changes in onset times, Mugalavai et al. (2008) indicates that, the onset of the monsoon in western Kenya has not changed. Based on rainfall for 1960 - 2003 from 26 locations, they found that the onset of the monsoon progressed southwards in the region. This would mean that changes perceived by farmers in the region are the opposite of the observed historical records. Considering the long term patterns between the rainfall seasons, the actual climate data show that dry conditions were more variable during the OND (short) season than in the MAM (long) season. The inter-annual variability of rainfall in Kenya has been shown to be higher in the short rains season than in the long rain season (Nicholson 1996), although much of the annual rainfall is accounted for in the long rain season. Farmers indicated that before the 1980's, the seasons had been more regular and less dry compared to the latter periods. This seems to compare well with the findings of Zhu et al. (2011) which show that over much of Kenya there was no significant droughts in more than half of the years between 1957 and 1983, similar to farmers feeling that they enjoyed better seasons. However, the perception of irregularity in the seasons after the 1980s signals a possibility of changes in the mechanisms driving the climate systems of the regions. An analysis of the last few years, indicate that, out of the 10 monsoon seasons between 2007 and 2012, about 4 of the long rains seasons recorded low rainfall or more dry conditions compared to the short rains and was possibly the reason why farmers reported low yields in the 2 regions. The delay in the monsoon might be related to farmers' reports indicated earlier that planting and harvesting times occur late. Delay of the monsoon and planting and harvesting dates in Laikipia have been documented recently (Huho 2011) while no changes in the onset of the monsoon are indicated in Vihiga (Mugalavai et al. 2008). One possible explanation for changes perceived by farmers in Vihiga might be driven by changes in rainfall patterns since 2008 which were characterised by more dry seasonal conditions than previous years.

Studies looking at malaria trends in the western highland regions (e.g. Minakawa 2012) have associated the shifts in malaria transmission with increasing temperatures and rainfall patterns in higher altitude areas in the region after the 1990's. Whereas farmers perceived that the rainfall amounts had declined since the 1990s, linear regression of the rainfall data only revealed that declining rainfall amounts occurred more in MAM relative to OND season in Laikipia and opposite trends in Vihiga. The results for Laikipia reflect those of Williams & Funk (2011) which indicate that rainfall has declined in the MAM season at least between 1980 and 2009 but contrast to Vihiga which seem to reflect Intergovernmental Panel on Climate Change reports for increased precipitation over eastern Africa.

Analysis of farmers' perceptions in regard to climate variability revealed that farmers have been managing their farms using numerous coping mechanisms. Similar to several other studies globally (e.g. Wilhelmi & Wilhite 2002, Ciais et al. 2005, Hertzler et al. 2006), farmers mentioned the frequency of droughts as one of the key obstacles they had to cope with. Crop (yields) reductions due to drought are a common feature in Kenya. Interestingly, farmers from the 2 areas selected their coping strategies according to the perceived behaviour of the rainfall and drought patterns (Table 6.6). For instance, in response to dry spell occurrence, farmers opted to mulch around their crops and use supplementary irrigation from trenches or pans, whereas a delay in the rainfall onset triggered delayed planting and replanting when crops failed. In other words most of the strategies are short-term or instant responses to climate variability, which suggests that long-term adaptation mechanisms are limited in the regions. Other studies in the region depict a similar picture (Speranza et al. 2008, Roncoli et al. 2010, Ogalleh et al. 2012). Because farming in sub-Saharan Africa is marred by poor adaptive capacity and technological capabilities, this requires integrated efforts between farmers, the government and other stakeholders. Access to community based micro-credits by farmers for instance is one way that has started to enhance farmers' ability to deal with climate variability (Duran 2005) and the government efforts to supplement rain-fed agriculture with irrigation schemes in some parts of the country.

The limitation to this study was a lack of climatological data for most locations in the study areas. The scarcity of long-term contextual information on farmers' perceptions of climate hindered adequate statistical or inferential comparisons between observations and farmers perceptions.

6.6. Conclusions

The study showed that, most farmers perceived changes in the seasonal and long term patterns of rainfall and dry conditions, with significant changes occurring after the 1980's while the actual records indicated that rainfall and drought conditions varied more in the short rain season than in the long rain season. This was more reflected in Vihiga compared to Laikipia. Nevertheless, rainfall patterns in both regions showed no significant trends in the overall period although a slightly higher number of farmers in Vihiga compared to Laikipia perceived the rainfall patterns to be regular prior to the 1980's than later. Farmers in Vihiga reported that the onset of rains and the planting times have changed and are later compared to Laikipia.

Farmers overwhelmingly responded to climate variability through short term actions mainly; changing planting times, crop diversification, water conservation and replanting, with more coping options being used in Laikipia compared to Vihiga.

The current results update the existing knowledge in regard to farming and management of climate variability in this region and maybe used to guide decisions of farmers and other stakeholders and future research in the region.

CHAPTER 7

THE CHANGING WATER CYCLE AND KENYAN SMALL-SCALE MAIZE FARMING SYSTEMS: PART 2. COMPARING FARMER AND FORMAL BASED CLIMATE FORECASTS

Abstract

Agricultural development policies might have failed because local knowledge and how it influences farmers' decision making has been ignored. In Kenya, benefits of use of indigenous (IF) or seasonal climate forecasts (SCF) by farmers in Kenya have not been quantified. This study focuses on maize farmers from semi - arid (Laikipia) and humid (Vihiga) locations of Kenya in relation to application of IF and SCF forecasts in agronomic decisions.

Using qualitative and quantitative approaches, this study revealed that, more (>50%) farmers from each of the areas used IF. About 60% of farmers in Laikipia indicated increasing maize yields in the last 5 years, which was consistent with the rainfall records in the area. Actual yields reached up to a maximum of 7.65 tonnes per hectare. In Vihiga, 67.6% of farmers indicated declines in maize yields which averaged <2 (90 kg) bags per hectare in the same period which again reflected the rainfall patterns in the period. Non-climatic factors were attributed to yields increases and climatic factors to yield declines in Laikipia. In Vihiga, yield increases and declines were linked to non-climatic factors. In other words, forecasts were probably not used because farmers believed they had little direct effect on maize yields.

The application of forecasts indicates clear differences between humid (Vihiga) and semi-arid (Laikipia) agriculture systems such that, less adaptive mechanisms feature in Vihiga compared to Laikipia. There is a gap between agriculture policies and use of forecasts by farmers in these regions. There is still need for more research to understand the trade-offs between use of IF and SCF in farm decisions in this regions.

7.1. Introduction

In several countries, agricultural development policies are thought to have failed because local knowledge and how it influences farmers' decision making was ignored (e.g. Moock & Rhoades 1992, Schoonmaker 1994, Hommes et al. 2009). Numerous studies (e.g. Holloway & Ilbery 1997, Graef & Haigis 2001, Letson et al.

2001, Roncoli et al. 2002, Luseno & Winnie 2003, Keogh et al. 2004, Hageback et al. 2005) indicate that farmers' perceptions that relate to climate and farming help them respond positively to climate variability. Such studies hypothesise that farmers hold some local knowledge that is useful for managing climate variability impacts in agriculture (e.g. Sulyandziga & Vlassova 2001, Borron 2006). Particularly the use of indigenous knowledge in sub-Saharan Africa is found to be multi-faceted, ranging from better conservation measures to carbon sequestration (e.g. Nyong et al. 2007). More specifically, farmers' responses to climate variability (see chapter 3) in the planting seasons were tailored according to how climate (rainfall onset, dry spells occurrence etc.) patterns evolved or were perceived by the farmers. In this context, it is now widely accepted that while the science of climate has been growing in the last several years, farmers experiences and knowledge must be integrated in agriculture policies to enable use of improved innovations in the management of climate risks (e.g. Stigter et al. 2005, Meinke et al. 2006). However, to achieve this, more effective and innovative links between farmers' knowledge and scientific knowledge should be created (DeWalt 1994).

In Kenya, a close relationship exists between climate variability and agriculture production since agriculture largely depends on rainfall. Drought has a greater impact on agriculture in Kenya than any other factor. The use of farmers' knowledge to respond to such impacts has been useful, but constrained by insufficient resources and poor agricultural practices (Eriksen et al. 2005, Sivakumar et al. 2005). For example, agro-pastoralist farmers extensively use indigenous forecasts (IF) which are bio-physical indicators of climate to manage drought in semi-arid regions of Kenya (e.g. Oba et al. 1987, Campbell 1999, Ngugi 2002, Western 2003, Wasonga et al. 2011) by adjusting their food production and grazing patterns to maintain stocks and yields (Fleurett 1986, Oba 2001, Ngugi 2002). Farmers' perceptions in Kenya have also been useful in the examination of soil and moisture characteristics (e.g. Okoba & De Graaff 2005, Mairura et al. 2007, Odendo et al. 2010), water conservation (e.g. Bahame 2009), land degradation (e.g. Roba & Oba 2008) and pest control (e.g. Chitere & Omolo 1993).

Despite numerous studies on the use of indigenous forecasts in Kenya, there is very little empirical analysis if farmers assess or know the quality of indigenous forecasts. However, a recent study in Kenya suggests that fuzzy logic can be used to contextualize indigenous climate knowledge by differentiating farmers experiences of extreme climatic events (Leclerc et al. 2013). The study demonstrated that farmers' perceptions on crop losses due to extreme climatic events were accurate and consistent with the historical climate records. Lybbert et al. (2007), had examined how pastoralists in Ethiopia and Kenya adjusted their beliefs in IF in response to SCF. Most of the pastoralists adjusted their perceptions upwards in response to the climate information but the study did not establish the skill of their choices. Kalungu et al (2013) reported that despite most farmers in semi-arid areas of Kenya have improved their farming practices through indigenous knowledge and other ways and are adapting to climate variability, their productivity remained low.

Whereas the use of IF predominate African farming systems, the use of more formal seasonal climate forecasts (SCFs) has been documented in Kenya (e.g. Ogallo et al. 2000, Ngugi 2002, Thornton et al. 2004). These studies mostly focus on the potential value of SCFs in agriculture (e.g. Patt et al. 2007), economic yield analysis (e.g. Amissah-Arthur et al. 2002, Hansen & Indeje 2004) and humanitarian and disaster planning (e.g. Orindi et al. 2007, Rarieya & Fortun 2010). However, farmers show high confidence in IF compared to other forecasts (e.g. Lybbert et al. 2007, Bahame 2009). A case study by Recha et al. (2008), found that most small scale farmers, using SCFs in semi-arid regions of Kenya, lacked confidence in SCFs and made farm decisions based on what they perceived, rather than what actually was. In contrast an earlier study showed that most farmers had increased confidence in SCFs, mostly due to awareness raised by the 1997/98 El Niño event (Ngugi 2002). A recent study conducted in Kenya, indicated that most farmers were likely to use climate forecasts for adapting to climate variability (Bryan et al. 2013).

Although it's clear that IF forms an essential part of the farming systems in Kenya, it is unclear how this knowledge can be translated into quantitative and scientific terms. In addition, there appears to be a need to integrate IF and SCFs at the local level. The main aim of this study therefore is to examine the use of indigenous forecasts (IF) and seasonal climate forecasts (SCF) by farmers in Vihiga and Laikipia districts of Kenya in response to climate variability. The specific objectives of this study are to:

i. Assess the associations between indigenous forecasts and observations of weather
ii. Explore farmer preferences with respect to indigenous and evidence based forecasts and relate climate patterns and maize (Zea mays L) yields
iii. Provide an inventory of indigenous and evidence-based forecasts

7.2. Research methods

7.2.1. Study area and data collection

The study locations used in this analysis are similar to those described in chapter 6. The study focuses on Laikipia west district which is semi-arid, with annual rainfall ranging from 400 mm -1200 mm and located in the central region of Kenya and Vihiga district which is humid and receiving about 1800 mm – 2000 mm of rainfall per year and located in western Kenya.

Both qualitative and quantitative methods were used to obtain information from farmers in regard to use of forecasts in farm decisions. Both empirical methods and other demographic data was used to estimate the sample size in both regions. During the survey, a total of 111 responses and one discussion group response was collected from Vihiga and 133 responses and one discussion group response obtained from Laikipia.

7.2.2. Characteristics of dry spell length and Aridity Indices for 2007-2011

The rainfall and dry condition patterns in the 2 study areas were analysed for the period between 2007 and 2011. Similar to Chapter 6, dry spell length in the study locations was calculated from daily rainfall as the sum of consecutive dry days while the Aridity Index (UNEP 1992) was used examine the degree of dryness whereby the Penman-Monteith method was used to calculate the Potential Evapo-transpiration.

7.2.3. Data analysis

(a) Questionnaire data analysis

Qualitative and quantitative responses extracted from questionnaires were subjected to both descriptive and inferential statistical analysis and results tabulated or presented in graphical forms.

(b) Associations within farmers' perceptions of climate and maize yields and between the use of IF and SCF attributes

Farmers' perceptions such as, why yields declined or increased, or the choice of seasonal forecasts rather than daily forecasts in farm decisions, may be influenced by other factors. Data on maize yields is analysed in 3 ways: Current actual yields for 2011 are defined as "Yield 2", yields 5 years earlier (2007/2008) are defined as "Yield 1" and the best guess scenario yields are identified as "Ideal Yield" or the yields that farmers would expect under the best conditions. In order to test the accuracy or skill of forecasts farmer's perceived score is based on a scale of 1 - 5 in which 1 means that a farmer deems the forecasts are least accurate and a score of 5 that the forecasts are extremely accurate or about 100% correct. This may be different with the statistical measure of accuracy which is based on the differences between a forecast and the actual or hind cast occurrence.

To test for significant associations between different variables (choices), a generalized linear model (GLM) was used within the frame work of the survey package in R (R Development Core Team 2013). In order to use the survey package and analyse the selected sample information on farmer's perceptions, a survey object or design must first be created. The **svydesign** () object simply stores the data to be used in the analysis and also defines how the variables are stratified according to the selected index or proxy such as gender or level of education, clusters and sampling weights. The sampling weights were generated using the 2009 population census in the 2 regions and were used to account for population variability between variable groups.

7.3. Results

7.3.1. Rainfall characteristics

Figure 7.1 shows the monthly total rainfall distribution for locations in Laikipia (a) and Vihiga (b) between 2007 and 2011. In Laikipia, the highest monthly rainfall was 297.6 mm (June 2007) in Rumuruti, 219.4 mm (August 2011) in Marmanet, 299.1 mm (September 2007) in Nyahururu. Overall the lowest rainfall amounts occurred in 2008, 2009 and 2011. In Vihiga, the highest rainfall amount was 625.8 mm (August 2011) in Vihiga, 330.1 mm (August 2011) in Sabatia and 353.1 mm (September) 2007) in Kakamega. Similar to Laikipia, the lowest rainfalls were recorded in 2008, 2009 and 2011. Clearly, the highest rainfall amounts were recorded in non-monsoon months in all the locations in the 2 study areas.

Linear regression results indicate that there is insignificant increasing trend in rainfall for most of the locations in both study areas during the period. Again, no trends are indicated in March – May (long) and October – December (short) rain seasons in both regions apart from increasing trend ($p = 0.02$) over Marmanet (Laikipia) in the long rain season.

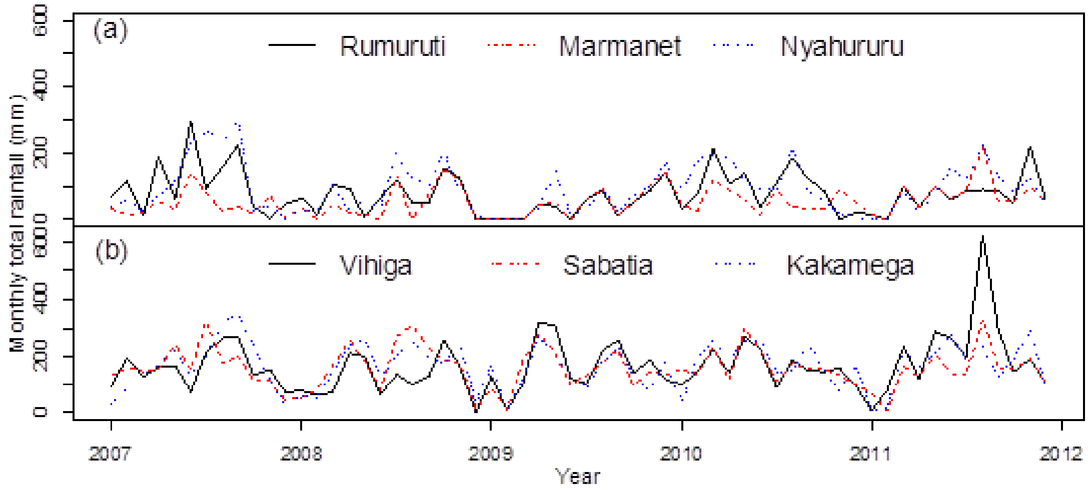


Figure 7.1: Monthly total rainfall for (a) Rumuruti, Marmanet and Nyahururu in Laikipia and (b) Vihiga, Sabatia and Kakamega in western (Vihiga) Kenya

7.3.2. Dry spells and aridity characteristics

The patterns in the dry spells lengths and aridity index (AI) for Nyahururu and Kakamega are given in Figure 7.2. Consistent with the rainfall patterns in the 2 study locations, the aridity index for Nyahururu and Kakamega shows that the driest periods (AI < 0.4) occurred in the first halves of 2007, 2008, 2009 and 2011 and the wettest periods (AI > 0.8) between May and August 2007 at Nyahururu and in August and September 2007 and June and November 2011 in Kakamega. The longest dry period was from September 2007 – May 2008 in Nyahururu and from September 2010 – March/April 2011. Clearly, in the 5 years period, some of the driest periods occurred around the growing seasons while wet periods were occurred after the monsoon seasons in the two locations.

A negative relationship was indicated between rainfall and the maximum dry spells lengths for these locations (Appendix A7), as would be expected. The coefficient of variation of the maximum dry spell length and aridity index exceeded 50% in both locations [Nyahururu (CV = 67.5%, AI = 88.3%) and Kakamega (CV=66.1%, AI=55%)]. Figure 7.2 shows the aridity index for Kakamega and Nyahururu between 2007 and 2012. Hyper-arid to semi-arid conditions (AI < 0.5) occurred in over 50% of the time in Kakamega (Vihiga) and Laikipia although Kakamega tended to indicate more dry conditions towards the end of the period. These results seem to be similar to those of the dry spells patterns (not shown) and those obtained for other locations from the two regions.

Considering the humid and semi-arid climates of these 2 areas, locations in Vihiga appeared to indicate drier conditions compared to Laikipia in the last 5 years.

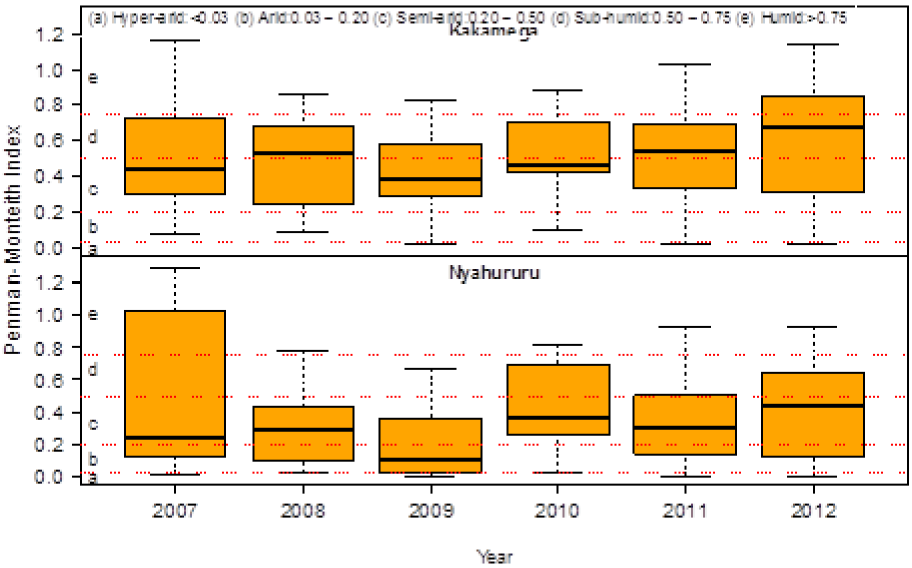


Figure 7.2: Box plots of Aridity index for Kakamega (top panel) and Nyahururu (bottom panel) for the period 2007 -2012.

7.3.3. Farm level information

Most farm sizes in Laikipia range from 1 - > 5 Ha (94.7 %) and 0.5 - > 0.5 Ha in Vihiga (92.8%). In Laikipia, over 50% of farmers are men and 43.6% are women. In contrast, most farmers in Vihiga (70.3%) are women. These results suggest farm size and gender differences in both areas. In both areas, most farmers are older than 45 years, regard maize as the most important crop, and farming is the main source of income (Table 7.1). Consistent with small-scale farming systems in Africa, more than half of farmers grow other crops such as beans and potatoes on a third of their farms. A relatively big number of farmers have high school or college education in Laikipia compared to Vihiga but more farmers have some agriculture skills in Vihiga (48%) relative to Laikipia (38%). Agriculture skills, in this context, mean attendance at agricultural seminars, shows, workshops or formal agricultural training. In general, family size per farm in both areas is roughly even, although the density is higher in Vihiga as the farms are much smaller.

Table 7.1: Frequency distribution (percentages of total) of farmer's responses on cropping and yields factor questions in Laikipia and Vihiga

Factor	Variable		Laikipia (N=133)	Vihiga (N=111)
			% of N	% of N
Education	Primary		42.1	64.9
	High		32.3	21.6
	College & above		9.8	3.6
	none		15.8	9.9
Agriculture training	With training		38.3	47.7
	With no training		61.7	52.3
Income. Source	Farm		94.0	100.0
	Employment		1.5	0.9
	Business		1.5	14.4
	Others		6.0	4.5
Farm. Size (Hectares)	Laikipia	Vihiga		
	<1	<0.5	5.3	7.2
	1 - 5	0.5	71.4	38.7
	>5	>0.5	23.3	54.1
Maize. Rating	Least important		0.8	3.6
	Somewhat important		3.8	3.6
	Important		15.8	6.3
	Most important		15.0	4.5
	Extremely important		64.7	82.0
Proportion of other crops (%)	0		12.8	0.9
	33		54.1	70.3
	34 - 66		21.1	16.2
	67 - 100		5.3	10.8
	Don't know		6.8	1.8

7.3.4. Farmers' perceptions on yields in the last 5 years

Results from both areas show that in the last 5 years (2007-2011) there were perceived changes in the yields (Table 7.2). About 70% of the farmers in Laikipia said that yields were "average" with an overall mean of 23.6 bags or 2.1 tonnes per hectare. Almost 60% of farmers indicated yield increases and only 1/3 of the farmers indicated yield declines. However, 10% of the farmers with yields "above average" had the highest yields (mean=3.4 tonnes per hectare). Overall, this results show that over 80% of farmers in Laikipia had "average" to "outstanding" yields which is consistent with the majority of farmers (57%) who indicated increasing yields. Actual yields reached up to a maximum of 7.65 tonnes per hectare.

In Vihiga, 67.6% of farmers indicated declines in yields with only about 20% indicating yield increases. These yield indications reflect the yield ratings which show that about 80% of the farmers indicated “below average” yields with an average of < 2 bags per hectare (Table 7.2).

Comparing the results with the rainfall and dry spell/aridity indices (Figure 7.1 and 7.2), there seems to be some consistency with the majority of farmers in Laikipia district indicating better yields possibly due to less dry conditions than Vihiga, where yields were relatively low.

7.3.5. Factors attributed to yields patterns

Numerous factors were linked to yield declines or increases in these regions. In broad terms, the factors can be classified as climatic and non-climatic and include agronomic, financial and technological factors (Appendix A6). Factors in this case are considered to be the terms that farmers use to express the performance of their yields. For example, a farmer used the term “lack of fertiliser” to mean a non-climatic factor and the “occurrence of dry spells” to mean a climatic factor in relation to yield declines, whereas the term “good rains” means a climatic factor relative to yield increases.

Table 7.2 shows that non-climatic factors were attributed to increases in yields by more than 50% of the farmers in Laikipia. However yield declines were linked to climatic factors by a few more farmers (24.1%) than non-climatic factors (21.8% of farmers). Similarly, most of the yield increases in Vihiga were attributed to non-climatic issues by 19.8% of farmers but in contrast to Laikipia, 60.4% of the farmers in Vihiga mentioned non-climatic factors as causes of yield declines, while only about 20% of the farmers said declines were due to climatic factors.

Of particular interest is whether there was any association between the yield estimates of farmers and the degree of dryness in the 2 regions. Results indicate that, out of all the climatic factors linked to yield declines by farmers (Laikipia = 24.1% and Vihiga = 19.8%), conditions of dryness i.e. dry spells, low rainfall, erratic rains was mentioned by over half of the farmers or 12.3% in Laikipia and 10.8% of the farmers in Vihiga as the causes of yields reductions. This suggests that, consistent with the rainfall and drought patterns in the 2 regions, dry conditions played a critical role in the determination yields and crop performances in the last 5 years.

Since cropping in Kenya is intricately linked with the rainfall seasons, farmers estimates of yields can be related with the climatic patterns in the long (March - May) and short (October – December) seasons. In view of the earlier results on yield performances, more dryness (AI < 0.4) was indicated in all the long growing seasons in all the 5 years (2007 – 2011) compared to the short growing seasons where it was only indicated in 2007, 2010 and 2011 in the study areas (Figure 7.2). Moreover, the rainfalls in these seasons and years were below 300mm which is the minimum amounts required for maize crop to mature (Figure 7.1). This means that, most of the yield declines may have been attributed to the long rain seasons in both study areas.

Table 7.2: Frequency distribution (%) of farmer's perceptions on yields (per acre) in Laikipia and Vihiga from 2007 - 2011

Factor	Variable	Laikipia (N=133)		Vihiga (N=111)	
		% of N	Current mean yield(bags/acre)	% of N	Current mean yield (bags/acre)
Yield Rating (Last 5years)	Outstanding	3.8	29.0	7.2	5.8
	Above average	9.8	38.1	11.7	4.2
	Average	69.9	23.6	27.0	2.8
	Below average	9.0	23.2	29.7	1.4
	Poor	3.0	21.3	23.4	1.7
	Not able to rate	3.0	-	0.9	-
Direction of Yield	Decline	32.3	31.4 - 20.9	67.6	4.5 - 2.0
	Increase	57.1	19.3 - 28.5	18.9	1.8 - 4.2
	No change	4.5	12.4	6.3	1 .0
	Not indicated	5.3	-	7.2	-
Yield causal factors	Climatic (Increase)	18.8		4.5	
	Non-climatic (Increase)	51.1		19.8	
	Climatic (decrease)	24.1		19.8	
	Non-climatic (decrease)	21.8		60.4	
	No responses	16.5		15.3	

The current yields (Yield 2) are compared with the yields 5 years earlier (Yield 1) and for the best guess scenario yields (Ideal Yield) as reported by farmers. Results indicated that, while maize yields varied between the two regions in the last 5 years, overall, "Yield1" was somewhat less than "Yield2" in Laikipia but the reverse was true in Vihiga (Figure 7.3). Moreover, farmers' expectations of maize yields or "Ideal Yield" was higher than their current situation in both regions, suggesting that factors earlier attributed to poor yield returns were a major obstacle to maximising agricultural potential in these regions. Whereas high variability in yields may not necessarily be “ideal”, it suggests that if farmers were given the right weather, inputs and incentives they would most probably increase their yields. Moreover, a look at the yields perceptions relative to the degree of aridity in the regions (inset Figure 7.2) might explain the cause of low yields. A long dry period starting in October 2007 to about mid 2008 suggests that farmers in Laikipia relative to Vihiga had poor yields probably due to failed or poor seasonal rains 5 years ealier. Similarly, drier conditions in 2011 could be linked to declines in yields 5 years later, consistent with the farmers’ reports. Prompted to describe what their ideal rainfall forecasts would be for good maize yields, over 60% of farmers in Laikipia indicated moderate rainfall. A similar number of farmers in Vihiga however, indicated high rainfall as their ideal forecast for good yields. This reflects farmers expectations in Laikipia who had mentioned that higher rainfall may lead to flooding and destroy crops, whereas their counterparts in Vihiga had mentioned that their maize variety requires more rainfall to achieve the desired yield outputs.

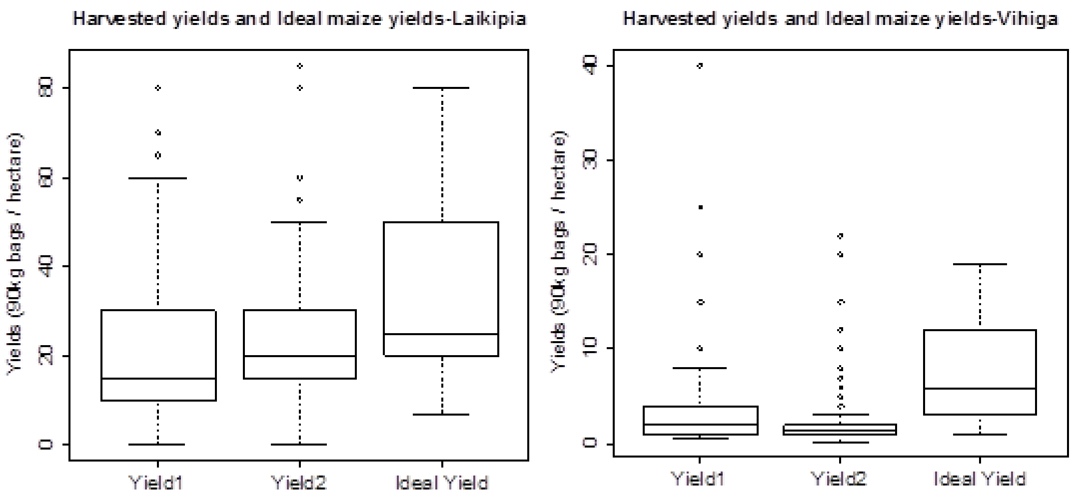


Figure 7.3: Comparisons between farmers yields in Laikipia (left) and Vihiga (right), 5 years earlier (Yield1), currently (Yield 2) and at the farmer’ best (guess) situation (Ideal Yield)

7.3.6. Farmers’ forecasts preferences and perceptions on forecasts accuracy and basis for forecasts usage

Farmers in Kenya, use both scientific and indigenous forecasts. A significantly high number of farmers in Vihiga (76%) use indigenous forecasts (IF) in farm decisions compared to 64% of the farmers in Laikipia (Figure 7.4a and 7.5d). In contrast, 45.9% of farmers in Laikipia indicated using SCF in farming decisions, which is almost double to those in Vihiga. This is strange as a higher proportion of farmers (88.3%) in Vihiga relative to Laikipia (78.2%) indicated that they preferred seasonal forecasts rather than other classes of forecasts like daily or weekly (Figure 7.4b and 7.5e). While a large number of farmers in Laikipia used SCFs, it is interesting that about one quarter of the farmers also used daily forecasts. This would probably be because, rainfall availability is more uncertain in Laikipia (dry location) and therefore farmers would require more regular (daily forecast) information than their Vihiga counterparts. On the other hand, a slightly higher number of farmers in Laikipia (19.5%) compared to Vihiga (16.2%) combined SCF and IF in their farm decisions. Farmers, who neither use SCF or IF, indicated that they used other forms of options, such as reliance on prayers, crying, doing nothing or climatology.

Accurate forecasts can facilitate better farming decisions and lead to better crop productivity. The farmers' view of forecast accuracy also varied between the two regions and seemed to take opposite directions. On a scale of 1 - 5 (1 = forecasts are least accurate and 5 = forecasts are extremely accurate), 44.4% of farmers in Laikipia deemed the skill of forecasts' were average (3) for either SCF or SCF and IF combined together, but, in contrast, 67% of farmers in Vihiga indicated that SCF were incredibly accurate compared to average skill (3) when combined with indigenous forecasts (Figure 7.4c and 7.5f). This is illogical since farmers in this region are mostly users of indigenous forecasts. A possible reason for the low number of farmers indicating a combination of SCF with IF being skilful could be attributed to a slightly higher proportion of farmers who did not combine (DC).

As would be expected the level of satisfaction with forecasts in Laikipia was average (3) and extremely satisfactory in Vihiga consistent with the views given on forecast accuracy.

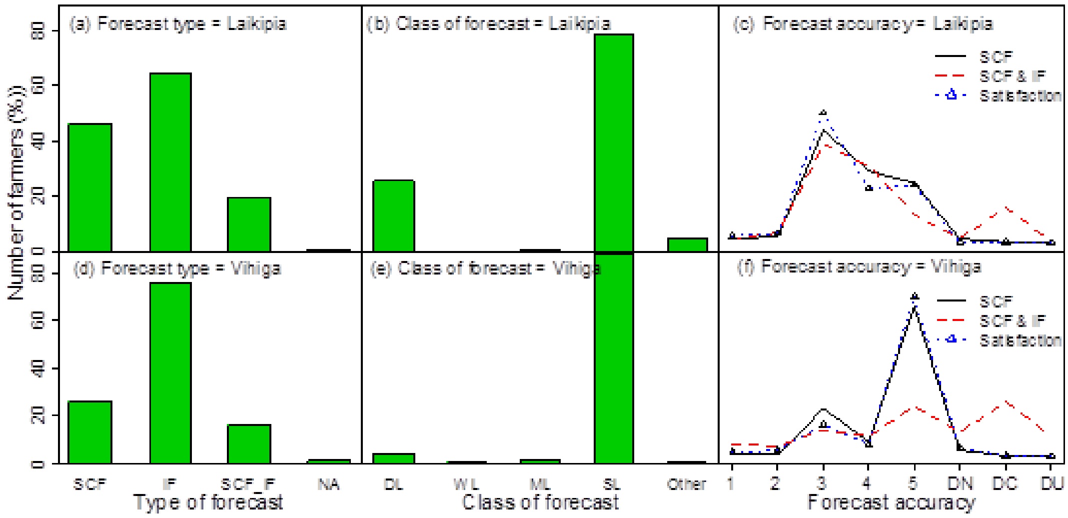


Figure 7.4: Left panel (a & d): Usage of forecasts by farmers (%) (SCF=seasonal, IF=indigenous, SCF_IF= combined SCF & IF, NA=non-user of forecasts), mid-panel (b & e): Category of forecasts used (%) (DL=daily, WL=weekly, ML=monthly, SL=seasonal, other=other type of option) and right-panel: (c & f) Forecast accuracy opinions (%) (1-5=accuracy level, DN=those who don't know, DC=those who don't combine SCF and IF, and DU=those who don't use forecasts) in Laikipia and Vihiga respectively.

Farmers obtained forecast information from numerous sources. The most common source was through personal experience and observations in Laikipia (83%) and Vihiga (77%). Some variations however existed in the forecast sources between the 2 areas. Farmers in Vihiga obtained more information from rainmakers, radio, prayers and from their neighbours. This was not the case in Laikipia with the exception of the use of radio. This can be because farmers from Laikipia can more easily access TV, radio, newspapers or the internet compared to their Vihiga counterparts due to their proximity to better infrastructure and trading network. Curiously, 3% of the farmers from Vihiga obtained their information by listening to both the radio and rainmakers which suggests that they may have been comparing the scientific and indigenous information. Moreover, slightly over 90% of farmers in both regions had indicated using various forms of forecasts for over 5 years, which means that they clearly knew where to obtain information. Farmers also showed that their neighbours were using similar forecast information in both regions but only <50% of those in Laikipia knew if their neighbours used forecasts compared to over 60% of those in Vihiga. This suggests that farmers in the later region shared more information compared to those in Laikipia.

One problem with scientific forecasts is the interpretation. In particular, when rainfall probabilities "normal", "above normal" and "below normal" are given, farmers and other users may not entirely understand them. In Laikipia, a majority of farmers understood below normal, normal and above normal to mean low, moderate and high rainfalls, respectively, apart from 12% of the farmers who regarded the latter category to mean extremely high rainfall (Figure 7.5). Differently from Laikipia, about half of the farmers in Vihiga did not have any idea what the 3 rainfall categories meant, which was far less than the proportion of those in Laikipia who didn't know the meaning of the terms. These suggest that, the higher number of farmers in Laikipia using SCF (Figure 7.4) compared to Vihiga understood climate forecasts.

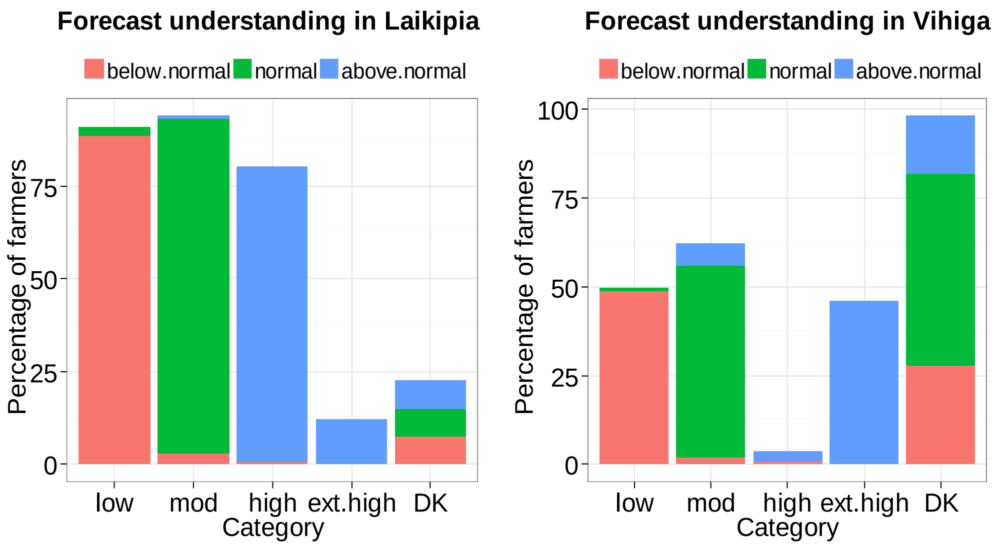


Figure 7.5. Bar plots of the percentage of farmers' level of understanding of the terms "normal", "below normal" and "above normal" in Laikipia (left) and Vihiga (right). The categories low = low rainfall, mod = moderate rainfall, high = high rainfall, ext.high = extremely high rainfall and DK = don't know.

7.3.7. Forecast indicators and usage

Forecasts utilise bio-physical environmental indicators, for example, farmers cited rainfall deciles, amounts, onset dates and temperature, as the main aspects they considered when using SCFs. In contrast, wind direction was crucial for farmers using IF to forecast rainfall. Table 7.3 is an inventory of the forecasts aspects that farmers considered important when forecasting in Laikipia and Vihiga. Wind direction is the key aspect mostly relied upon by farmers in Laikipia (65.4%) and Vihiga (57%). For example, in Vihiga, farmers regarded a west - east wind as a signal of the coming of seasonal rains, but the opposite wind direction as coming of dry conditions. To farmers in Laikipia, a west - east wind can bring rains, but it is more of a local effect, as opposed to the south easterly wind, normally linked with the main rain seasons. The use of climatic indicators by farmers in Vihiga was much higher than in Laikipia which reflects the higher rates of IF usage in Vihiga (Figure 7.6). In this regard, a unique difference between the study areas was the choice of precursors of drought in Laikipia, such as locusts' invasion and and weather in other regions, while in Vihiga pointers of a wet season were mentioned, such as birds singing and morning dew.

Table 7.3: Inventory of IF and SCF forecasts aspects used by farmers (%) in Laikipia and Vihiga and what they indicate.

Forecast aspects	Laikipia (%) n=133	Vihiga (%) n=111	What forecast aspects indicate
Clouds	14.3	21.6	Darkening of clouds, unusually
Rainfall onset	18.8	11.7	high night temperatures, black
Wind direction	65.4	57.0	ants, specific wind direction,
High temperatures	6.0	4.5	migrating butterflies and the croak
Rainfall amounts	13.5	8.1	of frogs indicated the coming of
Rain decile	4.5	-	rainfall whereas late appearances
Croak of frogs	6.0	17.1	of the moon and stars indicate
Migration of butterflies	3.0	2.7	delay in rain onset, locusts' signal
Appearance of black/safari ants	4.5	0.9	an impending drought, and the
Moist roof tops in the morning	1.5	-	change in weather patterns
Migration locusts and rare weeds	0.8	-	elsewhere such as floods
Moon and stars	0.8	0.9	occurrence in Bangladesh suggest
Weather in other regions	0.8	-	poor rainfall season.
Birds singing	-	8.1	Change of colour of leaves from
Change in leaves colour ("omusengeli")	-	1.8	dark green to pale suggests low
Falling of leaves	-	3.6	rains season and falling of leaves
Spotting of black birds	-	0.9	the time for planting as rains are
Birds singing	-	7.2	near. Cool water than usual
Rainmakers proclamation	-	0.9	suggests rains while warm water
Unusual morning dew after a dry season	-	12.6	than usual suggests a dry season.
Cooler than normal water	-	3.6	Unusual appearance of dew in
Warmer than normal water	-	0.9	early morning signals the
Thunderstorms	-	5.4	likelihood of early onset and good
Weakening of the body	-	0.9	rains as does singing of birds.

7.3.8. Relationship between forecast indicators and farm decisions

Environmental predictors used by farmers are structured according to specific farming needs. According to farmers, the rainfall onset date is critical for determining activities like planting times and what crop to plant. Most farmers generally prepared their land in advance, bought seeds, and prepared seed holes on their farms, a few weeks prior to the start of rain season based on forecast expectations. While this is shown in both regions, a slightly higher proportion of farmers in Laikipia (18.8%) than in Vihiga (11.7%) considered the onset dates to be important, possibly due to the information being readily available in the daily and seasonal forecasts provided by the climate services providers. However, other local indicators such as, the croak of a frog or morning dew after a dry season were popular aspects of rainfall onset in western Kenya (Table 7.3), where most farmers mentioned that this triggered the selection of their seeds and spread of manure in preparation of planting before the rainfall onset.

Wind direction, as mentioned earlier, was important not only as a precursor of rainfall activities but was also associated with the general preparation of the land by most farmers. In both regions, farmers ploughed their land when the winds originated from the inland or dry continental regions and close to the planting season. Farmers indicated that during such times, they noted a sudden increase in the wind speeds which would calm down gradually and change toward the opposite directions before the start of the rains. Strong winds have been reported by some farmers to cause destruction of crops in western Kenya. Interestingly, warmer than normal night temperatures, were used by farmers to indicate the possibility of heavy rainfall occurring later in a few days, or even hours, particularly following a prolonged dry season. This reinforced the farmers' confidence, to go ahead, or continue, with land preparation. In contrast, when temperatures were unusually high during the day, this did not generate activities, since drier conditions were going to prevail. In such cases, low rainfall may occur in the season and lead to poor crop performance.

Although some indicators are useful in farm decisions, it is, for example, unclear how abnormal cooling of water in Vihiga was associated with the triggering of normal rains and warmer than normal water related to heavy rainfall. One possible explanation may be that water, because of its higher specific heat capacity, may create a suitable condition for local condensation of the available moisture in the atmosphere.

7.3.9. Relationships between yield performances and other factors

The performance of maize yield may be related to specific factors or attributes indicated by farmers in the 2 regions. To find out, yield directions (increase, declines or no change) were regressed against farmers responses to use or not use of forecasts and other factors as predictors. The results are summarised in Table 7.4 and Table 7.5.

It can be seen from Table 7.4 and 7.5 that there is a strong statistical relationship between yield performance and some of the farmers perceptions (factors). Where yields increased in Laikipia for instance (Table 7.4), not using forecasts had a positive impact ($p=0.004$) with a similarly strong but negative impact related to family size and the proportion of other crops. The last 2, can be interpreted to mean that yield increases less for larger family sizes and when more other crops rather than maize were grown. On the other hand, declining maize yields were affected by growing of other crops and a combination of both climatic and non-climatic factors such as low rainfall and poor seeds. Whereas having some agriculture training may enhance better farming practices and yields, it was insignificant, as was the effect of using SCF or IF.

In contrast, for the results in Laikipia, agriculture training, the proportion of other crops and non-climatic factors had a positive impact ($p<0.003$) on yield increases, while not-using forecasts had a negative impact in Vihiga (Table 7.5). Interestingly, yield declines in Vihiga were negatively related with family size, having or not having education as well as growing of other crops. In contrast to Laikipia, yields increase with larger family size and growing other crops but this is insignificant in the first case. The relationship with climatic and non-climatic factors was insignificant.

Table 7.4: Relationship between yield performances and farm size, family size, level of education, agriculture training, use and non-use of forecasts and other crops in Laikipia. Significance is at 95% (0.05) CI. The estimated effect (slope) (of the factors) on yield direction is indicated by (-) or (+) symbols (values).

Factor	Yield Effect significance (p-value) and slope				95% Confidence intervals (Yield Increase effect)	
	Increases	Declines	Constant	Dont know	Lower -	Upper
Farm size	-	-	-	-	-	-
Family size	0.048 *(-)	0.095 .(+)	-	-	- 0.02	0.01
Education: primary	-	-	-	0.064 .(-)	-	-
high	-	-	-	0.091 .(-)	-	-
college	-	-	-	-	-	-
None	-	-	-	-	-	-
Agriculture training	-	-	0.028 * (+)	-	-	-
SCF usage (Yes)	-	-	-	-	-	-
IF usage (Yes)	-	-	-	-	-	-
SCF.IF combined	-	-	-	-	-	-
Non-use of forecasts	0.004 **(+)	0.011 *(-)	-	-	0.17	0.85
Other crops: 0 %	-	-	-	-	-	-
1 -33%	-	-	-	-	-	-
34 - 66%	-	-	-	-	-	-
67 -100	0.017 * (-)	0.008 **(+)	-	-	- 0.75	- 0.08
DN	0.004** (-)	0.003 **(+)	0.068 . (-)	-	- 0.93	- 0.19
Non -climatic	0.075 . (+)	-	0.025 *(-)	-	-0.02	0.44
Climatic	-	-	-	-		-
Climatic & Non climatic	-	0.001 **(+)	0.024 * (-)	-		-

Table 7.5: Statistical relationships between yield performances and farm size, family size, level of education, agriculture training, use and non-use of forecasts and other crops in Vihiga. Significance is at 95% (0.05) CI. The estimated effect (slope) (of the factors) on yield direction is indicated by (-) or (+) symbols (values).

Factor	Yield Effect significance (p-value) and slope				95% Confidence intervals (Yield Increase effect)	
	Increase	Decrease	Constant	Dont know	Lower -	Upper
Farm size	-	-	-	-	-	-
Family size	0.087 .(+)	<0.0001***	-	-	- 0.003	0.06
Education: primary	-	<0.0001***	-	-	-	-
high	-	<0.0001***	-	-	-	-
college	-	-	-	-	-	-
None	-	<0.0001***	0.060. (-)	-	-	-
Agriculture training	0.003 ** (+)	-	-	-	0.09	0.40
SCF usage (Yes)	-	-	-	-	-	-
IF usage (Yes)	-	-	-	-	-	-
SCF.IF combined	-	-	-	-	-	-
Non-use of forecasts	0.047 * (-)	0.021 *(+)	-	-	- 0.65	- 0.02
Other crops: 0 %	-	-	-	-	-	-
1 -33%	0.008 **(+)	0.003 **(-)	-	-	0.12	0.74
34 - 66%	0.032 * (+)	0.006 ** (-)	-	-	0.04	0.78
67 -100	0.034 * (+)	-	-	-	0.03	0.57
DN	0.009 **(+)	0.036 *(+)	-	-	0.09	0.60
Non -climatic	0.024 *(+)	0.062 . (-)	-	-	-	-
Climatic	-	-	0.068 .(-)	-	-	-
Climatic & Non climatic	-	-	0.018 *(-)	-	-	-

7.4. Responses in regard to Focus Discussion Groups (FDG)

Discussions from focus groups (FDG) in both regions were intended to validate individual farmers' responses. The FDG in Laikipia said that yields were fairly good across the region in the last 5 years with 2009 being a bad drought year in most areas compared to 2011. Due to changing climatic patterns, few farmers mainly from the lower south western parts changed to small irrigation farming owing to presence of seasonal rivers and wetlands in those areas. The farmers mainly grow vegetables such as cabbages which are not only a drought evasion strategy but an income generating activity. This area was again the only one that was frequently affected by frost in the region. Climate forecasts (SCF) raised more interest mainly when extreme weather (above normal or below normal rainfall) was predicted but this only complemented their observations and experiences.

In Vihiga, responses from the FDG reaffirmed that indigenous forecasts were the most used tools to manage climate risks on their farms. For example, if rains occurred in January, it was an indication of an impending drought in the coming (planting) season (MAM) and farmers would mostly plant a local maize variety which was more drought resistant compared to a hybrid maize variety. Similar to Laikipia, the FDG were instrumental to giving more information about the climate of the region in the last over 3 decades. Although climate forecasts were less popular in the region, the FDG expressed that SCF, may help to manage the erratic climate patterns and particularly, if used together with IF. However, an interesting issue was that, farmers listening to radio said that the forecasts (SCF) given seemed to contradict the actual weather occurrence. This suggests that farmers are keen on the reliability and skill of climate forecasts in this region.

In summary for the FDGs and farmers in both areas, some of the factors identified as important in facilitating better use of IF and SCF in these regions was that:

- Farmers should be educated on understanding the climate patterns in their region and how this is linked to forecasts for their areas. They believed this can help them make better decisions. Additionally, meteorologists should help farmers understand/interpret the terminologies used in the SCFs because these are often hard to understand.
- The government should set up research centres in the farming areas to manage climate issues and especially drought. This should include testing the soil fertility

which they think has decreased over the years and dealing with the changing climate.

- Quality seeds and fertiliser should be provided at subsidised prices to boost more crop production in these regions. Economists may disagree with this but the farmers and FDGs believed that better seeds and fertilizer combined with reliable and skilful forecasts can help them mitigate climate extremes.
- Indigenous forecasts must be recognised by the government and the scientific community, and ways of harmonising them with climate forecasts should be sought. Farmers are willing to work with the meteorologists and agricultural experts to see how best this knowledge can be tapped and used.
- There should be regular and continuous monitoring of climate forecasting and dissemination as well as awareness to farmers rather than the normally ad hoc pattern in which forecasts become important only around the growing seasons.
- The government should put in place a system of alleviating farmers suffering from the negative effects of drought which is a major problem in these areas. In particular, farmers should be given some financial or farm-input relief to enable them get back to productivity. The FDG recommended that forecasts should be developed specifically for when drought (dry spells) will occur so that farmers can know in advance how to avoid losing their seeds and inputs.

7.5. Other interventions in farming in Laikipia and Vihiga

Whereas the survey was focussed on assessing the role of forecasts in farm decisions, the role of the government as the custodian of agricultural policies was examined. From the information obtained from the local agriculture administrators in the 2 regions, there is little or no clear efforts in place to integrate climate or indigenous forecasts with agriculture plans in these regions.

In summary for the agriculture related interventions/policies in the 2 areas;

- Agricultural shows, farmers' forums and extension services are the main tools used to interact with farmers.
- Promotion of high quality and early maturing crops and afforestation are the main tools encouraged to cope with climate risk.
- Less attention has been placed on the use of climate/indigenous forecasts in agriculture policies and interventions.

7.6. Discussion

7.6.1. Relationship between climatic patterns, use of forecasts and maize yields

Climatic patterns and agronomic practices in Kenya can shape the understanding of farmers' perceptions on scientific (SCF) and indigenous (IF) forecasts. For example, according to Table 7.3, various forecast indicators inform farmers' expectations and push to use forecasts in farm decisions, and from Table 7.2, perceived actual yields and possible reasons for crop/yield performances can be related to the climate patterns of the study areas (Figure 7.1 and 7.2).

Interviews with farmers in the 2 study areas revealed that, maize yields were better in Laikipia compared to Vihiga, consistent with the rainfall and drought patterns in the 2 areas. These results contrast with those of a recent study in eastern Laikipia where farmers indicated poor yields due to increased droughts (Ogalleh et al. 2012). Huho et al. (2010) had earlier reported yield declines in the region prior to 2007. Prevailing declining rainfall trends in western Kenya (Vihiga) are consistent with those reported recently (see, for example, Omondi et al. 2013).

In light of the above, the impact of climate forecasts in farm decisions relative to use of indigenous forecasts was more highlighted in Laikipia than in Vihiga. However, no relationship was indicated between the use of forecasts and maize yields (indicator of rainfall) in the 2 areas. This may not necessarily imply that farm decisions based on forecasts were absent and this can be argued using a number of examples. Firstly, a majority of farmers (>50%) from both regions identified the wind direction as the most significant factor they used to forecast rainfall among other factors. This agrees with climatological and atmospheric processes related to wind (Wagner & da Silva 1994). It has been suggested that as a result of the easterly winds weakening of the westerly wind anomalies over the central Indian Ocean, rainfall is enhanced in eastern Africa but reduced in the sub-Indian region (Black et al. 2003). As opposed to Laikipia, rainfall patterns in western Kenya are influenced by local factors, mainly Lake Victoria currents and the Congo equatorial air-mass (Anyah et al. 2006). For instance, Camberlin (1997) show that, above normal daily rainfall is strongly associated with westerly wind anomalies over western Kenya. However, the rainfall patterns in Laikipia are mainly linked to the general north-easterly and south-easterly wind regimes (e.g. Sun et al. 1999). This confirms that wind is a significant determinant of rainfall occurrence in these regions.

Secondly, climatic factors were suggested to be responsible for yield declines in Laikipia (~25% of farmers) and Vihiga (~20% of farmers). This agrees with similar studies that link climate extremes in the growing seasons to crop losses (e.g. Roncoli et al. 2002, Orlove et al. 2010, Ogalleh et al. 2012). Furthermore, most of the forecast indicators used by the farmers in these areas (Table 7.3) are technically related with climatological processes or aspects normally applied in contemporary scientific forecasts. For example, weather in other regions such as cyclones and clouds are used in the prognosis of future weather.

Thirdly, farmers consulted various sources for climate information prior to the planting seasons. It is shown that substantial number of farmers in Laikipia relied on daily forecasts which they received through radio, whereas those in Vihiga sought the information from their neighbours or rainmakers, among other sources. Field and other studies suggest that climate information is needed by both small-scale and large-scale farmers as one way to increase food security (e.g. Carberry et al. 2000, Meinke & Stone 2005, Blench 2009). Additionally, due to climate change and variability some of the indicators used by farmers are becoming increasingly uncertain and therefore climate forecasts may become more useful to farmers (Ndegwa et al. 2010).

7.6.2. Impacts of level of education on use of forecasts

Farmers' responses in relation to education or agriculture training would be expected to have some impact on use of forecasts in farm decisions. As indicated earlier in this study, <30% of farmers in Vihiga and 42% of the farmers in Laikipia have a high school or college education. This means that the majority of the farmers have primary education or no formal education in these regions. Without additional explanations, it may be difficult connecting farmers' levels of education and use of forecasts. However, Table 7.4 indicates that, in Laikipia, no significant relationship exists between farmers who have high school or primary school education or with no training in agriculture, and the usage of climate (SCF) or indigenous (IF) forecasts. Nevertheless, farmers with college education are negatively related and those with and no formal education have positive relationships with the usage of indigenous forecasts ($p \leq 0.05$). There was a further positive relationship with those combining SCF and IF ($p = 0.04$) and having agriculture training. In contrast, use of indigenous forecasts has a positive relationship ($p = 0.02$) with farmers who have primary education in Vihiga. Interestingly, a strong positive correlation occurs between farmers who have agriculture training and the usage of climate forecasts. In contrast, those with no formal training do not use climate forecasts. This was probably due to the fact that climate forecasts may be of some interest to the farmers (positively related to training) in boosting their farm decisions. Whereas an estimated 80% of the farmers in Vihiga used IF, a large proportion (64%) of the farmers had primary education which might be the reason for the positive and strong relationship. This may support the results in Table 7.5 from which, agriculture training (farmers) had a positive effect on increasing yields in Vihiga. Whereas O'Brien & Vogel (2003) says that, usefulness of forecasts depends on the characteristics of farmers such as having education, they also admit that the value of climate forecasts in small-scale African farming systems is less evident despite the use of forecasts by most farmers in the region.

In Laikipia, the regression results are less transparent and appear to exaggerate the impact of college education on use of IF. Never the less, it can be speculated that, there is something to do with the large number of farmers (>60%) using indigenous forecasts compared to farmers using climate forecasts. This is simplistic, but may be a valid reason, considering that out of all the farmers having a college education, a significant number (1/3) plus almost all those without education use indigenous forecasts. Besides, there was a positive relationship between farmers with agriculture training and constant yields in this region (Table 7.4) implying that, there may be a link with the strong effect occurring with combined use of SCF and IF (Table 7.6).

In a nutshell, farmers' level of education in relation to forecasts use does not draw concrete scenarios for meaningful generalisations. This may be because farmers are not essentially the most receptive to forecasts (Meinke & Stone 2005) although Ingram et al. (2002) suggests that different levels of education and training have potential to influence the use of forecasts. Agricultural training and other factors may be more effective if they are specific to use of forecasts in decision making. If farmers are trained to understand the various aspects of forecasts, they may be in a better position to apply them. One suggestion for farmers to use forecasts, is that they must be willing to appreciate the concepts of probability and climate variability and how this influences their activities (Hammer et al. 1996).

In view of forecast usage and level of education in the 2 regions, results suggest that stronger framework for usage of IF can be developed in the regions if more emphasis is given to educating or training farmers and in addition provide an opportunity to also integrate climate forecasts in the region.

Table 7.6: Relationship between level of education and forecast use in Laikipia and Vihiga: Agric-TR and No Agric-TR means agriculture training and no agriculture training respectively and No Edu. = No Education

Level of education	Laikipia						Vihiga					
	Slope estimate			p-value			Slope estimate			p-value		
	SCF	IF	SCF/IF	SCF	IF	SCF/IF	SCF	IF	SCF/IF	SCF	IF	SCF/IF
Primary	-	-	-	>0.1	>0.1	>0.1	+	+	-	>0.1	**0.02**	>0.1
High	+	+	+	>0.1	>0.1	>0.1	-	-	+	>0.1	>0.1	>0.1
College	+	-	+	>0.1	**0.05**	>0.1	-	-	+	>0.1	>0.1	>0.1
No Edu.	-	+	-	>0.1	**0.001**	**0.01**	+	-	-	>0.1	>0.1	>0.1
Agri-TR	+	-	+	>0.1	>0.1	**0.04**	+	+	-	**0.05**	>0.1	>0.1
No Agri-TR	+	-	+	>0.1	>0.1	>0.1	-	-	+	**0.05**	>0.1	>0.1

7.6.3. Monsoon and the value of indigenous forecasts

Because indigenous forecasts are used most often by farmers in the study areas, it is expected that they may influence the times of planting in the monsoon seasons. For instance, some indicators identified by farmers (Table 7.3), were used to ascertain or estimate the occurrence, intensity or start of the monsoons. Late appearance of the moon or the stars for example, suggested a delayed onset while the migration of locusts was linked with shorter rainfall season or prolonged dry conditions although unusual appearance of dew in early morning signalled early onset. Similar findings have been reported in other parts of the world (e.g. King et al. 2008, Anderson 2009, Chaudhary & Bawa 2011). However, indigenous knowledge fails at times to capture changes in the weather patterns (Roncoli et al. 2002) probably due to climate change and variability (Ndegwa et al. 2010), in which case, Laux et al. (2008) suggests that farmers' demand for scientific forecasts may increase.

Despite some relationship between farmers' perceptions (IF) and climate patterns, no study has analysed the ability of IF in predicting onsets and cessation of the monsoon seasons in the region. No significant relationship was established from farmers responses in regard to changes in planting times (early, late, 50/50, or no change) and IF in Laikipia and Vihiga. One exception however is that, a significant association (p = 0.02) was found for IF and the 50/50 (planting comes early or late) scenario in Vihiga. In this view, while it is difficult to quantitatively predict onsets or other climate characteristics using IF, the last result suggests that it may be possible to regularly monitor and predict onset and cessation of the monsoon if an elaborate framework to collect and update the information is developed.

7.6.4. Does growing other crops have an impact on maize yields?

In Kenya, rainfall is highly variable and erratic, making agriculture more vulnerability to drought. One of the strategies frequently used to manage drought in the region is mixed or inter-cropping (e.g. Mendelsohn & Dinar 1999, Morton 2007, Rockström et al. 2009). This study found that, alongside maize, farmers grow other crops such as beans, millet and cassava. While these provide food, growing of other crops and mainly drought tolerant crops ensures resilience to food insecurity (Campbell 1990). Currently, most farmers in Laikipia (54.1%) and Vihiga (70.3%) indicated that other crops comprised 1/3 (33%) of the total crop grown in the regions (Table 7.1), which confirms that maize remains the single most important crop in Kenya (Hassan & Karanja 1997, Songa 2012). These results further corroborate other studies in the region which show that crop diversification or mixed cropping is a very popular risk aversion strategy (e.g. Downing et al. 1989, Campbell 1999, Speranza 2010, Ogalleh et al. 2012).

Regression results in Table 7.4 indicated that the overall increasing maize yields in Laikipia were not influenced by other crops while growing of up to 60% of other crops had a negative impact ($p<0.01$) on maize yields in Vihiga, consistent with the overall decline in maize yields in the region (Table 7.2). Omamo (1998) recognises that, staple food like maize can be impacted by choice of other crops while Van Rheenen et al. (1981) opines that, mixed-cropping is associated with nutrient competition and disease or pest infestations which may lead to yield reductions. Nevertheless, growing other crops will continue in the region as this might ensures food availability when maize fails.

7.6.5. Relationship between family size and yields

A high global population is expected to increase the demand for food (Daily et al. 1998). However production may be slowed by the effects of climate change (Schmidhuber & Tubiello 2007). Family sizes in the 2 study areas reflects the population statistics in the country but varies and is about ½ million in each of the study areas (Chapter 3, Table 3.2). As shown before, maize yields increased in

Laikipia and declined in Vihiga in the last 5 years. Out of the non-climatic factors attributed to yield declines, a small fraction (5%) of the farmers in Vihiga cited family size as the cause of yields reductions consistent with maize yields decline ($p<0.0001$) in the region. Different from Vihiga, family size was not mentioned to affect maize yields in Laikipia but was negatively related to increased yields ($p < 0.05$) rather than decline in yields, meaning that the family size can impact yields in the region. Other studies in SSA (Conway & Toenniessen 1999, Smith et al. 2000, Baro & Deubel 2006) suggest that bigger families can impact the food supply. Smith et al. (2000) for instance, shows that, food availability and access in developing countries are strongly related to poverty and poor farming systems. While it can be argued that bigger families are a distraction to better yields as they may require more food, it may not be entirely true if other factors that (non-climatic factors (mainly inputs) led to yield increase and decreases) enhance crop production such as good rains and quality inputs are available.

7.6.6. Can the results of the survey be used to develop better forecasts?

The proportion of farmers who combined climate and indigenous forecasts (20% in Laikipia and 16% in Vihiga) suggests that there is a potential of increasing use of combined forecasts in the 2 areas. Farmers in Laikipia think that the accuracy of the climate forecasts are at best average in contrast to farmers in Vihiga who think the forecasts are less skilful. Whereas farmers were not asked to indicate their views in regard to the skill of indigenous forecasts, the large number of farmers using IF suggests that they have relatively higher confidence in their skill. This finding further strengthens the above arguments that incorporation of IF with SCF can benefit farmers in managing climate variability.

In view of the above, by integrating some features of IF and SCF, it might be possible to develop better forecasts. Firstly, historical climate records by meteorologists can be cross-checked against farmers' responses on climate variability. More dry conditions were associated with reduced yields in Vihiga and less dry conditions to better yields in Laikipia which compared well with empirical evidence from the climate records in the 2 areas. This means that, farmers were able to identify the connection between yields and poor weather as reflected in the historical rainfall records. Farmers in these regions can identify changes in the local climate and have evolved numerous coping options (e.g. Oba et al. 2002, Hassan & Nhemachena 2008, Speranza et al. 2010).

The bio-physical factors indicated by farmers can be identified with climate variables that are used to analyse and predict climate. While farmers identified wind as the most significant forecast indicator of the rains/drought in the 2 regions, surface and upper air winds for large spatial areas are normally analysed by meteorologists in preparation of weather forecasts. This shows that climate forecasts can be downscaled using the local (indigenous) features to improve prediction in the local areas. Wind direction (and speed), dew in the morning, temperatures and other indicators can act as proxies in the formulation or development of integrated forecasts. In the recent times, there has been some efforts towards combining SCF and IF (e.g. Ndegwa et al. 2010, Guthiga & Newsham 2011). Similar studies have also been conducted in Malawi (Kalanda-Joshua et al. 2011), Tanzania and Zimbabwe (Kijazi et al. 2013). Ndegwa et al (2010) incorporated indicators used by farmers in south-eastern Kenya to downscale seasonal forecasts to the local level. Evaluation of the forecasts revealed that, farmers were able to identify and select appropriate farm decisions which helped in the selection of seeds, onset of the rains and other decisions. Some of the limitations to these efforts is the lack of technical capacity, framework and information delivery systems in the local areas and the forecasts skills are not yet clear.

7.7. Conclusions

This study focussed on indigenous forecasts and observations of weather in relation to farmer preferences and maize yields in Kenya. Results revealed that, >50% of the farmers used IF and <50% used SCF along other agronomic options to make farm decisions. Forecasts were an effective way to monitor and know when climatic conditions such as start of rains or type of rains were expected.

Forecasts were found to have little direct effect on maize yields but both climatic and non-climatic factors had impacts on maize yield. The benefits of IF and SCF on maize yields therefore were intricately related with other agronomic factors but climate factors (rains) were consistent with the observed yields.

More than 15% of the farmers in the study locations combined IF and SCF in farm decisions, suggesting that there is potential for integration of IF and SCF as a way to improve forecasts in the region. This area is still under explored in many regions and requires further research, particularly, how to translate and update IF into quantitative and scientific terms.

Most farmers from the 2 regions used numerous indigenous and scientific options to cope with climate variability and which were mostly related to timing and occurrence of rainfall or dry conditions in the regions.

CHAPTER 8

GENERAL DISCUSSION AND THESIS CONCLUSIONS

The impacts of drought on agriculture in Kenya and Australia are well documented. However, the greatest challenge of drought research in these regions is its predictability. The aim of this thesis is to forecast dry spell lengths at 1, 3 and 6 months lead times and also at the annual scale. The contribution of this is to improve the management of climate impacts for agriculture in these regions.

8.1. Main findings

1) The observed dry spell distributions in Kenya and the MDB can be summarised using the log-normal distribution.
2) The mean monthly dry spell length based on averaging of dry days in a month cannot represent drought conditions in a region reliably, because it underestimates the observed dry spells.
3) It is difficult to calculate the mean monthly dry spell length and to use this in forecasting. Dry spell length calculated by taking into account series of dry days which go across monthly boundaries give the real picture of the observed underlying drought conditions but this results in some double counting of dry spells.
4) Drought probabilities for critical dry spells derived from empirical cumulative density functions of observed dry spell length can be used as an indicator of drought risk.
5) Crop production in the short rain season (OND) in Kenya and in winter in the MDB is at a higher risk because there appear to be more increasing trends in dry spell lengths compared to the longer and abundant rainfall season (MAM) in Kenya and Autumn in the MDB.
6) The existence of trends in the dry spells lengths cannot always be summarised using linear relationships because both linear and non-linear trends exist across time and locations, in a more complex manner.
7) The spatial variation of the log-normal distribution parameters of the dry spell lengths shows stronger trends with latitude than with longitude in Kenya but also seem to increase with southerly latitudes and increasing rainfall in the MDB.

8) Specific phases of the Southern Oscillation Index (SOI) have an impact on dry spells lengths across locations in Kenya and the MDB at 1, 3 and 6 months lead times but this may vary in time and space in these regions.
9) Climatic factors cannot in general be taken to be the key determinants of farm decisions as would be expected. Mostly, non-climatic factors control what farmers do relative to climatic factors.

8.2. Implications in Kenya and Australia

8.2.1 Dry spell lengths distribution

The log-normal distribution was used to fit the dry spell data series in Kenya and the MDB. It was found to describe the observed dry spell data best in most of the locations based on the minimum Akaike Information Criterion. The density estimation and key feature of the observed dry spell data in these regions was found to be heavy-tailed and positively skewed, similar to that of some other geo-physical or climatic variables such as streamflow, windstorms and rainfall (e.g. d'Almeida 1987, Berg & Chase 1992, He et al. 2012), which also tend to follow the lognormal distribution.

Considering that most areas in these regions are semi – arid and have limited or no data, the implication of this is that the lognormal probability distribution functions can be used to estimate the dry spell statistics or climatic conditions in such areas and hence provide better estimates of drought in contrast to traditional proxies such as climatology or analogues (e.g. Unganai & Kogan 1998, Sorooshian et al. 2000, Gergis et al. 2012). For example, the correlations of the log-normal distribution parameters with rainfall in chapter 3, suggest a strong negative relationship in Kenya and a clear relationship with latitude which is correlated to the rainfall. This means that, drought conditions for locations with similar rainfall and latitude can be derived from such relationships. This is may particularly have some implications in the MDB, where rainfall normally has a strong east-west (longitude) trend (e.g. Drosdowsky 1993, Cook & Heerdegen 2001, Ummenhofer et al. 2008). The analysis of dry spell length distribution parameters in chapter 3 indicated that latitude explained 47% and 38% of the variance in the shape and scale parameters but longitude explained very little variation. Again the shape and scale parameters increased with southerly latitude and increasing rainfall. This would suggest that drought has a strong North-South orientation with dry spells relative to longitude. In other words, latitude can be used to estimate dry spell patterns and prediction of dry spells in semi arid regions.

8.2.2. Actual observed dry spell lengths distribution and understanding of drought

Calculation of the mean monthly dry spells length using dry days at the monthly scale and also dry days that go across months has complications. Averaging dry days only within the monthly boundary leads to under-estimation of the actual mean dryspell length and including dry days going across months may under or over estimate the mean dry spell length depending on whether a dry spell starts or ends in a previous, current or the next month. This suggests that the use of the mean monthly dry spell length which is frequently used to represent the state of drought in a region may not be reliable. Drought is particularly sensitive since the length of drought tends to indicate its severity. This scenario yet again brings to light the increasingly complex definition of drought. However, dry spells can arguably be a better way to explain drought in a region. Dry spells can be taken to mean drought if the precipitation during the period is below the normally occurring levels and cannot support maturity of crops (MacDonald 1998). A general view of drought is that, a deficiency in precipitation leads to water shortage which fails to adequately meet the needs of some activities (Wilhite & Glantz 1985). Drought is seen as an extreme event. For agriculture, this requires definitions of: what is “extreme” for agriculture; what “extremes” are relevant to agriculture and how long is “extreme” for agriculture.

In general, it may therefore be more practical to consider a number of options rather than the mean monthly dry spell length. This can be counting the number of dry days in a month or the longest dry spell length in a month. Alternatively, shorter dry spells (“<month”) within cropping stages may be useful. In the case of counting the number of dry days, again, there remains an issue with dry spells going across successive months. However, one study (Stern et al. 1982a) suggests that in such a case, where a dry spell goes across 2 months, it can contribute to the individual dry spell lengths ending in either month (periods). This argument however, can only apply if one considers counting dry days/spells starting from the first to the last day in each month and not across consecutive months. For agronomic purposes, the number of dry days or the dry spell in different crop stages can be an indicator of the level of

water stress. The impacts of water stress on crop growth during different phenology stages of crop has been studied and found to indicate crop failure or yield reductions (e.g. Pantuwan et al. 2002, Blum 2005). This information can complement the rainfall amounts (soil moisture) available for crops at different stages and facilitate improvement of crop water management against drought conditions in Kenya and the MDB.

8.2.3. Drought risk

In chapter 3, the application of the derived dry spell distributions was demonstrated in the derivation of the probabilities of exceeding any given dry spells lengths in the planting season for maize in Kenya and wheat in the MDB. This contrasts some previous studies that only considered probabilities of the occurrence (e.g. Stern et al. 1982b). A study by Barron et al. (2003) using Markov models had found that the probability of exceeding 10 dry days in the long (March-May) and short (October-December) growing season was <20% for 2 semi-arid locations in east Africa. This result differs in this study (chapter 3) for most of the semi-arid locations analysed in which, higher probabilities of exceeding 10 dry days (> 20%) in the long growing season were indicated. This would probably be because Baron et al (2003) used a higher daily rainfall threshold (0.85mm) to define a dry day which may have included relatively wet days in the calculation. Whereas maize or wheat yields reductions due to drought have been documented before (e.g. Ribaut et al. 1997), these are generally based on the cumulative effects of drought (e.g. Vasic et al. 1997, Hlavinka et al. 2009).

The implication of the probabilities of exceedances of dry spells in the growing seasons is that they can be used to develop drought risk maps which may be used in management decisions for agriculture in these regions. In other words, the probabilities can be used as indicators of drought risk in contrast to other drought indices such as the drought severity index (Palmer 1965) and the standardized precipitation Index (McKee et al. 1993) which are not suitable for the relatively shorter cropping stages. Moreover, the dry spell probabilities can complement seasonal climate forecasts which often double in the provision of climate information for both rainfall and drought conditions.

8.2.4. Chance of crop failure

Using a generalized linear model (GLM), it was shown that the risk of crop failure is higher in the short rain season (OND) in Kenya and also in the winter season in the MDB because of more increasing trends in dry spell lengths in these seasons compared to the longer and abundant rainfall season (MAM) in Kenya and drying autumn season in the MDB. Several studies have suggested that crop failures in Kenya occur more in the long rain season than in the short rain season (Downing et al. 1989, Wafula 1995, Rao & Mathuva 2000, Ngigi et al. 2005). The long rains contribute to 70% of the total annual rainfall in Kenya and would therefore be expected to be more useful for crop production. Crop failures in the long rain seasons could be due to its unpredictable nature. Crop failures and yield reductions occurred as a result of delay in the long rains (e.g. Wafula 1995) or occurrence of low rainfall (e.g. Ong et al. 2000). Another reason may be the tendency of poor rains occuring more frequently in the MAM season than in the OND season (e.g. Muti & Kibe 2009, Speranza et al. 2010). Regardless, it is the occurrence of inadequate rainfall, rather than rainfall failure, that causes crop failure. In the MDB, increasing drying trends in rainfall patterns in the past have been highlighted more in autumn compared to other seasons. Autumn rainfall has a greater impact on crop and pasture production in the MDB but is less reliable than winter rainfall (e.g. Austen et al. 2002, Clark et al. 2003). Therefore increasing trends indicated in dry spell length in Kenya and the MDB could have significant ramifications for crop production in these regions because the short rain season in former is more reliable for crops and pasture production in the semi-arid and pastoral areas and particularly for short maturing crops whereas winter crops such as wheat in the MDB (Nicholls 2004) contribute to the larger proportion of the total agriculture output for Australia (e.g. Sandhu et al. 2012, Ejaz Qureshi et al. 2013)

8.2.5. Consistency in short and longer dry spell lengths trends

In chapter 4, long-term trends in the dry spell lengths were analysed at the annual and monthly seasonal time scales. Results suggested that the estimated trends for shorter ("<month") were similar to those of the longer ("Long") dry spells in the study locations and occurred more often than by chance. This finding is significant and contrasts to other analysis that mostly focussed on longer time scales (e.g. Seleshi & Camberlin 2006, Nasri & Modarres 2009). For instance, Nasri & Modarres

2009 found trends in the annual maximum dry spells over Iran but the regional trends were more a random occurrence. This means that for agriculture, whereas increasing trends for longer dry spells may suggest increased and prolonged drought risk/conditions and hence severe effects on crops, similarly severe effects may also occur due to shorter dry spells occurring in the crucial cropping stages. This is to say, for successful formulation of adaptation strategies for agriculture; both the short and longer effects of dry spells/drought must be considered.

8.2.6. Linear and non-linear trends

Analysis of trends in dry spell lengths using a generalised additive model (GAM) indicated that some locations had more complex patterns. Both linear and non-linear trends emerged which suggest that dry spells trends cannot only be summed up as linear. These 2 trend types suggest there is variability in the climates of the regions that may be explained by other processes in local or climatic factors like the El Niño Southern Oscillation (ENSO). For example, fitting a GAM model to the observed dry spell lengths for Lodwar (Kenya) using only the El Niño and La Niña years shows more variability in the long-term (year-year) and monthly trends for La Niña years ($p \leq 0.05$) compared to the El Niño years (Figure 8.1). Whereas the long-term trend is insignificant in El Niño years, a non-linear and possibly positive trend occurs with La Niña years. Both monthly trends follow seasonality in Kenya. The trend in La Niña years could be because the La Niña phenomena is strongly associated with low or deficient rainfall in Kenya (Mati et al. 2006, Nduru & Kiragu 2012) and El Niño years with higher rainfalls (Usher 2002, Ambenje 2004). La Niña is related to severe droughts in Kenya and intense rainfall in eastern Australia (MDB) with El Niño events giving the opposite rainfall patterns in both regions.

Generally, trends at the monthly scale would be noisier than the year – year variability because in the latter, long periods smooth out the seasonal cycles and highlight the long-term cycles. As a result, estimating non-linear trends and their statistical significance may be problematic for the finer (monthly) temporal scale compared to the longer (annual) scale. This may be why most drought studies consider longer time scales (annual) than shorter periods to analyse non-linear trends (e.g. Griffiths et al. 2003, Bordi et al. 2009).

The implication of this is that, statistical approaches that have the ability to model complex temporal patterns in drought should be used. In this study, GAMs were used to model the temporal and spatial characteristics and prediction of dry spell length because they are flexible and efficient for modelling both linear and non-linear behaviours in a data series.

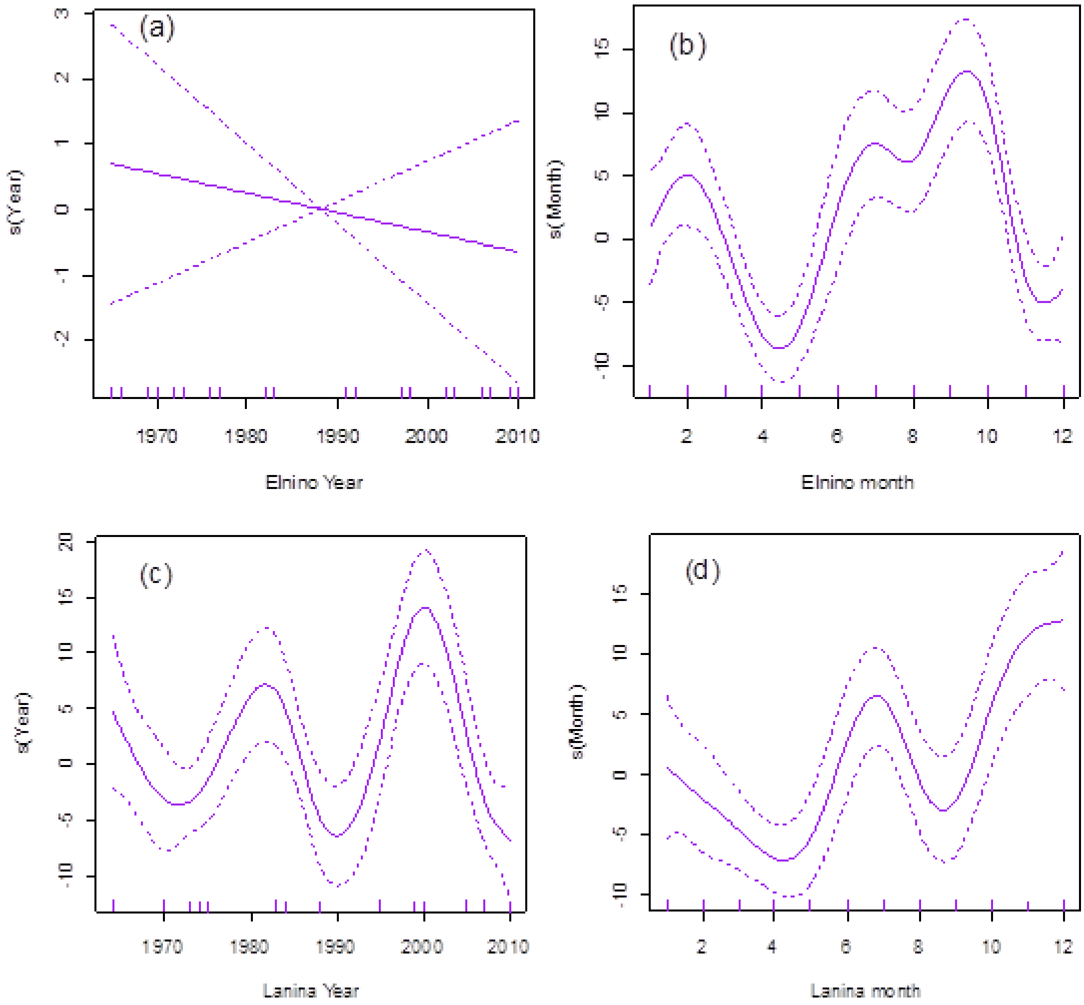


Figure 8.1: The effect of year and month on dry spell length for Lodwar (Kenya) during El Niño years ((a) and (b) respectively) and La Niña years ((c) and (d)) between 1961 and 2010.

8.2.7. Spatial characteristics of dry spell length lognormal parameters

The effects of droughts are mostly felt at a regional or broader scale as opposed to local (Booth et al. 2006). It therefore makes sense to examine whether trends in dry spell length are visible at a larger scale. This can be useful to better understand the geo-physical dynamics or processes driving drought in different regions. The information may also be used to adjust plans for food security, agricultural marketing and so on at the national, regional and local level.

In Kenya, the present analysis indicated strong increasing trends in the dry spell length in the long dry (June –September) season compared to the short dry (January – February) season and again in the short wet (October-December) season compared to the long wet (March-May) season. Interestingly, most of these increases occurred in locations in southern half of the country which contains over 80% of the high potential agricultural areas. The result of this is that, the country is at a higher risk of a food crisis as drought conditions may increase in the high potential regions normally referred to as the maize basket. This suggests that these areas should be prioritised for study so as to understand the effects of drought on agriculture production and the best way to mitigate or manage the impacts. One way to start can be to integrate dry spell information together with rainfall distributions in these regions.

In contrast to Kenya, a significant number of locations with increasing trends in dry spell lengths occurred in autumn and winter in the MDB as mentioned in section 4.3.4 and the spatial distribution of these trends (chapter 4: Figure 4.7) indicated that these mostly occurred in locations in the southern half of the basin and the eastern parts. This suggests that changes in drought may be felt more in the winter-dominant rainfall (south and east) regions than in northern regions. Crop production in this regions may not only be affected by drought. Because agriculture is the single most greatest employer (60%) in rural Australia, unemployment, income losses among other issues can occur if the drought impacts of the “2002 -2003” magnitude reoccur. Efforts should therefore be scaled up to improve agriculture adaptation to such changes.

8.2.8. Relationships between dry spells and El Niño Southern Oscillation

Significant correlations between rainfall and ENSO in Kenya and Australia (MDB) are widely documented (e.g. McBride & Nicholls 1983, Kane 1997, Indeje et al. 2000, Camberlin et al. 2001, Amissah-Arthur et al. 2002, Risbey et al. 2009). This has been the basis for precipitation and drought predictability in these regions (e.g. Drosdowsky 1993, Mutai et al. 1998). Using lagged Southern Oscillation Index (SOI) phases, it was shown that different patterns occurred with dry spells lengths at each phases and time lag. The importance is that specific lagged SOI phases were better determinants or predictors of dry spells length of specific characteristic (e.g. median or maximum dry spell length or lags) and for specific locations or regions.

This has potential implications for forecasting dry spell lengths in this regions. For example, Stone & Auliciems (1992) demonstrated this concept for rainfall in Australia, arguing that using the correlations between Southern Oscillation Index (SOI) alone and rainfall did not explain most of the variability as "within cycles" of the SOI (phases) held some of this information. For instance, they found that one SOI phase represented well 'above median' rainfall and another 'below median' or 'median' rainfall.

8.2.9. Farmers perceptions on forecasts and effect on farm decisions

In chapter 6, it was shown that most farmers in Kenya used indigeneous forecasts compared to climate forecasts as they were easily accessible (through experience and observation). But significant differences exist in the use of climate forecasts between farmers in the high rainfall and dry (semi-arid) study areas. This strengthens other studies which indicate that farmers first utilise what they know best relative to other innovations (e.g. Orindi et al. 2007, Onduru & Du Preez 2008, Ogallo 2010). Application of forecasts in farm decisions have the potential of improving farmers ability to cope with climate extremes such as dry spells. However, constraints to adequately use forecasts also exist (e.g. Ingram et al. 2002). Factors such as the level of forecast skill, interpretation, lack of taking into account users needs and context of the information are some of the obstacles highlighted in forecasts usage (Lemos et al. 2002, Blench 2009). For example, farmers in the Sahel interpreted climate forecasts according to their own expectations, experiences and observations (Roncoli et al. 2002). According to Blench (2009), farmers or users of forecasts typically have a broader range of management options to respond to climate risks and would therefore not just focus on say "skillful" forecasts. However, a majority of farmers in Kenya expressed the need for dry spell forecasts because dry spells occurred in several occassions during the planting seasons. This means that, there is potential to increase forecast usage and food security if reliable dry spell/drought forecasts are provided and used by farmers in their decisions.

Whereas the results from the current analysis showed that climatic factors (use of climate forecasts etc.) were secondary to non-climatic factors (agronomic factors etc.) in the determination of farm decisions/choices, an important implication is that recommendation of management strategies based only on non-climatic factors would be counter-productive in the management of climate risks. This is because farmers in

Kenya and other regions are interested in climate information such as onset of rains, amounts of rainfall, and chance of dry spells in the season (O'Brien et al. 2000, Ziervogel 2004, Blench 2009) which can be provided through sound scientific framework. Moreover, this means that integration of both scientific and indigenous forecasts may help farmers to improve their adaptive capacity to climate change.

8.3. Research limitations

There are a number of limitations to this thesis. Firstly, a single rainfall threshold was used to define a dry day for all the locations in the study areas. This may have the limitation of misrepresenting the true picture of drought in a location because the climates for the different areas are not homogeneous. Secondly, calculating the mean monthly dry spell length is challenging due to the fact that dry days/spells that go across months contribute to both periods. This also poses a problem at how the observed actual ("Long") dry spells that go across 2 or more months can be matched with covariates that are usually at a monthly step. Thirdly, in modelling of dry spell length, one major limitation is how to account for uncertainty of extremes in the dry spell length predictions. For instance, the model outputs under-predicted longer dry spells in some occasions and no schemes were used to account for uncertainty in these models. Again, the skewed nature of the dry spell distributions meant that adjustments/transformations of underlying observed distribution was needed in order to adequately accommodate the covariates in the model. For instance, the log transformation was applied on the dry spell lengths for some locations. These patterns may be due to the presence of both linear and non-linearities in the dry spell distribution.

Lastly, research on application of forecasts in farm decisions indicate that there is a disjoint between the knowledge farmers (indigenous/scientific forecasts or experiences) have and how this is translated into benefits for agricultural management of climate risks in the study areas. For instance, wind direction was mentioned as the key indicator used by most farmers to forecast rainfall but how this can be integrated into quantitative structure and used for planning remains unclear.

8.4. Future research directions

This thesis was divided into 4 main research themes and thus numerous additional research questions arose. Some of the research questions which may be important in the future include;

1. Does a daily threshold rainfall amount make a difference on definition of a dry day? Further investigation on whether by varying the definition of a dry day using different daily rainfall thresholds for different climatic zones / locations would yield different results or conclusions. This is motivated by the fact that different studies use varied thresholds (e.g. Brunetti et al. 2002, Wauben 2006) but it is unclear how this affects the analysis or understanding of drought.

2. Mean dry spells length versus the monthly and across month boundaries

Whereas difficulties were met in the calculation of the monthly mean dry spell lengths at the monthly and across monthly scales, it may not be entirely possible to ignore the fact that the mean monthly dry spell length will still be useful in the analysis of drought. For example, when forecasting drought, covariates normally used are monthly sea surface temperatures, SOI and so on. And because more than one dry spell may exist in a month, taking the average or using the median or maximum dry spell length as a response variable would mostly be the only option. Future work will need to explore how best the mean dry spell length can be calculated without compromising the actual underlying dry spell length.

3. Development of dry spell length index

Dry spell indices such as the standardized precipitaion index (McKee 1993) are used to monitor drought in many regions. While the SPI has its pros and cons just like any other drought monitoring tool, the development of a dry spell length severity index may be a better tool. The question however will be how to scale the dry spell length versus the rainfall amount prior and after a dry spell.

4. Examine novel ways that can address under-prediction of long dry spell length

In chapter 5, the problem of under-prediction of dry spells was noted. Future research can investigate if the dry spells can be modelled in two parts possibly using mixed distribution models. Possible candidates may include generalized additive or linear mixed models (GAMM/GLMM). Such models can allow addition of random effects that account for over-dispersion due to seasonal or other effects (McCulloch & Neuhaus 2006).

5. Prediction of dry spells at the seasonal and long term time scales

The current thesis concentrated on forecasting dry spells at 1 month and 3 month lead times and using only the SOI (phases) and Niño3. As a continuation of this, focus can shift to modelling seasonal to long term dry spell lengths in both regions and including other potential predictors and combinations. At the same time, this can be extended to exploring how to improve the quality of the monthly forecasts in the current study.

6. Integration of farmers perceptions into scientific terms

In the study on farmers survey in Kenya, one of the objectives was to determine how indigenous forecasts (IF) could be translated into quantitative and scientific terms and then integrated with seasonal climate forecast (SCFs). As this was not achieved, this objective will be pursued as an extension of this research. This question still remains a major research challenge (e.g. Hansen 2002, Roncoli 2006, Orlove et al. 2010, Hansen et al. 2011). It was noted in this study that both indigenous and scientific forecasts rely on environmental factors that are intricately connected and in both cases the forecasts provide probabilities of expected conditions such as rain, onset and so on but with uncertainty. This suggests that there could be ways of integrating the two paradigms to better predict and manage climate change and variability.

7. Explore the value and quality of dry spell forecasts in farm decisions.

In chapter 6, farmers indicated that the number of dry days was one of the key factors that affected crop production during the planting season. To better understand this issue, the ability of the dry spell models developed in the current thesis and subsequent analysis can be tested in practice using a sample of farmers. Forecasts specifically predicting dry spells or drought conditions are not normally in use or available since seasonal climate forecasts are provided. This may later be compared with the seasonal climate forecasts by the meteorological service providers. The outcome of this research may provide additional information that may help in improving the quality or application of forecasts.

8.5. Conclusions

The outcomes from this research have the potential to improve the management of climate extremes in Kenya and Australia and other regions. In particular, dry spells characteristics such as the temporal and spatial distributions are useful and potential for planning and boosting the resilience of rain-fed agriculture for these regions.

Short-term (monthly) and medium-term (3 & 6 month) forecasts can provide much needed information about future farming activities.

Because Kenya and Australia are typical semi-arid environments and water and dry spells are a limiting factor to agriculture production, this thesis is expected to form a basis for future developments of robust prediction models for drought in these regions. This can compliment the numerous other coping innovations farmers and water managers use in these regions.

APPENDIX

A1: The mean annual rainfall for the study locations in Kenya

Station Name	Latitude (^{0}North (+) / ^{0}South (-))	Longitude (^{0}East)	Mean Annual Rainfall (mm)
Mandera	3.93	41.87	282.5
Moyale	3.53	39.05	712.3
Lodwar	3.12	35.62	206.4
Marsabit	2.32	37.98	721.4
Wajir	1.75	40.07	339.5
Namandala	1.05	34.93	1107.6
Chorlim	1.03	34.8	1124.5
Colcheccio	0.63	36.8	600.4
Eldoret	0.53	35.28	1085.9
Isiolo DAO	0.35	37.58	679.6
Nyahururu	0.33	36.37	999.9
Kakamega	0.28	34.77	1856.1
Meru	0.08	37.65	1330.2
Timau	0.08	37.25	660.5
Laikipia Air Base	0.05	37.03	685.9
Kisumu	-0.1	34.75	1374
Nakuru	-0.28	36.07	973.1
Garissa	-0.48	39.63	534
Kisii	-0.68	34.78	1940.6
Thika	-1.02	37.1	956.4
Narok	-1.1	35.87	781.8
Dagoretti	-1.3	36.75	1055.8
Katumani	-1.58	37.23	731.1
Lamu	-2.27	40.9	1056.9
Makindu	-2.28	37.83	606.2
Malindi	-3.23	40.1	1340.5
Msabaha	-3.27	40.05	1150.6
Voi	-3.4	38.57	581.7
Mtwapa	-3.93	39.73	1295.1
Mombasa	-4.05	39.63	1080.5

A2: The mean annual rainfall for the study locations in the Murray Darling Basin

Station Name	Latitude (^{0}South)	Longitude (^{0}East)	Mean Annual Rainfall (mm)
Augathella Post Office	25.8	146.59	577.7
Charleville Aero	26.41	146.26	483.7
Waverley Downs	26.61	148.54	564.7
Chinchilla Water T.W	26.74	150.6	720
Westbrook	27.62	151.83	712.7
Condamine Plains	27.72	151.29	658.8
Cunnamulla Post Office	28.07	145.68	401.1
Wondalli	28.5	150.59	605.8
Boggabilla Post Office	28.6	150.36	736.8
Gum Lake (Albemarle)	32.53	143.37	264.6
Mungindi Post Office	28.98	148.99	558.4
Enngonia (Shearer Street)	29.32	145.85	384.3
Collarenebri (Bundabarina)	29.54	148.4	512
Collerina (Kenebree)	29.77	146.52	409.5
Inverell Research Centre	29.78	151.08	804.7
Narrabri (Mollee)	30.26	149.68	623.8
Barraba Post Office	30.38	150.61	721.4
Cobar (Tambua)	31.42	145.25	382.6
Quirindi Post Office	31.51	150.68	700
Broken Hill (Kars)	32.22	142.03	235.2
Wellington	32.56	148.95	655.5
Ivanhoe Post Office	32.9	144.3	334.7
Lake Cargelligo Airport	33.28	146.37	440.7
Pooncarie (Tarcoola)	33.43	142.57	281.4
Bathurst Agricultural Station	33.43	149.56	661.1
Cowra Agric. Research Station	33.8	148.7	643.4
Marrabel	34.14	138.88	558.6
Mildura Airport	34.24	142.09	281.9
Groongal (Groongal Station)	34.44	145.56	412
Euston (Sunnyside)	34.56	143.08	293.1
Yas (Linton hostel)	34.83	148.91	693.2
Murray Bridge Comparison	35.12	139.26	361.4
Wagga Wagga AMO	35.16	147.46	574.2
Nyah (Yarraby Tank)	35.17	143.28	349.4
Ainslie Tyson St	35.26	149.14	654.6
Pinnaroo	35.27	140.91	393.1
Huntly	35.28	148.98	706.9
Lake Boga	35.46	143.63	350.3
Echuca Aerodrome	36.16	144.76	419
Tallangatta (Bullioh)	36.19	147.36	841.8
Cooma (Kiaora)	36.2	149.06	536.1
Yackandandah	36.33	146.85	1057.2
Raywood	36.53	144.21	446.4
Horsham	36.7	142.2	432.7
Redesdale	37.02	144.52	607.9
Tongio (Brooklands)	37.18	147.71	618.3
Lake Eildon	37.23	145.91	860.5

A3: Summary statistics for rainfall in various locations between 1935 and 2010 in (a) Kenya and (b) MDB

	Statistics summary					
(a) Kenya	**1935 - 1960**		**1961 - 2010**		**1935 -2010**	
	Mean (mm)	CV (%)	Mean (mm)	CV (%)	Mean (mm)	CV (%)
Moyale	54.3	**152.7**	59.8	**143.5**	57.9	**146.5**
Lodwar	13.3	**181.8**	17.2	**176**	15.9	**178.8**
Marsabit	69.4	**130.6**	60.1	**160.6**	63.3	**149.5**
Wajir	20.1	**172.1**	28.3	**197**	25.5	**194.8**
(b) MDB	**1910 - 1960**		**1961 - 2010**		**1910 - 2010**	
Augathella	43.3	**118.7**	48.1	**115.8**	45.7	**117.3**
Wondalli	50.2	**94.8**	50.5	**90**	50.3	**92.4**
Groongal	29.6	**95**	34.3	**94.6**	32.0	**95.3**
Redesdale	44.8	**87.1**	50.7	**71.7**	48.0	**78.5**

A4: Questionnaire used in the farmers survey in Kenya

THE UNIVERSITY OF SYDNEY

A survey looking into how farmers plan their decisions using climate information in KENYA

This survey aims at understanding how farmers make decisions using climate information. The information you provide will be kept anonymous and used for intended research purpose only. This information will be used to improve the future ability to forecast variability in climate and hence provide farmers with better decision making tools. We will share with you the key results from this survey on the Kenya Meteorological Department website and the local agriculture office in your area or if you provide an e-mail address.

Please answer all questions using [X]. Select more than one where applicable

(**Acronyms**: KMD=Kenya Meteorological Department, SCF=Seasonal Climate Forecasts, IF=Indigenous Forecasts)

Section A: Participant and other farming practice information

1 a) Name:________________________ b) Sex: [ ] Male [ ] Female
c) Age: [ ] 20 – 45 years [ ] Over 45 years
d) Level of education [ ] Primary [ ] High School [ ] College and above
e) Do you have any agricultural training [ ] Yes [ ] No
f) Location of farm: ________________Sub-location _________________Village
g) Size of family on farm: __________________
h) Sources of income: Farm only [ ] Employment [ ] Business [ ]
Other [ ] Prefer not to answer [ ]
i) Size of your farm? _______________ (acres/hectares)

2 a) How important is Maize crop in your farming on a scale of 1 to 5?
Least important>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>most important
[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5
b) If you grow other crops on your farm, what is the percentage?
[ ] 0% [ ] 1 - 33% [ ] 34 - 66% [ ] 67 - 100% [ ] Don't know
c) Which of the following best describes your maize yields in the last 5 years?

Rating		Please explain your rating (e.g. bags per hectare etc)
Outstanding	[ ]	
Above average	[ ]	
Average	[ ]	
Below average	[ ]	
Poor	[ ]	
Unable to rate	[ ]	

Section B: Forecasts and farm decision making information

3 a) Please characterize your use of the following by selecting what applies to you

I am User of:	Type of information I use is:	I get my information from
Seasonal Climate Forecasts [ ]	Daily forecasts [ ]	Personal experience [ ]
	Weekly forecasts [ ]	Observations [ ]
Indigenous Forecasts [ ]	10 day forecasts [ ]	KMD website [ ]
	Monthly forecasts [ ]	Newspaper [ ]
Seasonal Climate Forecasts & Indigenous Forecasts [ ]	Seasonal forecasts (3 month) [ ]	Television [ ]
	Other [ ]	Radio [ ]
None of the Above [ ]	______________________	Consult rainmaker [ ]
		Local Agriculture office [ ]
		Others [ ]

b) How long have you been using the forecasts or your choice(s) in 3 (a)?
Less than 5 years [ ] Last 5 years [ ] Over 5 years [ ]

c) Why did you use the forecasts?

____

____

c) With respect to rainfall forecasts explain briefly what you understand by the terms "Normal", "Above normal" and "Below normal" rainfall

Forecast term	Explanation	
Below normal rainfall	Extremely high rainfall [ ]	0 mm [ ]
	high rainfall [ ]	1 - 50 mm [ ]
	moderate rainfall [ ]	51 - 100 mm [ ]
	low rainfall [ ]	101-150 mm [ ]
	Don't know [ ]	151 -200 mm [ ]
		Above 200 mm [ ]
Normal rainfall	Extremely high rainfall [ ]	0 mm [ ]
	high rainfall [ ]	1 - 50 mm [ ]
	moderate rainfall [ ]	51 - 100 mm [ ]
	low rainfall [ ]	101-150 mm [ ]
	Don't know [ ]	151 -200 mm [ ]
		Above 200 mm [ ]
Above normal rainfall	Extremely high rainfall [ ]	0 mm [ ]
	high rainfall [ ]	1 - 50 mm [ ]
	moderate rainfall [ ]	51 - 100 mm [ ]
	low rainfall [ ]	101-150 mm [ ]
	Don't know [ ]	151 -200 mm [ ]
		Above 200 mm [ ]

d) What would you describe to be the ideal rainfall forecast you have used for a good maize yield from your farm?
Extremely high rainfall [ ] high rainfall [ ] moderate rainfall [ ] low rainfall [ ] Don't know [ ]

Please provide details of how much maize you harvested in response to (d)

____
____
____

e) Please give a practical example and show how you applied any aspects in the forecasts in making farm decisions such as; crop to plant in the short or long rain season

Farm decision	Forecast aspect (Indicator used).		What did you do?
	Rainfall decile	[ ]	______________________________
	Rainfall amount	[ ]	______________________________
	Wind direction	[ ]	______________________________
	Croak of frogs	[ ]	______________________________
	Falling of leaves	[ ]	______________________________
	Onset dates	[ ]	______________________________
	Others	[ ]	______________________________
	(list)_______________		______________________________
	____________________		______________________________
	____________________		______________________________
			______________________________

4. In your opinion, how best would you describe the accuracy of the forecasts you have been using on a scale of 1 to 5?

Not accurate>>>>>>>>>>>>>>>>>>>>>>>>Extremely Accurate					I don't know
1 [ ]	2 [ ]	3 [ ]	4 [ ]	5 [ ]	[ ]

5. In your opinion, by combining SCF and IF how best would you describe the accuracy of the forecasts?

Not accurate>>>>>>>>>>>>>>>>>Extremely Accurate					I don't know	I don't combine SCF/IF
1 [ ]	2 [ ]	3 [ ]	4 [ ]	5 [ ]	[ ]	[ ]

6. How satisfied are you with the forecasts you have been using?

Very Dissatisfied>>>>>>>>>>>>>>>>>>>>>>>>>>>Very Satisfied					I don't know
1 [ ]	2 [ ]	3 [ ]	4 [ ]	5 [ ]	[ ]

7. Do your neighbours make use of forecasts in farm decisions?
i) Yes [ ] ii) No [ ] iii) Don't know [ ]

8. Is there anything you would like to suggest regarding the use of forecasts? (E.g. Constraints etc)

____
____
____
____
____
____
____

9 a) During the rain season, have you ever experienced dry periods after planting?
[ ] Yes [ ] No

b) If you said 'Yes' in 9(a) give one example of how you dealt with the situation

____
____
____
____
____

c) In your opinion, have the planting and harvesting dates changed? [ ] Yes [ ] No

____
____
____

d) If you said 'Yes' in 9(c) how have planting and harvesting dates changed?

Change in planting dates	[ ] Comes early [ ] Comes late [ ] have not changed [ ] I don't know
Change in harvest dates	[ ] Comes early [ ] Comes late [ ] have not changed [ ] I don't know

10. Please indicate if you would like to participate in future research Yes [ ] No [ ]

A5: Focus Group Discussion Questions

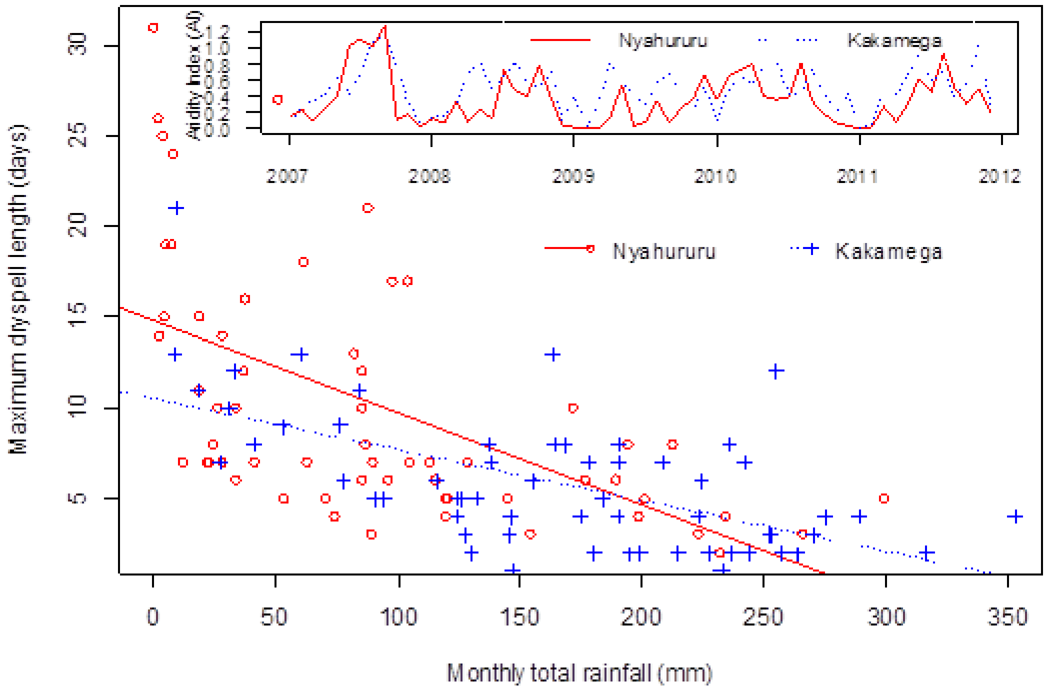
These QUESTIONS are intended to inquire about specific issues regarding use of climate information in Kenya. The questions will revolve around similar or emerging issues from the individual responses on the main questionnaire administered in the areas. The following questions will guide the discussions.

1. Is maize the most important crop in your area? Please explain, why you think maize is important.
2. Do you have other crops you think are important in your area and what benefits do they give you?
3. How on average can you describe the performance of the crops in your area in terms of yields?
4. Are there any climatic or others factors you think have influenced maize production / yields in your area in the last 5 or more years. What strategies did you use to cope with these?
5. The year 2011 was a severe drought year in Kenya in the recent times.
    - i) Was maize crop in your area affected by this drought? (Provide some evidence, yields, market prices etc)
    - ii) Do you remember any other similar drought or extreme events (floods, pests etc) in your area? Please list as much as you can remember and explain how it affected your crop (maize).
    - iii) In your opinion, has rainfall increased or declined in your area in the last 10 years?
6. i) Are you aware of climate forecasts (Meteorological and Indigenous)?
   ii) Do you know what the terms “Below normal rainfall”, “Normal” and “Above Normal” mean? Discuss
    - iv) Do you have any indicators from the environment that you use in your forecasts?
7. Do you use the forecasts in planning your farm activities?
    - i) What specific attributes do you use from the forecasts
    - ii) Please discuss how you use them before the rain season, during and after the rain season. (selection of crop/ seeds, land preparation etc)
    - iii) Give 2 examples of how you planned your farm activities when and if you had below normal rainfall and above normal rainfall forecast.
8. Are the forecasts you use accurate? Discuss how you determine the accuracy in the forecast
9. Are there any obstacles or constraints you have experienced regarding use of forecasts in your area? Please list or explain.
10. Do you have any other suggestions you want to discuss regarding use of forecasts?

A6: Perceived reasons related to yield increase or declines in Laikipia and Vihiga districts

Yield effect	Terms used as indicators of decline or increase in yield	
	Climatic	Non-climatic
Increase	• Good weather patterns • Good rains • Favourable rainfall • Improved rains • Increased rainfall amounts • Rainfall availability • Better rains • Timely rains • Early rains • Correct timing of rains season • Sufficient rainfall • improved weather	• Use of fertilizer • More farming experience • Increased cost of farm inputs • Use of improved quality seeds • Improved farm practices • Better agricultural practices • Use of treated seed fertilizer and manure • Improved agriculture practice • Reduced cost of inputs • Combining manure and fertilizer • Double ploughing before planting • Appropriate planting methods • Advice from local agriculture office • Use of better quality seeds • no tillage • Use of pesticides (cat worms) • Change of farm inputs • change from local to hybrid seeds • use of manure • early land preparation • welfare financial support • additional agricultural training • Use of advanced farming equipment (tractor) • Fallowing of land • Appropriate weeding
Declines	• Frost effect • Too much rains • Rainfall failure • Erratic rains • Delay in rains • Reduced rains • Less rainfall • Unreliable rains • Weather and climate change • Occurrence of dry spells • Low rainfall • Poor rainfall • Rainfall deficit • No change in weather • Wind destruction • Hailstorms • Change in rain patterns • Occurrence of floods • High rainfall	• Old age • Insufficient farming skills • Change to other crops • Big family size • Low soil fertility • Lack of fertilizer • Poor farm practices • Lack of quality seeds • Poor seeds and fertilizer quality • Poor farming methods • inadequate capital • reduction of farm size • not using fertilizer • reduced land size • theft • pests invasion • lack of subsidies • negative fertilizer effect on yield • new weeds variety invasion • poor land preparation

A7: Correlation between monthly total rainfall and the maximum dry spell length for Nyahururu (red dots) and Kakamega (blue (+) symbols. Inset is the temporal distribution of AI values for the period 2007 – 2012



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