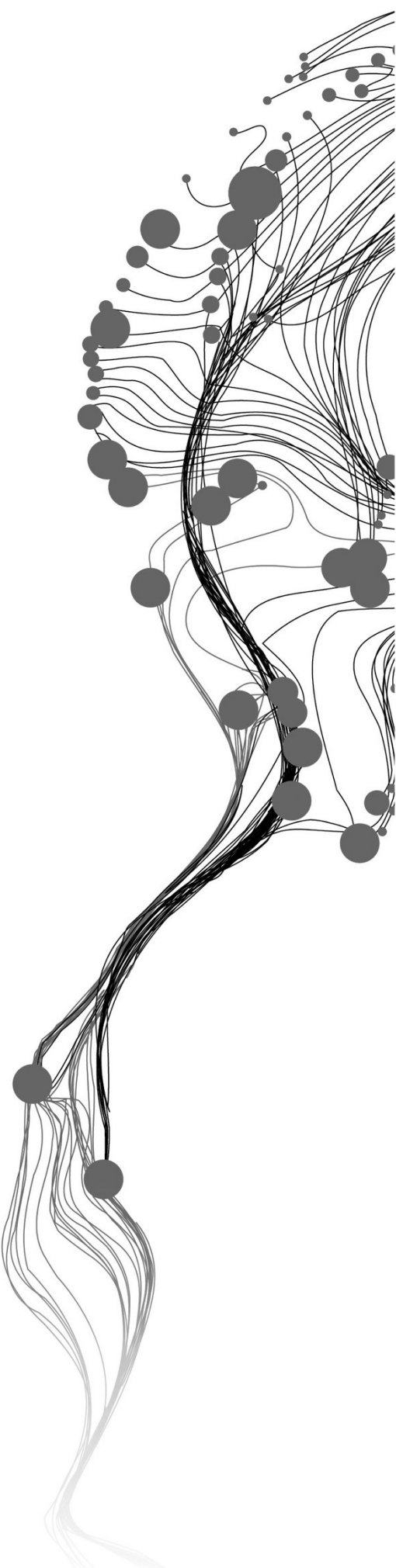


EXAMINING SATELLITE RAINFALL ESTIMATES AS AN ALTERNATIVE TO NDVI FOR LIVESTOCK INSURANCE IN EAST AFRICA.

WAITHAKA LILIAN NJERI
February, 2016

SUPERVISORS:
Dr. A. Vrieling
Dr. C .A.J.M de Bie (Kees)



EXAMINING SATELLITE RAINFALL ESTIMATES AS AN ALTERNATIVE TO NDVI FOR LIVESTOCK INSURANCE IN EAST AFRICA.

WAITHAKA LILIAN NJERI

Enschede, The Netherlands, February, 2016

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.

Specialization: Natural Resource Management

SUPERVISORS:

Dr. Ir. A. Vrieling

Dr. Ir. C. A.J.M de Bie

THESIS ASSESSMENT BOARD:

Prof. Dr. A.D. Nelson (Chair)

Dr. Francesco Fava (External examiner)

DISCLAIMER

This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author and do not necessarily represent those of the Faculty.

ABSTRACT

Weather related shocks, such as drought pose a constant threat to the livelihoods and security of pastoralists. In response to these challenges pastoralists in the arid and semi-arid areas of Kenya and southern Ethiopia have taken up index based insurance as a mitigation strategy against the risk of drought-related livestock mortality. Index-based insurance contracts, indemnify the insured based on a transparent and objectively measured variable as an attempt to circumvent issues of moral hazard, adverse selection and high transaction costs prevalent in the conventional insurance contracts.

The current insurance scheme insures the pastoralists based on an area aggregated, seasonal forage scarcity index derived from satellite normalized difference vegetation index (NDVI) time series. However, NDVI as a forage scarcity index suffers some drawbacks that include, temporal filtering requirements; making filtered images available a month later, the low signal-to-noise ratio in very arid regions and sensitivity to changes unrelated to drought such as infestation by invasive species. For these reasons, the study aimed at evaluating if a drought index derived from satellite rainfall estimates (RFE) would overcome some of the drawbacks in NDVI and consequently be used as an alternative index for insurance against livestock mortality.

The standardized precipitation index (SPI), a multi-time scale meteorological drought index that is based only on precipitation was calculated from both the, 10-day composites of 0.05° resolution- Climate Hazard group Infrared Precipitation with Station data (CHIRPS) and 0.04° resolution- Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT). The RFE was first averaged over the defined spatial units, then cumulated over the growing season i.e., over the start of season (SOS_R) and end of season (EOS_R) dates, in order to capture the period during which rainfall is considered to be effective for forage development, then subsequently compared between years to estimate the relative seasonal drought conditions.

To better understand the inter-annual relationship between the seasonal forage scarcity index and drought indices, a comparative analysis of the indices at different spatial scales was performed, based on an average year (2001-2015). The indices were found to have an agreement based on varying degree of positive correlation with a higher percentage and stronger coefficients ($r > 0.75$) in the short rains than in the long rain seasons. However weak correlations coefficients especially in the long rain season, indicated that there were large unexplained variances between the indices, possibly brought about by factors such as temperature, soil types and errors inherent in the satellite images that negatively influenced this relationship.

Generally, the analyses showed that, although rainfall estimates overcome some of the drawbacks of using the current NDVI derived forage scarcity index. SPI cannot simply be expected to entirely replace forage scarcity index, as a proxy for livestock mortality. However, this does not rule out the possibility of using the SPI to complement the forage scarcity index in cases where disagreements concerning indemnity payment may arise.

KEYWORDS: *Drought index, Forage scarcity index, IBLI, Index Insurance, NDVI time series, RFE*

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my first supervisor Dr. A. Vrieling for his relentless efforts in supervision, insights and guidance throughout all stages of my research work. I am overwhelmed by the patience, optimism and encouragement he provided during this process. It has been nothing short of a great experience to have worked with you sir. I am also extremely grateful to Dr. A.G. Toxopeus and my second supervisor Dr. C.A.J.M. de Bie for the constructive criticism and forming part of my defence committee. I have without a doubt amassed a wealth of knowledge and skill from my interactions with you.

I would also like to extend my appreciation to Andrew Mude of International Livestock and Research Institute (ILRI) for taking me in as an intern in the IBLI team and providing me with all the necessary support to make my field and office experience a success. To Dr. Francesco, Remote sensing officer at IBLI, Diba, Oscar, Eddy, Rupsha and Brenda for the well-informed discussions and insights throughout my stay at ILRI. I am also thankful to Mr. Dennis Macharia, Mr. Ian Asige, Mr. David Ongo of the Regional Centre for Mapping of Resources for Development (RCMRD) and Mr. Dennis Ojwang' of ICRAF, Kenya for providing much needed insights and study materials relevant to my thesis. To Mr. Donald T. Rwasoka for taking his time to checking my work and for challenging me to work harder, thank you.

Many thanks to the Dutch government for awarding me this coveted scholarship, and granting me a chance to study in the Netherlands, this has been a once in a lifetime and eye-opening experience for me. I would also like to thank Mr. Eric Nyandimo, the Managing Director of Oakar Services Limited (OSL) for allowing me to pursue my study and granting me a study leave.

To my colleagues at ITC, students and staff alike for the continuous motivation and advice on how to tackle academic and social hurdles as well as being my family for the 18 months. It has been a pleasure to have crossed paths with all of you, and all the best in your future endeavours.

Finally my family and friends, for being a continuous source of motivation and support throughout the entire period of my study. I strive to always make you proud!

Above all, God the Almighty for the gift of life, good health, sustenance and resilience.

TABLE OF CONTENTS

1.	INTRODUCTION	1
1.1.	Background and problem statement.....	1
1.2.	Research Objectives.....	3
2.	STUDY AREA AND DATA.....	4
2.1.	Study Area.....	4
2.2.	Data.....	7
2.2.1.	Satellite rainfall estimates	7
2.2.2.	NDVI Time series.....	7
2.2.3.	Spatial units	8
2.3.	Software used.....	8
3.	METHODS	9
3.1.	Phenological analysis of NDVI	9
3.2.	Evaluating seasonality from RFE	10
3.2.1.	Defining seasonality regimes	10
3.2.2.	Seasonal temporal integration periods for RFE.....	10
3.3.	Index Construction.....	12
3.3.1.	Forage Scarcity index computation	12
3.3.2.	Drought index computation.....	13
3.4.	Spatial and Temporal relationship of NDVI and RFE derived indices.	13
4.	RESULTS.....	15
4.1.	Spatial patterns of rainfall seasonality regimes.....	15
4.2.	RFE – derived start- and end- of season (SOS _R and EOS _R) dates.....	17
4.3.	Spatial and Temporal relationships between TAMSAT, CHIRPS derived SPI and the ZNDVI.....	20
4.3.1.	Spatial relationship between TAMSAT, CHIRPS derived SPI and the ZNDVI	20
4.3.2.	Temporal relationship between the SPI and ZNDVI.....	24
5.	DISCUSSION.....	27
5.1.	Spatial patterns of rainfall seasonality.....	27
5.2.	Spatio-temporal responses of ZNDVI to SPI.....	27
5.3.	Operational implementation and future outlook.....	29
6.	CONCLUSION	32
	APPENDICES	41

LIST OF FIGURES

Figure 1: The study area map; the thin lines represent the 131 spatial units in Kenya and Southern Ethiopia. The background shows mean annual RFE (2001-2015) from 10-day CHIRPS composites.....	4
Figure 2: The topography of the area of study	5
Figure 3: The land use/land cover map of the study area (Source: Mayaux et al., 2003, JRC)	6
Figure 4 : Temporal graph showing average, minimum, and maximum rainfall (TAMSAT) and NDVI (eMODIS) for the Central Wajir insurance unit (Source: Michele Meroni, JRC) with arrows indicating the results of phenological analysis of NDVI, average SOS _N and EOS _N dates for the long rains as (10 th -18 th) and short rain as (30 th – 3 rd).....	11
Figure 5: Forage scarcity index computation (source: Vrieling et al., 2016).....	12
Figure 6: Maps indicating a classification of the seasonality index (SI) based on Walsh and Lawler (1981) as assessed at the level of (a) the insurance units, and (b) the CHIRPS raster cell.....	15
Figure 7: Temporal graphs representing the three main rainfall regimes in the study area (a) Turkana: precipitation spread throughout the year (b) Borana: Seasonal (c) Wajir: Markedly seasonal with longer dry season.....	16
Figure 8: Rainfall seasonality analysis of CHIRPS time series data based on Liebmann et al. (2012): (a) average SOS for long rains per unit (b) per CHIRPS raster cell (c) average EOS for long rains per unit (d) per CHIRPS raster cell (e) phenology legend for interpreting seasonality with outer circle as first dekad of each month.	18
Figure 9: Rainfall seasonality analysis of CHIRPS time series data based on Liebmann et al. (2012): (a) average SOS for short rains per unit (b) per CHIRPS raster cell (c) average EOS for short rains per unit (d) per CHIRPS raster cell (e) phenology legend for interpreting seasonality with outer circle as first dekad of each month	19
Figure 10: Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the seasonal SPI derived from CHIRPS and TAMSAT for (a) the long rains (b) the short rain season.....	20
Figure 11 : Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the CHIRPS based SPI and the ZNDVI (a) for the long rain season per unit, (b) at CHIRPS raster cell; with the red circle showing Melka Soda in Borana, (c) for the short rain season per unit, (d) at CHIRPS raster cell; with blue circle showing Habaswein in Wajir.....	21
Figure 12: Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the TAMSAT derived SPI and the ZNDVI (a) in the long rains (b) in the short rain season.....	22
Figure 13: The scatter plots showing the seasonal SPI derived from CHIRPS against ZNDVI at both the units and corresponding sample pixels in (a) Melka Soda: weak agreement between the indices (b) Habaswein: strong agreement between the indices.....	23
Figure 14: Temporal graphs showing for the drought years the annual profiles against the long term annual average profiles for rainfall and NDVI in (a) Mogadashe –Garissa (b) Central Wajir (c) Melka Soda – Borana (Ethiopia).....	26

LIST OF TABLES

Table 1: The Seasonality Index classes (using average monthly data)	10
Table 2: The SPI values and related drought classes (source: McKee et al., 1993).	13
Table 3: The ranking coefficient indicates which proportion of the four years with the lowest forage scarcity index are also among the four years with the lowest drought index for the long and short rains seasons.....	24

LIST OF ABBREVIATIONS

CCD	: Cold Cloud Duration
CHIRPS	: Climate Hazards Group InfraRed Precipitation with Station data
eMODIS	: Enhanced Moderate Resolution Imaging Spectroradiometer
EOS	: End of Season
GPM	: Global Precipitation Measurement
IBLI	: Index Based Livestock Insurance
ILRI	: International Livestock Research Institute
LRLD	: Long Rains, Long Dry season (March – September)
MAM	: March -May
NASA	: National Aeronautics and Space Administration
NDVI	: Normalized Difference Vegetation Index
NOAA	: National Oceanic and Atmospheric Administration
OND	: October -December
RFE	: Rainfall Estimates
SOS	: Start of Season
SRSD	: Short Rains, Short Dry season (October – February)
SPI	: Standardized Precipitation Index
TAMSAT	: Tropical Applications of Meteorology using Satellite data and ground-based observations
TIR/IR	: Thermal InfaRed / InfraRed
UN	: United Nations
USGS	: United States Geological Survey
ZNDVI	: Standardized (z-scored) Normalized Difference Vegetation Inde

1. INTRODUCTION

1.1. Background and problem statement

Globally, drought is one of the most geographically extensive hazards on the earth's surface (Belal et al., 2012). Due to climate change and increasing population, effects of droughts have become more severe and as a result, garner a lot of attention from national and international organizations (Dai, 2011). The UN Secretariate General (1994) defines drought as “a naturally occurring phenomenon that exists when precipitation is significantly below normal recorded levels, causing serious imbalances that adversely affect land resource production systems.” It occurs in virtually all climate zones and is attributed to a deficiency in precipitation over extended periods of time such as a season or year, resulting in water shortage, causing adverse impacts on vegetation, livestock and human beings (Mishra & Singh, 2010).

Drought has been classified into four types; (1) meteorological drought, is a period of months or years with below-normal precipitation, (2) hydrological drought occurs when streamflow and water storage fall below long-term average levels, (3) agricultural drought occurs when crop growth is reduced due to below-average precipitation, intense but less frequent rain events, or above-normal evaporation, and (4) social economic drought occurs when the demand for an economic good exceeds the supply as a result of a weather related shortfall in water supply (Eklund & Seaquist, 2015; Chopra, 2006; Mishra & Singh, 2010; Dai, 2011; Wilhite, 1996).

Given the large number of people and livelihood affected by drought as well as the economic costs involved (Belal et al., 2012; Hewitt, 1997) countries and organizations are increasingly pursuing strategies aimed at mitigating negative consequences of drought. Examples of such strategies include food or cash aid by international donors during or after drought events. However, in many cases these responses are not timely as funding for ad-hoc strategies are often secured long after the disaster strikes. Furthermore, foreign food or cash aid may create post - disaster dependency of the beneficiary states on foreign aid. A promising alternative strategy to deliver more effective and faster responses to drought could be to offer insurance that pays out at the moment when a drought takes place. This could be achieved at macro-scale as in the Africa Risk Capacity ARC (2012) or at micro-scale by offering insurance to individual households.

Traditional claim based insurance pays out an indemnity following a claim of loss by the insured customer, high transaction costs associated with verification of claim losses, makes it impractical and costly to offer at macro-scale or even to remote rural smallholder households. Furthermore, it is often plagued by cases of fraud, moral hazard and adverse selection. Moral hazard entails a change in behaviour (reckless behaviour) by insured whereas adverse selection is hidden information that would otherwise lead to additional risk (Barnett, 2004). Index-based insurance, in contrast, indemnifies the policy holder based on a predetermined index correlated with the insured variable (de Leeuw et al., 2014). Benefits accruing from index-based insurance are; it makes insurance affordable to markets that have long been neglected by traditional claim based insurance, eliminates cases of fraud, moral hazard, adverse selection and transaction costs that would otherwise be incurred in verification of loss, hence enabling cheaper and faster indemnity payments to the insured (Miranda & Farrin, 2012; de Leeuw et al., 2014).

Many indices have been considered as a proxy for index insurance design, these include weather variables such as temperature, humidity, rainfall and other indices that are not strictly weather variables but serve as proxies such as crop yields, reservoir levels, livestock mortality rates, satellite-derived vegetation and rainfall indices (Miranda & Farrin, 2012). Since the late 1990s, World Bank has established and supported the piloting of remote sensing based, index insurance in developing countries and since then there has been an increase in insurance uptake (Smith & Watts, 2009) in nations worldwide.

As outlined in De Leeuw et al. (2014) and Vrieling et al. (2014) there exists a great potential for remote sensing derived indices in insurance provided that they; (1) correlate well with the insured variable (livestock mortality, crop losses) and can be reliably constructed, (2) cannot be manipulated by either the insurer or insured (Mude et al., 2010), (3) are available for sufficiently long record to properly represent climatic variability for estimating probability of pay outs (Bell et al., 2013), and (4) can be obtained at near real time, so that shortly after losses are incurred payment is done. The principle challenge that exists in designing an index-based insurance scheme is to minimize the “basis risk”, i.e. the risk that a policyholder suffers a loss and is not indemnified or does not suffer a loss and is indemnified (Barnett, 2004).

Following the benefits of remotely sensed index insurance, many countries and institutions have undertaken insurance feasibility studies and pilot projects to provide cover for events such as drought-related livestock losses in Kenya and Mongolia, agricultural crop losses in India, Peru, Malawi and Vietnam. These projects base insurance premiums and payouts on empirical relationships between the insured variable and indices like rainfall or NDVI (Miranda & Farrin, 2012).

In the arid and semi-arid areas of Mongolia, Ethiopia and Kenya, households strongly rely on livestock for their livelihoods, social and cultural value (Onono et al., 2012). Drought has been a constant hazard in these regions, leading to widespread death of the herd and as a result, placing the pastoralists at a high risk of being trapped in chronic poverty (Barnett et al., 2008). This led to the conceptualization of Index-Based Livestock Insurance (IBLI), in 2006 in Mongolia (Mahul & Skees, 2007) and 2010 in Marsabit, Northern Kenya (Mude et al., 2010) which has gradually expanded to other areas of Kenya and Southern Ethiopia.

Chantararat et al. (2013) describes the original IBLI design, piloted in Marsabit County, Northern Kenya where satellite-derived Normalized Difference Vegetation Index (NDVI; Tucker, 1979) was statistically fitted to household livestock mortality data, but due to poor quality and lack of data in some regions, it has necessitated the move to a more objective forage scarcity contract. In an attempt to also reduce basis risk the original method to translate NDVI series into an index has also changed over the years (Vrieling et al., 2015; Vrieling et al., 2016). In the current design, the 10-day, 250m spatial resolution, eMODIS NDVI time series from, United States Geological Survey (USGS) are spatially averaged per insurance unit, temporally averaged per growing season i.e. start and end (SOS and EOS) and subsequently compared between years to estimate the relative seasonal forage conditions per unit. Payment is made when the index reading is less or equal to the multiyear NDVI average reading.

Nevertheless, the use of NDVI time series as a forage scarcity indicator suffers some drawbacks. In arid and semi-arid areas the limited vegetation cover makes that, the soil background affects reflected signal (Vicente-Serrano et al., 2006) resulting in a low signal to noise ratio. Furthermore, NDVI is sensitive to changes that are unrelated to droughts such as land use/cover change or infestation by the invasive *Prosopis* which is an evergreen and drought tolerant species giving a false impression of forage. Pre-processing requirements such as temporal filtering of the NDVI images makes the filtered image available a month later (Vrieling et al., 2015) causing a delay in temporal integration of NDVI. Therefore, it is

worthwhile to evaluate and test alternative indices that may overcome some of these drawbacks of the NDVI-based forage scarcity index.

Precipitation time series are a potential alternative for the assessment of drought risks. Rainfall data from weather stations have shown great potential for insurance especially because they are relatively simple, low-cost and provide a direct measurement of rainfall (Tapiador et al., 2012). One such application is described in Johnson (2013) where automated weather stations form the basis of Kilimo Salama weather index insurance offered to over 150,000 farmers in Kenya and Uganda. Nevertheless weather station networks in East Africa often suffer from poor maintenance and low data continuity (Rientjes et al., 2012) they are expensive to maintain, and provide a limited observation density in large areas, resulting in a poor capturing of the spatio-temporal variability of rainfall (Muthuwatta et al., 2010; Kidd & Levizzani, 2011).

Satellite rainfall estimates have therefore been increasingly used as an alternative rainfall data source. Observation of rainfall by geostationary or orbital satellites provide information over large spatial domains with a short revisit time hence making time series information available for analysis into climatic conditions (Tolo et al., 2014). Satellite estimates of precipitation can be derived from a range of observations. Retrieval methodologies make use of sensors that operate in the visible domain through the assessment of cloud presence, infrared domain mostly from geostationary satellite to assess cloud top temperature, indicative of the vertical development of the cloud and passive and active microwave domain, obtained from polar orbiting satellites that measure the emission, absorption and scattering of radiation by particles such as water vapour, distributed clouds and precipitation particles in the atmosphere. Merging information from the different spectral domains offers the opportunity to combine the good temporal sampling in terms of movement of the precipitation system from the visible and infrared domains, with more accurate precipitation retrievals from the microwave domain to provide improved estimates both in temporal and spatial resolution (Kidd & Levizzani, 2011; Tapiador et al. 2012).

This research aims to evaluate if satellite-based rainfall estimates (RFE) can be used as an alternative to NDVI as a drought index in the IBLI Insurance scheme. Although the accuracy of RFEs may vary depending on the product and location within East Africa (Dinku et al., 2008) , they provide a good alternative to interpolated station data and large international efforts such as the Global Precipitation Measurement (GPM) mission aim to improve their accuracy further (Tapiador et al., 2012).

1.2. Research Objectives

The main objective of this research is to compare and discuss whether a seasonal drought index, derived from satellite-based rainfall estimates (RFE) has a similar inter-annual variability as the satellite derived forage scarcity index (NDVI) currently used in the index-based livestock insurance scheme.

The specific objectives are:

- To estimate season–start and –end dates from satellite rainfall estimates (RFE) time series in order to obtain accurate temporal integration periods for calculating a seasonal drought index.
- To construct unit-level time series of seasonal drought indices from TAMSAT and CHIRPS rainfall estimates and evaluate if their inter-annual variability is similar across the study region.
- To compare the similarity of the inter-annual variability of the seasonal RFE-derived drought index and the NDVI-derived forage scarcity index, for current insurance units and at finer spatial scales.

2. STUDY AREA AND DATA

2.1. Study Area

The study area is located between the Geographic coordinates 34°E – 42°E and 6°N – 6°S and encompasses Kenya and the southern part of Ethiopia. It comprises of nine Kenyan counties namely, Baringo, Garissa, Mandera, Marsabit, Isiolo, Samburu, Tana River, Turkana, Wajir and Borana in Southern Ethiopia as shown in Figure 1.

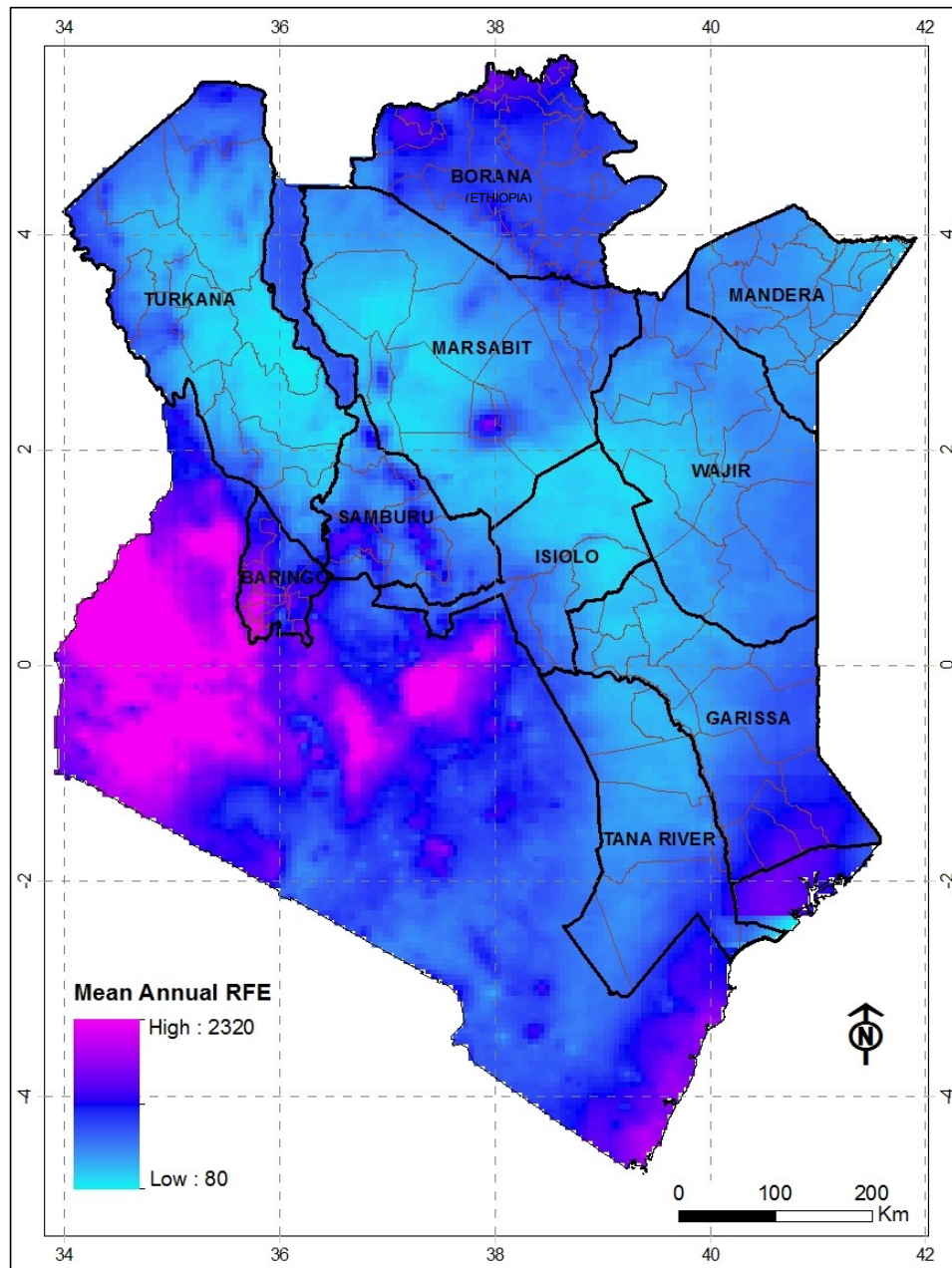


Figure 1: The study area map; the thin lines represent the 131 spatial units in Kenya and Southern Ethiopia. The background shows mean annual RFE (2001-2015) from 10-day CHIRPS composites.

The Kenya part of the area is commonly referred to as the Arid and Semi-Arid Lands (ASALs), covering over 80% of the country and occupied by about 20% of Kenya's population (The Government of Kenya, 2010). The ASALs are characterized by aridity, which results from a generally hot and dry climate (The Republic of Kenya, 2011). Average annual rainfall in the arid areas ranges between 0 and 300 mm while in the semi-arid areas it is 300 - 600 mm per year. Temperatures in the arid areas are high throughout the year resulting in high rates of potential evapotranspiration. Rainfall is the most significant climatic variable affecting vegetation productivity in these areas (Meroni et al., 2014). The seasonal rainfall patterns over the study area are controlled by the seasonal migration of the intertropical convergence zone (ITCZ), complex topographical patterns, the presence of large lakes, variations in vegetation type and land ocean contrasts that give rise to high spatial and temporal variation in precipitation over the region (Indeje et al., 2000).

The topography of the study area has a distinct profile as shown in (Figure 2). In Kenya the central region is much higher than the rest of the country, topography rises gradually westwards from a narrow coastal plain in a series of plateaus, culminating in a highland area that is bisected by the Great Rift Valley. The north eastern regions of the country consist mainly of arid plains (McSweeney et al., 2009). In Borana rangeland, the topography is distinguished by plain rangelands, intersected with occasional mountain ranges, volcanic cones and depressions (Coppock, 1994).

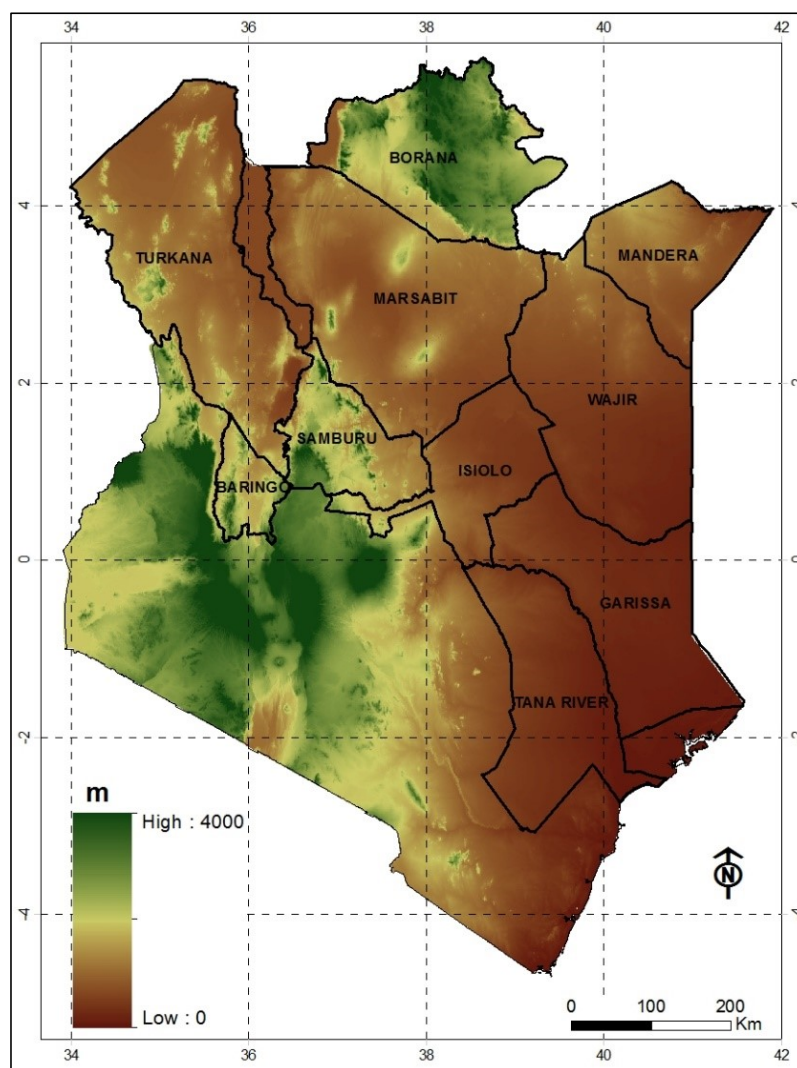


Figure 2: The topography of the area of study

The economic activity practiced in the arid and semi-arid areas is predominately mobile pastoralism where most of the inhabitants depend on livestock for their livelihoods. Pastoralism can be defined as the extensive production of livestock in a rangeland environment (The Republic of Kenya, 2011). As a coping mechanism to recurrent drought events, rangeland resource degradation, increased vulnerability of cattle and growing demand for adaptive species, pastoralists are diversifying their current cattle herd to include the more drought tolerant camels, sheep and goats, the herd composition varies according to geographical locations and the resources available (Boru et al., 2014; Megersa et al., 2014).

The land cover over the study area exhibits a heterogeneous vegetation pattern but largely dominated by natural grasslands. In the Kenyan part, in Tana River and Garissa dominant vegetation types include; open and closed grasslands with shrubs, while at the Rift valley area of Kenya: Turkana, Marsabit, Samburu and Baringo, sparse grassland and woody savanna dominate, in the northern and north eastern areas: Wajir, Mandera and Isiolo, desert scrubland and grassland are the dominant vegetation species (Edwards, 1940). The Borana rangelands are dominated by varying portions of open grasslands with shrubs, and croplands in the northern part (Figure 3).

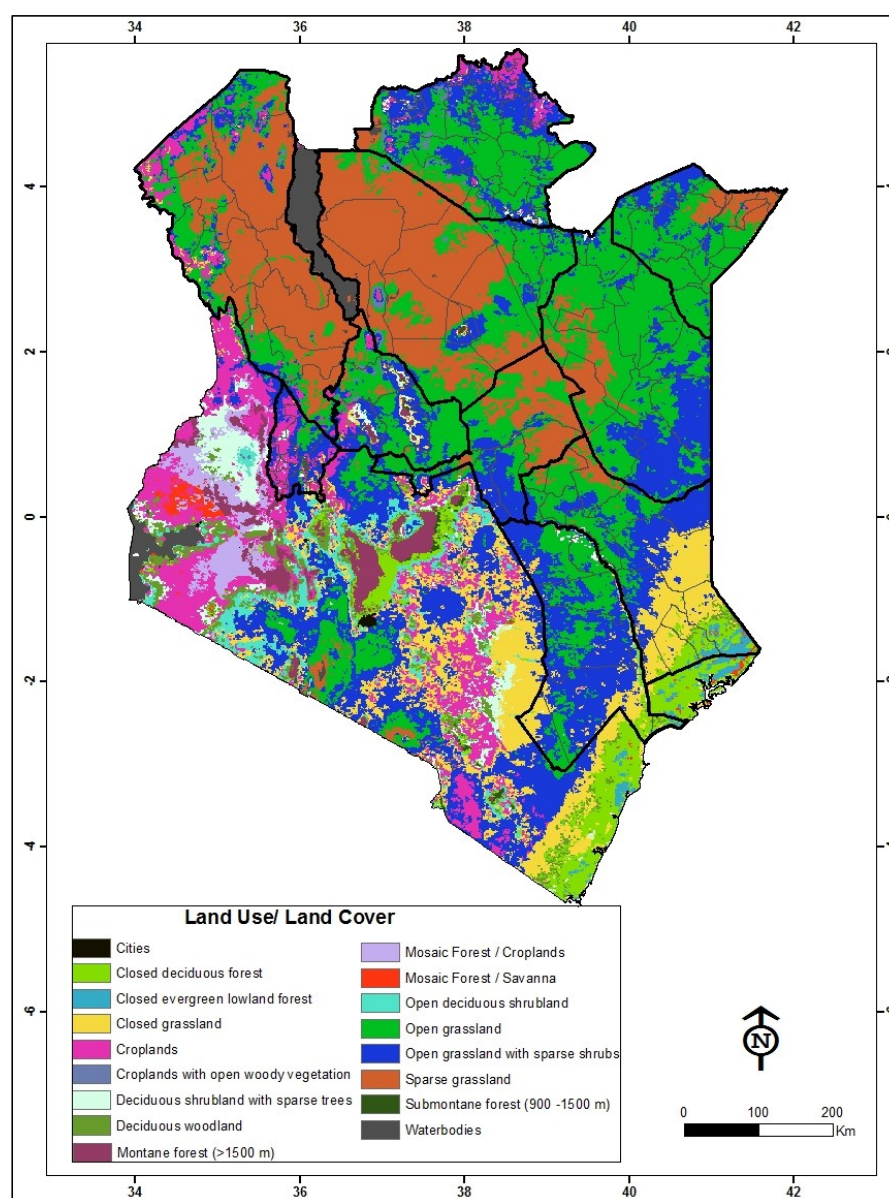


Figure 3: The land use/land cover map of the study area (Source: Mayaux et al., 2003, JRC)

2.2. Data

2.2.1. Satellite rainfall estimates

Retrieval techniques for estimating precipitation from satellite data use visible and infrared observations from geostationary satellites, passive and active microwave observations from polar orbiting satellites and merged techniques (Tapiador et al., 2012; Kidd & Levizzani, 2011). The satellite rainfall products selected in the research are adjusted against gauge data which allows for reduction of the bias in the satellite precipitation estimates resulting in a relatively higher accuracy (Toté et al., 2015). Two commonly applied rainfall products were selected for this study, which both are readily available online in near real time and cover a long time frame (more than 30 years). The rapid availability is a necessity for timely calculation of potential indemnity payments while the long time series are required for the design and pricing of the insurance. The two products are CHIRPS and TAMSAT.

CHIRPS: The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset is developed by the United States Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara, providing data from 1981 to present. It is a blended product combining, quasi-global geostationary Thermal Infrared (TIR) satellite observations from two National Oceanic and Atmospheric Administration (NOAA) sources, the Tropical Rainfall Measuring Mission (TRMM) 3B42 product from NASA, atmospheric model rainfall fields from NOAA Climate Forecast System and in situ precipitation observations obtained from a variety of sources including national and regional meteorological services. CHIRPS time series have been used for trend analysis and seasonal drought monitoring. It is available at daily, pentad, dekadal, and monthly temporal intervals (Funk et al., 2015). This research used the ten day (dekadal) cumulative rainfall estimates at 0.05° (~5km) spatial resolution data for the period 2001 -2015 covering the Africa window. The data can be freely downloaded at:

<ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/>

TAMSAT: The Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) product is developed by the Department of Meteorology at the University of Reading, and offers daily, dekadal, and monthly rainfall for 1983 to present. TAMSAT rainfall products are derived from geostationary Meteosat thermal infrared (TIR) channels, based on the recognition of rain based on cloud top temperature and calibrated against ground-based rain gauge data. The working principle of TAMSAT is based on cold cloud duration (CCD), that is the total time that the temperature of the top of a cloud is below a certain threshold (Maidment et al., 2014). The ten-daily (dekadal) cumulative rainfall estimates from 2001-2015 (to capture the same period used for the NDVI time series data) was used in this research at 0.0375° (~4km) spatial resolution. The data can be freely downloaded at:

<http://www.met.reading.ac.uk/tamsat/about/>

2.2.2. NDVI Time series

The NDVI time series used in this study is the eMODIS product that the United States Geological Survey (USGS) produces from MODIS data acquired by the Terra satellite (Jenkinson et al., 2008), currently operationally used in IBLI. The eMODIS product consists of 10-day maximum value NDVI composites at 250m resolution. The USGS uses a temporal smoothing algorithm referred to as Swets algorithm (Swets et al., 1999), to reduce atmospheric effects that degrade the NDVI signal (e.g. clouds, vapour) for pre-processing NDVI time series. The filtered eMODIS data for the East Africa window from 2001 to 2015 was used to calculate the forage scarcity index.

2.2.3. Spatial units

The comparison between seasonal drought indices and forage scarcity indices in this research was carried out at two levels of spatial aggregation, i.e. the insurance unit and the CHIRPS raster cell level. The current IBLI contract comprises of 131 insurance units (Figure 1). These are based on administrative boundaries, but a number of adjustments have been made in collaboration with local stakeholders to better reflect agro-ecological conditions and rangelands utilized by households residing in the units (Vrieling et al., 2016). They are the basic units for which insurance premiums and indemnity payments are evaluated. The unit size ranges from approximately 100km² to 13,000km² with an average unit size of 3000km².

Given that pastoralists are not sedentary, but move their livestock to access suitable forage and water conditions, it is assumed that these units are big enough to accommodate the dominant livestock movement patterns. Although the units do not always accommodate the pastoral movements, particularly during intense drought, travelling for long distances has detrimental effects on the conditions of the livestock. This further provides some level of confidence in using unit level, forage scarcity as a plausible index for insurance, even where livestock is continuously moving (Vrieling et al., 2016). Additionally these units are used in an effort to regulate the contract to locations that are clear to the parties involved in the contract (i.e. the pastoralists, insurance companies). This avoids conflict that may arise due to disagreements as to where an insured pastoralist should be indemnified especially noting that livestock is an emotive issue amongst the pastoralists.

However, within a single insurance unit, substantial spatial variability can exist in rainfall, vegetation, topography, and soil properties. This could be an argument against averaging rainfall and NDVI for those units, as the aggregation may not well reflect the varying rainfall-vegetation interactions within the unit. For this reason, the analysis was also carried out at a finer spatial resolution, i.e. at the level of the 0.05 degree resolution CHIRPS raster cells. A total of 13083 0.05 degree cells cover the study area.

2.3. Software used

- **IDL programming language** – The Interactive Data Language (IDL) is a powerful programming language for data analysis, visualization and application development that is commonly applied for analysing large image time series. It was used in this research to organize and aggregate RFE and NDVI time series data.
- **R programming language** – It provides a software environment for statistical computing, data analysis and graphical techniques. In this research it has been used to carry out statistical analyses.
- **ArcGIS version 10.2.2** – ArcGIS has been used to create and interact with maps i.e. view, edit, manage and analyse geographical data.
- **Microsoft Excel** – This package has been used for analysing large time series data and providing descriptive statistics on the data.

3. METHODS

3.1. Phenological analysis of NDVI

To compare a seasonal drought index with a forage scarcity index, an accurate assessment of season - start and - end dates from rainfall is needed. This should account for the fact that vegetation green-up usually occurs after the start of rainfall. Previously, IBLI used a temporal integration for NDVI defined as the long rains-long dry season (LRLD: March - September) and short rains-short dry (SRSD: October - February) season (Chantararat et al., 2013). However, for many areas, this included the dry periods (approximately July - September for LD and January - February for SD) when the available forage is dry, not photosynthetically-active, and its presence can thus not be captured by indices like NDVI. Moreover, the need for season completion to calculate the final index meant that indemnity payments were made after animals suffered for long in case of adverse forage conditions. While for the initial IBLI scheme that aimed to replace livestock after incurred losses this was not necessarily problematic, however, pastoralists demanded for earlier indemnity payments to allow for livestock protection (Vrieling et al., 2016).

To better describe the season during which forage biomass develops, a phenological analysis is performed on the NDVI time series, as outlined in Meroni et al. (2014) and Vrieling et al. (2016). Phenology can be defined as the study of the timing of recurring biological events. The term land surface phenology is used to refer to the analysis of spatial-temporal patterns of vegetation development from satellite observations (White et al., 2009).

Many retrieval approaches exist to perform phenological analysis from NDVI time series data (de Beurs & Henebry, 2010). The selected phenological retrieval algorithm is well capable of capturing the bimodal seasonality dominant in East Africa. The approach first masks out pixels for which seasonality was low, a periodogram is then used to evaluate whether the behaviour per pixel is overall unimodal or bimodal. After setting breakpoints between seasons based on a median NDVI pixel profile, the start- and end-of-season (SOS/EOS) are subsequently estimated on a year-by-year basis. This was achieved by modelling the NDVI profile based on a double hyperbolic tangent model, the SOS was estimated as the moment when the fitted model for season exceeded 20% of local growing amplitude and EOS as the moment when it falls below 80% of the decay amplitude. Finally, the pixels were averaged per spatial unit, to determine the unit-specific SOS and EOS dates.

To account for the inter-annual variability half of a standard deviation was subtracted from the SOS, and half a standard deviation added to EOS per spatial unit. The dates were further translated into a forage scarcity index compared between years to estimate the relative seasonal forage condition per unit (Vrieling et al., 2016). In this research, the NDVI-derived start and end of season dates shall be referred to as SOS_N and EOS_N where N stands for NDVI.

3.2. Evaluating seasonality from RFE

3.2.1. Defining seasonality regimes

As a preliminary step towards defining season-start and –end dates, we first evaluated for each unit/pixel whether the average rainfall distribution within a year showed a clear seasonal pattern. This was achieved through the computation of a seasonality index (SI; Walsh & Lawler, 1981) which is defined as:

$$SI = \frac{1}{R} \sum_{n=1}^{12} |X_n - \frac{R}{12}| \dots\dots\dots (1)$$

Where X_n is the average monthly rainfall for month n and R is the average annual rainfall. The index has a value of 0.0 if all the months have equal rainfall amounts and 1.833 if all rainfall occurs in a single month. The value of 0.60 has been used as threshold value between limited and clear seasonality. In this study SI was calculated at both unit and pixel level of aggregation of the CHIRPS data for the multi-year average (2001-2015). Three classes of the SI computations shall be used (Table 1):

Table 1: The Seasonality Index classes (using average monthly data)

SI class limits	Rainfall regime
< 0.60	Precipitation spread throughout the year
0.60 – 0.80	Seasonal
> 0.80	Markedly seasonal with a long dry season

3.2.2. Seasonal temporal integration periods for RFE

The temporal integration period for NDVI cannot readily be applied to the RFE data for calculating a seasonal drought index because rainfall generally precedes vegetation green-up. Therefore, in this study, an analysis was carried out to estimate the start and end of the rainy season(s) at both the current insurance units and CHIRPS raster cell level. As done for the NDVI-based SOS_N and EOS_N (Vrieling et al., 2016), we cannot assume uniform season start and end dates for RFE because seasonality likely differs across the study area.

Several approaches exist for deriving SOS and EOS from rainfall data (including RFEs). An approach developed in West Africa defines the start of season as the first dekad with 25mm rainfall that is followed by at least 20mm in the next two dekads (Sivakumar, 1988; Brown & de Beurs, 2008). These thresholds are however region-dependent and cannot be expected to give good results across the entire continent because this hinders the performance of any meaningful comparison between regions. A simpler approach could be to qualitatively estimate season start and end dates from temporal rainfall graphs. In this study, this could potentially be operationalized by examining whether a common rule can be identified to adapt the SOS_N and EOS_N that were determined previously (Figure 4), for example by subtracting a specific number of dekads. Nonetheless, the preference was given to assess seasonality in a more operational and quantitative manner.

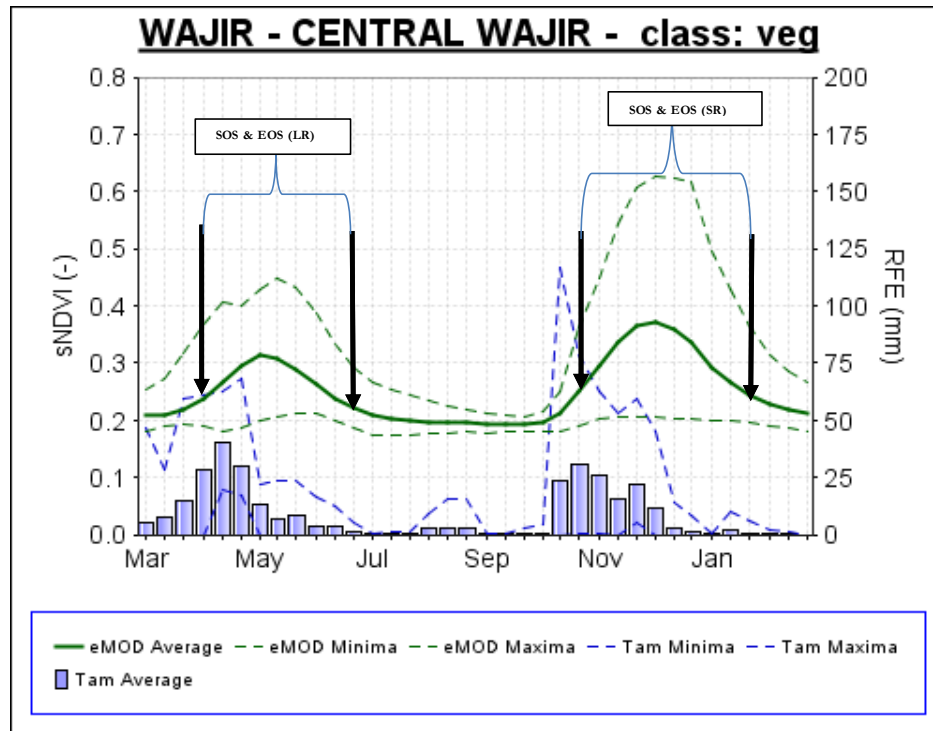


Figure 4: Temporal graph showing average, minimum, and maximum rainfall (TAMSAT) and NDVI (eMODIS) for the Central Wajir insurance unit (Source: Michele Meroni, JRC) with arrows indicating the results of phenological analysis of NDVI, average SOS_N and EOS_N dates for the long rains as (10th -18th) and short rain as (30th - 3rd).

The approach followed here was proposed by Liebmann et al. (2012), because it is documented to be a robust, relatively consistent, objective and well-tested method that can be uniformly applied across wide regions that have a clear seasonality in rainfall distribution. It is based on the local climatology of an area of interest and attempts to account for false start that may occur when an apparent rainfall start is followed by a long dry period, thus not permitting effective vegetation growth.

Liebmann's rule simply defines SOS as the moment when daily precipitation consistently exceeds its local long-term annual daily average and ends when precipitation drops below that value. In this research, the rule was applied to the precipitation climatology of the study area using 15 years (2001-2015) of dekadal CHIRPS data at both the pixel and unit level of aggregation. At each unit/pixel, an anomalous accumulation (the sum of the difference between the long-term dekadal average precipitation and long-term annual dekadal average) is calculated. The first dekad past the minimum value of anomalous accumulation marks the SOS and the dekad when the anomalous accumulation reaches its maximum value marks the EOS. Similarly, this rule was also applied to individual years to retrieve the annual SOS/EOS dates (or dekad numbers). To account for the inter-annual variability while limiting the chance of overlap between seasons, half a standard deviation is subtracted from the average SOS dates and added to the average EOS dates per pixel/per unit. This corresponds to the procedure followed for NDVI-based retrievals (Vrieling et al., 2016). In the remainder of the thesis, we refer to these adjusted dates as SOS_R and EOS_R , where R refers to RFE.

For areas without clear seasonality (SI less than 0.60), Liebmann et al. (2012) seasonality rule is inadequate to retrieve reasonable seasonality dates due to the complex rainfall distribution patterns in such areas. For such cases, the SOS_N and EOS_N were used to obtain a temporal integration period for rainfall that approximately relates to the vegetation green-up during the period for which the forage scarcity index is calculated. However, to acknowledge the fact that vegetation green up does not start until after rains have raised soil moisture content (Vrieling et al., 2011; Vrieling et al., 2013). A dominant difference (lag period)

between NDVI and RFE of one dekad was subtracted from SOS_N and five dekads subtracted from EOS_N for both the long and short rains season across the study area. These dates were also adjusted to capture the inter-annual variability resulting in meaningful estimates of the RFE based SOS_R and EOS_R for these areas.

3.3. Index Construction

3.3.1. Forage Scarcity index computation

The forage scarcity index indicates how forage conditions for a specific season and unit compare to the units multi-annual average forage conditions. The steps followed in calculating the index from NDVI time series were outlined in detail in Vrieling et al. (2016). These consist of (1) for each dekadal composite NDVI values were averaged per insurance unit, excluding all pixels for which phenological analysis found no clear seasonality, (2) for each unit the dekadal NDVI values were averaged over the season, based on unit-specific SOS_N and EOS_N (3) this seasonal average was then compared with the historic series (2001-2015) for the same (long rain, short rain) season resulting in a z-score. The z-score indicates how much the seasonal average NDVI is above or below the normal forage conditions. The steps are summarized in Figure 5.

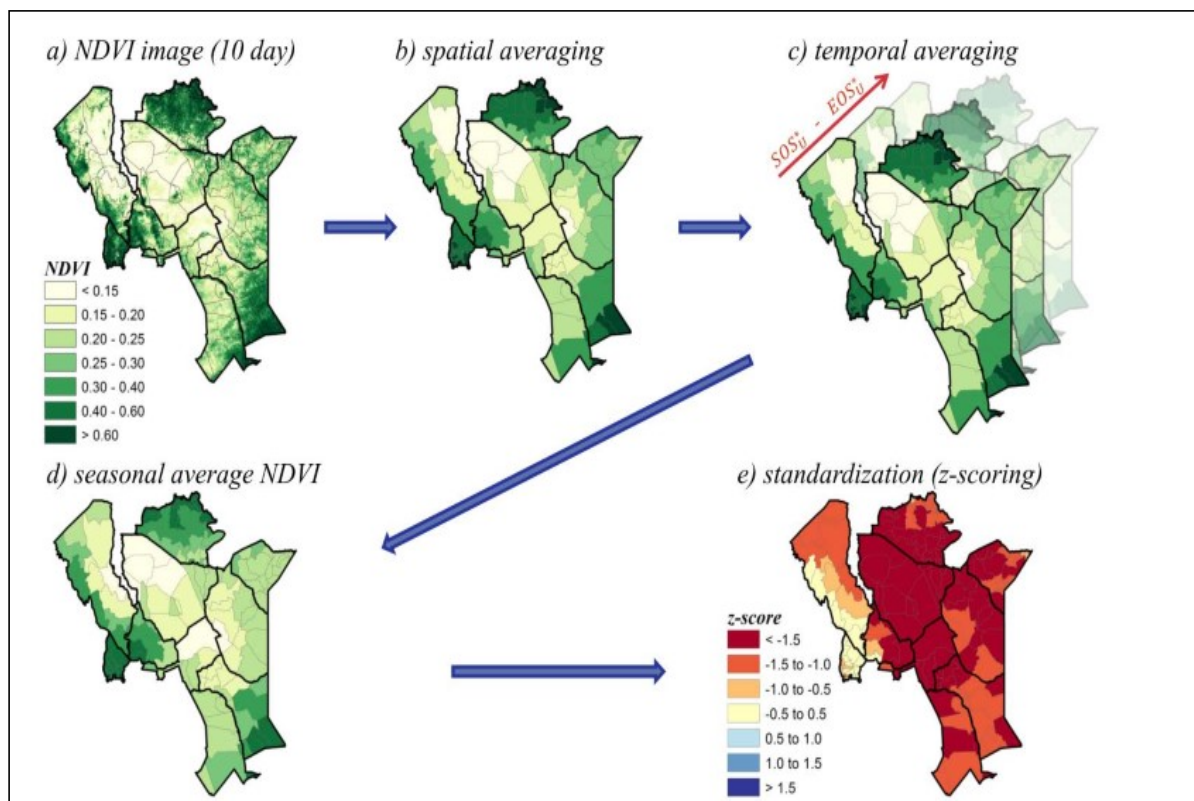


Figure 5: Forage scarcity index computation (source: Vrieling et al., 2016)

Besides computing the forage scarcity index for the insurance units, it is also computed at the 0.05° CHIRPS resolution by aggregating the 250m resolution eMODIS NDVI values to the CHIRPS raster cells and using the raster-based SOS_R and EOS_R dates as the temporal integration periods. In this research, the computed forage scarcity index shall be referred to as ZNDVI.

3.3.2. Drought index computation

Drought indices are quantitative measures that characterize drought severity by comparing data from variables such as precipitation, soil moisture, evaporation, groundwater and surface water levels against their historical means (Heim, 2002; Zargar et al., 2011). Drought indices that describe meteorological drought include, the standardized precipitation (SPI; McKee et al., 1993), the Palmer drought severity index (PSDI; Palmer, 1965), the Surface water supply index (SWSI; Doesken & McKee, 1991) and the Crop Moisture Index (CMI; Loucks et al., 2005). As outlined by Ji & Peters, (2003) and Hayes et al. (1999) many studies show that SPI has advantages over other indices in that it is relatively simple, spatially consistent as it can allow for comparison between locations in different climates, it is temporally flexible thus allowing observation of water deficits at multiple timescales, it reliable for detecting emerging drought and can provide early warning of drought events (Guttman, 1998; Guttman, 1999; Hayes et al., 1999; Ceglar et al., 2008).

The SPI requires only precipitation data as input. It quantifies deficit or excess moisture conditions at a location for a specific time interval, i.e. the SPI value indicates the number of standard deviations that the observed precipitation deviates from the long-term average (McKee et al., 1993). SPI can be applied at multiple time scales, for example, 1-month SPI reflects short-term conditions and its application can be related closely to soil moisture; the 3-month SPI provides a seasonal estimation of precipitation; 6- and 9-month SPI indicates medium-term trends in precipitation patterns (Ji & Peters, 2003). In this research, SPI was used to quantify precipitation anomalies over a unit/pixel between start and end of season dates (SOS_R and EOS_R) for the year 2001-2015. Notably, the SPI is directly equivalent to the ZNDVI as they both indicate the number of standard deviations an observed variable is above or below the long-term mean.

For the rest of the study, the seasonal drought index shall be denoted as SPI. Drought intensity is defined for values of the SPI as shown in Table 2.

Table 2: The SPI values and related drought classes (source: McKee et al., 1993).

<i>Drought Classes</i>	<i>SPI</i>
<i>Extreme Drought</i>	< -2.0
<i>Severe drought</i>	< -1.5
<i>Moderate drought</i>	< -1.0
<i>Mild drought</i>	< 0.0
<i>No drought</i>	> 0.0

3.4. Spatial and Temporal relationship of NDVI and RFE derived indices.

First a statistical comparison between the drought indices (seasonal SPI) derived from the two RFE sources (CHIRPS and TAMSAT) was performed to evaluate if the inter-annual variability of the SPI deviates much depending on the RFE product used. Pearson correlation analysis was performed between the indices per insurance unit for the average year 2001 to 2015. This analysis is done under the assumption that a linear relationship is expected between the indices.

To evaluate the degree of agreement between the inter-annual variability of the seasonal SPI and the ZNDVI, comparative analyses were performed between these indices. This was done at both the insurance unit level (using both CHIRPS and TAMSAT rainfall estimates) and at the CHIRPS raster cell level. Besides the Pearson correlation coefficient assessing the linear correlation between SPI and ZNDVI, the Spearman rank correlation coefficient was also determined to account for the possibility of non-linear

relationships. Previous research has attempted to model the within-year relationship between RFE and NDVI, accounting for lags between rainfall and vegetation response (Udelhoven et al., 2009; Gessner et al., 2013; Boschetti et al., 2013). In this research, the relationship between the two variables is evaluated on a seasonal basis (i.e. long and short rains season), and the lag between rainfall and vegetation response was accounted for by using different time periods for integrating the variables (i.e. defined by SOS_N , EOS_N , SOS_R and EOS_R). To further assess to what extent the SPIs explain the variance in the ZNDVI, the R^2 of the regression equation between the two indices was used and points on the area of study that gave important insights on this relationship were sampled and represented in scatterplots.

In an effort to determine whether the drought events are captured similarly by the seasonal SPI from both (TAMSAT and CHIRPS) and ZNDVI. A ranking analysis is performed between the three indices, over the long and short rains seasons for the fifteen-year time series. It aims at comparing the seasons from each year, ranked either as the best or worst year, in terms of the severity of the drought. In this research, the interest lies in the worst drought years where insurance is considered most relevant. For this reason, a period of four years in the “dry-end” of the ranking was taken to be a reasonable threshold for assessing the trend in performance of the indices, whereas the currently used NDVI based forage scarcity index was used as the base index for comparison. A rank coefficient of *1 means that both the NDVI and RFE derived indices, capture 100% of the bad years while a rank of *0 means that the indices disagree (IRI Report, 2014). Temporal graphs were further used to explore the temporal properties of NDVI and rainfall in each of the years ranked as drought years, the temporal graphs basically show the comparison between the mean annual profiles and the long-term mean annual profiles of NDVI and rainfall to establish if the pattern of inter-annual variability is comparable between them.

4. RESULTS

4.1. Spatial patterns of rainfall seasonality regimes

The SI results were classified into three major regimes. Areas with a clear seasonal rainfall distribution ($SI \geq 0.60$) constitute more than 75% of the study area at both spatial units (Figure 6). Areas with limited seasonality ($SI < 0.60$) are mostly observed in western Turkana, Baringo, Samburu, Tana River and northwest Borana. These areas have a more uniform rainfall distribution for the average year, which could mean either that no clear dry seasons are present, or alternatively that the within-year rainfall distribution varies much from year to year. Figure 6b shows the same seasonality classification at the resolution of CHIRPS pixel. The general spatial pattern is consistent in both maps.

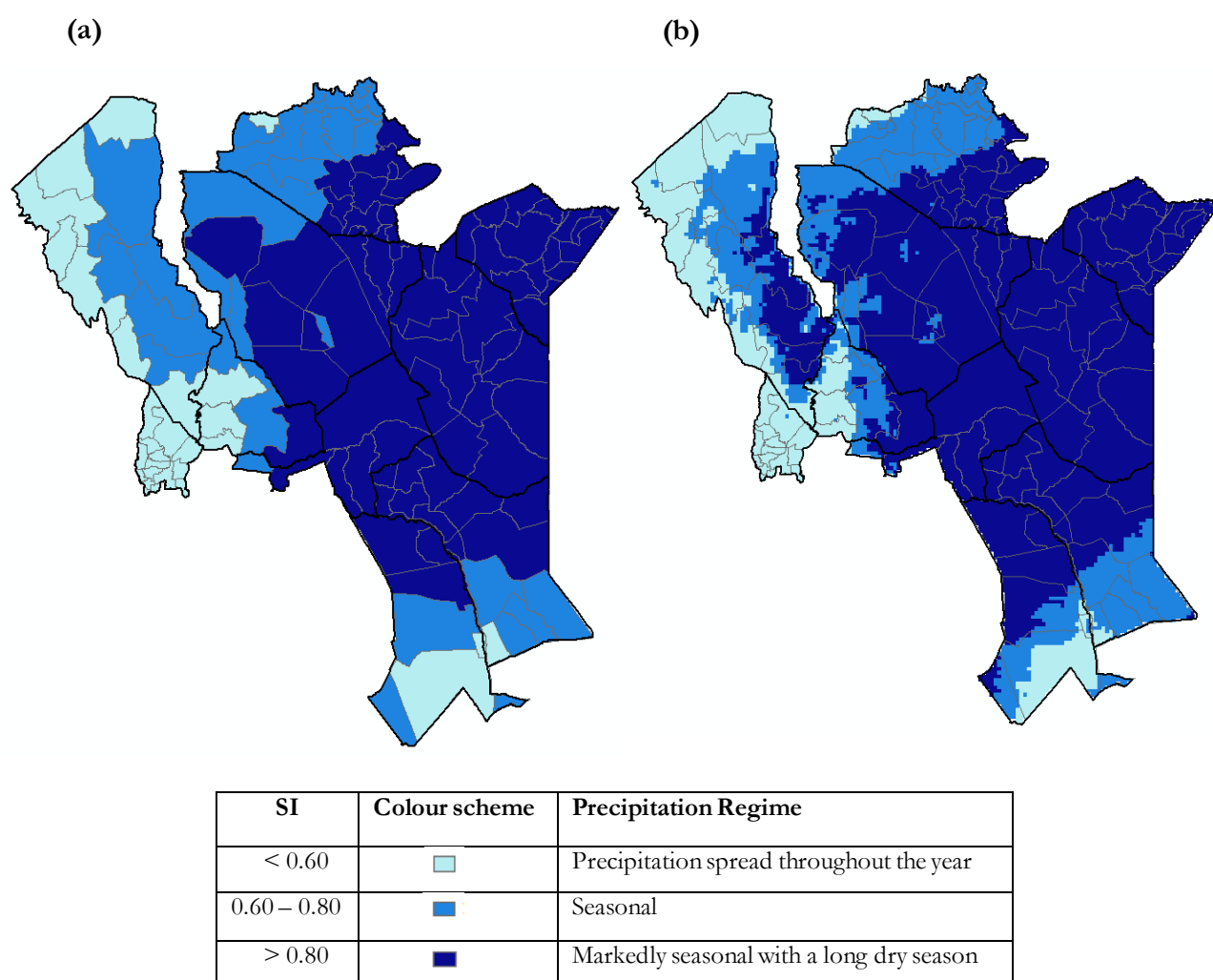


Figure 6: Maps indicating a classification of the seasonality index (SI) based on Walsh and Lawler (1981) as assessed at the level of (a) the insurance units, and (b) the CHIRPS raster cell

Figure 7 shows temporal graphs for three example insurance units, each representing a different rainfall distribution regime as per Figure 6. In areas where a seasonal regime was identified (Figure 7b, c), rainfall and NDVI generally show a distinctly bimodal seasonal cycle, over 80% of the study experiences bimodality (Appendix I) with two as the dominant number of seasons. These findings are consistent with the studies done by Conway et al. (2005) and Herrmann and Mohr (2011) that describe that rainfall in East Africa displays a bi-modal regime, with two main rainfall seasons in March to May (MAM) which mark the long rains period and October to December (OND) which mark the short rains moderated by coastal and topographic influences (Mutai et al., 1998). Figure 7 moreover shows the close correspondence between NDVI and RFE fluctuations, with maximum NDVI mostly occurring after the peak of the rainy season, due to lagged effects of vegetation green-up which links to soil moisture availability rather than rainfall. In contrast, Figure 7a gives an example of the more uniform rainfall distribution throughout the average year that is common across parts of Baringo, Samburu and Turkana. Notable differences also exist between Figure 7b and 7c where Gurar in Wajir (7c) is very dry during the dry months and has shorter seasons compared to Dugda Dawa in Borana (7b).

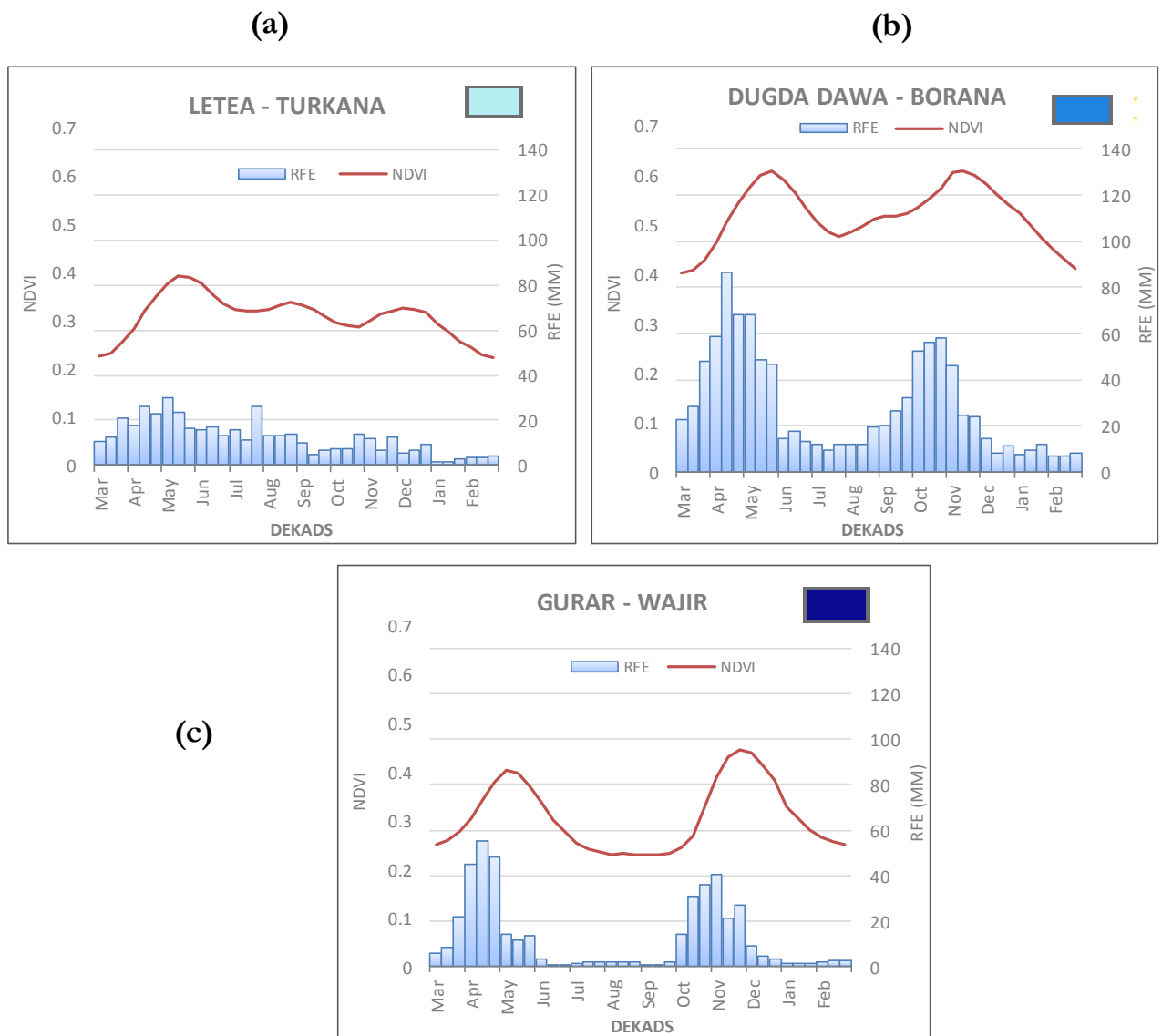


Figure 7: Temporal graphs representing the three main rainfall regimes in the study area (a) Turkana: precipitation spread throughout the year (b) Borana: Seasonal (c) Wajir: Markedly seasonal with longer dry season.

4.2. RFE – derived start- and end- of season (SOS_R and EOS_R) dates

Based on the adjusted dates SOS_R and EOS_R, the long rains growing season covers on average per unit, the period between early March (Figure 8a) to early June (Figure 8c) while the short rains growing season covers on average the period between early September (Figure 9a) to late December (Figure 9c). For comparison using finer resolution the spatial pattern of the seasons seems to be consistent (Figure 8b, d) and (Figure 9b, d) with the unit aggregates, although some pixels deviate significantly from this average. For example, the long rains end much later (early July) along the coastal zone in Garissa and high elevation zones of Baringo and Turkana (Figure 8d), the start of short rains season (Figure 9b) start much earlier (mid-August) in the high elevation zones in Baringo, Turkana and Borana, while along the Lake Turkana and around Chalbi desert in Marsabit the rains start much later (mid-November).

The start of season for the long rains shows less spread with the dates falling between early March and early April whereas the end of season dates for the long rains has a higher spatial heterogeneity i.e. from mid-April to late June, (Figure 8c,d). This is however, opposite case for the short rains, the start of season shows the highest spatial variability i.e. from late August in high elevation zones like Baringo, early September in arid Turkana, Samburu, northern Borana and mid-November in the arid areas of Marsabit (i.e. Chalbi desert), whereas the end of season has a low spread with late November to late December as the prevalent dates. Regions in western Turkana, Baringo, Samburu and northern Borana evidently tend to have significant deviations in the average SOS_R/EOS_R dates

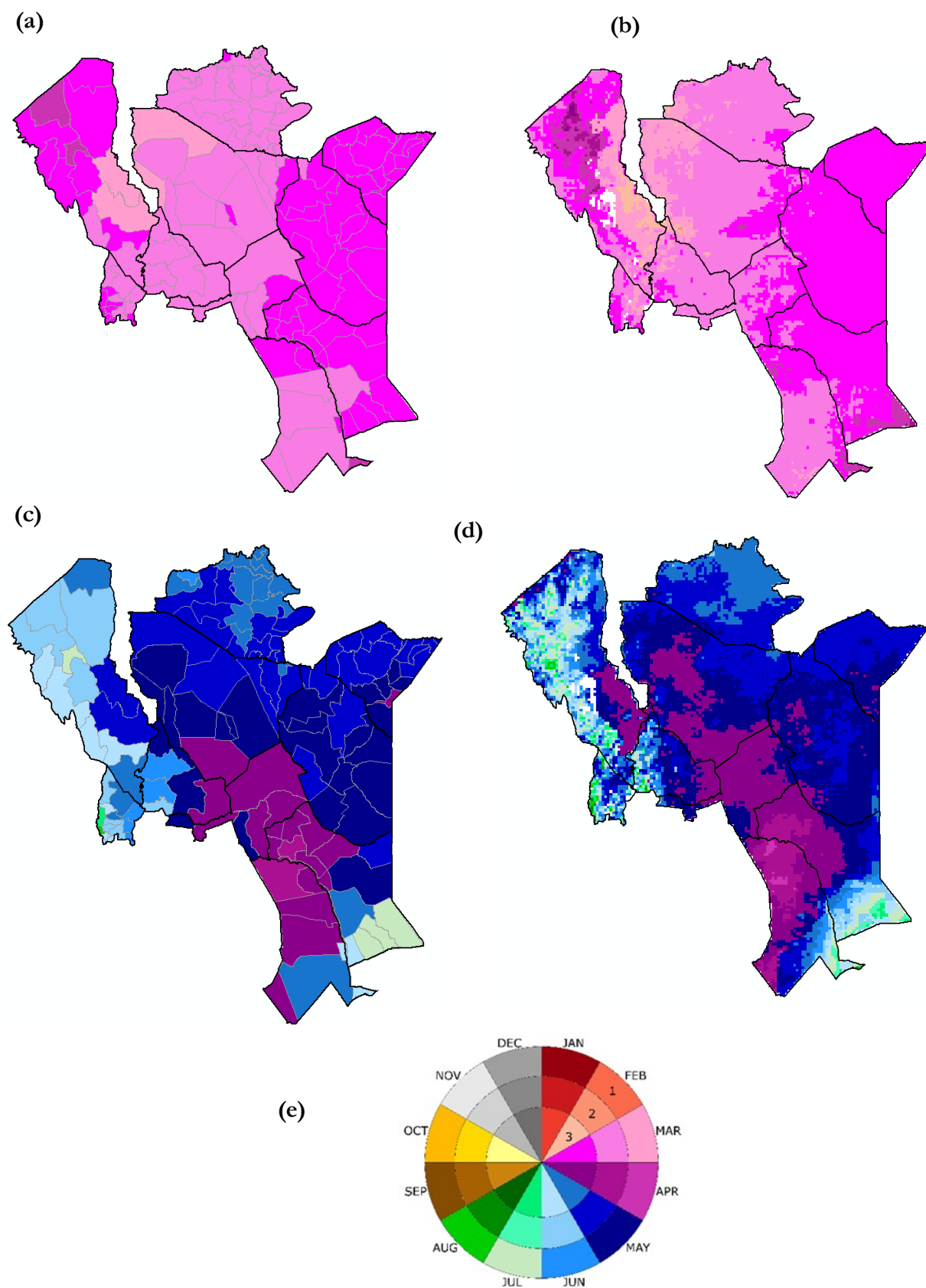


Figure 8: Rainfall seasonality analysis of CHIRPS time series data based on Liebmann et al. (2012): (a) average SOS for long rains per unit (b) per CHIRPS raster cell (c) average EOS for long rains per unit (d) per CHIRPS raster cell (e) phenology legend for interpreting seasonality with outer circle as first dekad of each month.

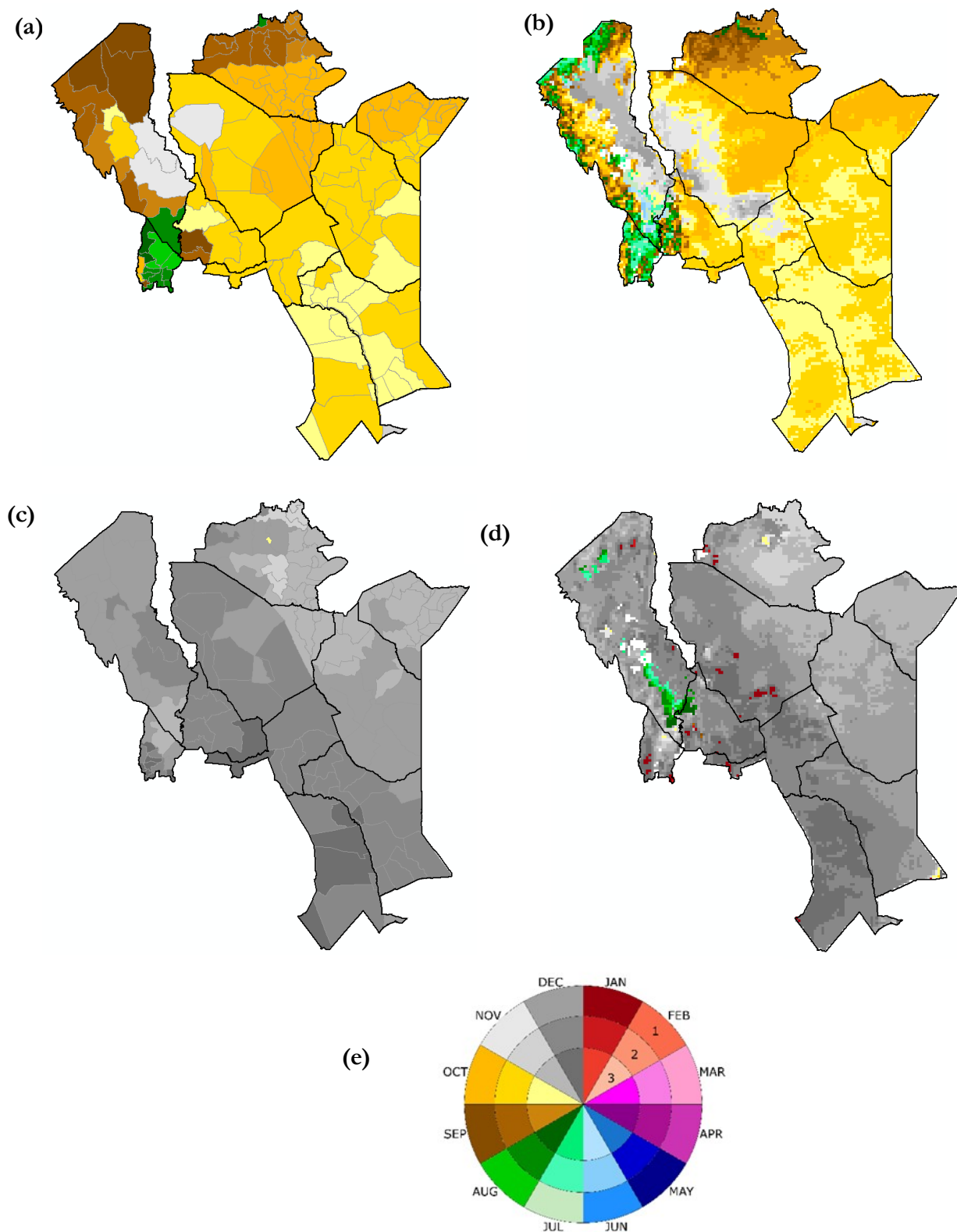


Figure 9: Rainfall seasonality analysis of CHIRPS time series data based on Liebmann et al. (2012): (a) average SOS for short rains per unit (b) per CHIRPS raster cell (c) average EOS for short rains per unit (d) per CHIRPS raster cell (e) phenology legend for interpreting seasonality with outer circle as first dekad of each month

4.3. Spatial and Temporal relationships between both TAMSAT and CHIRPS derived SPI with ZNDVI.

4.3.1. Spatial relationship between TAMSAT, CHIRPS derived SPI and the ZNDVI

The Pearson correlation coefficient between unit-level drought indices from CHIRPS and TAMSAT suggests that the two satellite rainfall product have a strong but not perfect agreement across the study area in both seasons (Figure 10), with about 90% of the units having a positive correlation coefficient larger than 0.75. Although the drought indices from TAMSAT and CHIRPS agree in most locations, this is not the case in units of southern Garissa in the long rain and western Turkana, northern Borana in the short rain season. Those units have a weak agreement ($r < 0.55$), indicating that the satellite products pick out rainfall events differently in these locations which had also been previously identified as having limited seasonality.

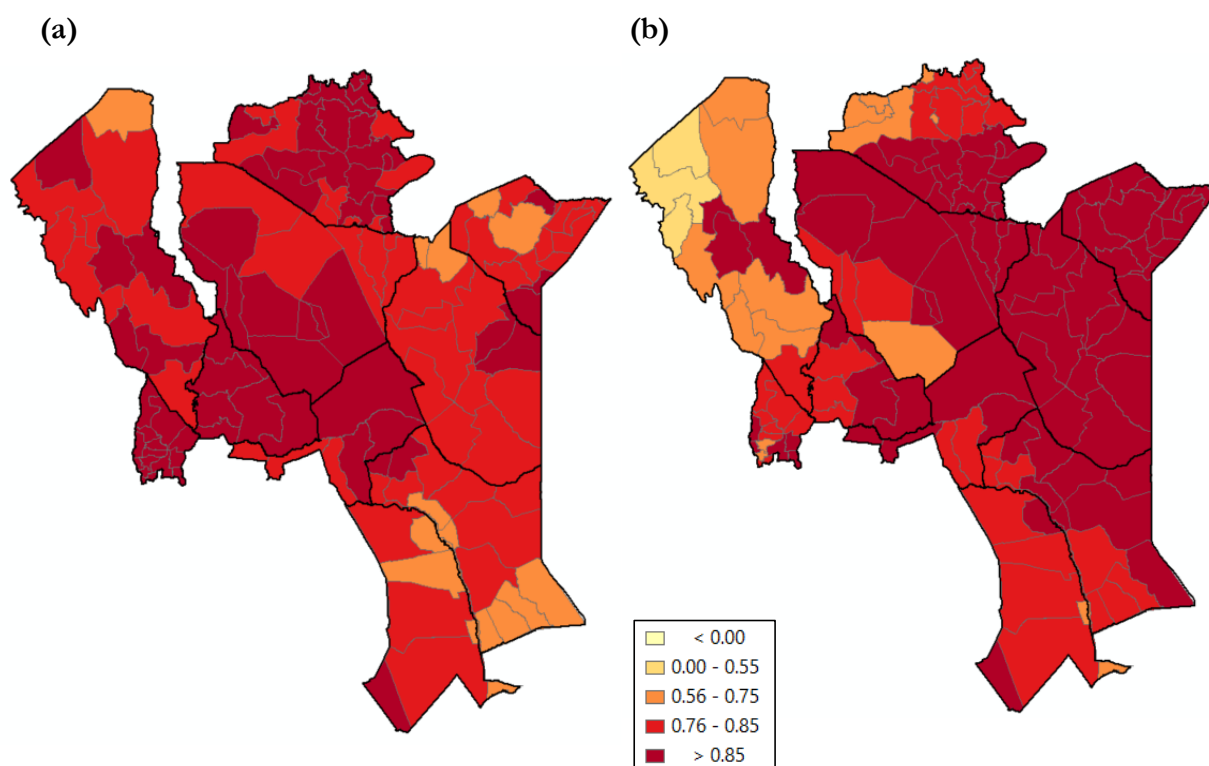


Figure 10: Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the seasonal SPI derived from CHIRPS and TAMSAT for (a) the long rains (b) the short rain season.

The Pearson correlation coefficient between the seasonal SPI from CHIRPS and the ZNDVI (Figure 11) suggests that in general a positive relationship exists across the study area. Approximately 39% of the units in the long rains and 73% in the short rains have a correlation coefficient larger than 0.75. Instead, for the CHIRPS pixel the overall correlation is significantly lower, i.e. 19% of the pixels in the long rains and 53% in the short rains have a correlation coefficient above 0.75. However, the spatial pattern that indicates where strongest correlation is found is comparable between the unit- and pixel-results.

The SPI has a better correspondence with the ZNDVI in the short rain season (Figure 11c, d) compared to the long rain season (Figure 11a, b) across the study area. The structure of the spatial distribution of the correlation coefficients shows that the highest coefficients run up from the drier, in terms of mean annual

rainfall (approximately 200-400mm) of Mandera, Wajir, Isiolo and northern Garissa, in the short rains season.

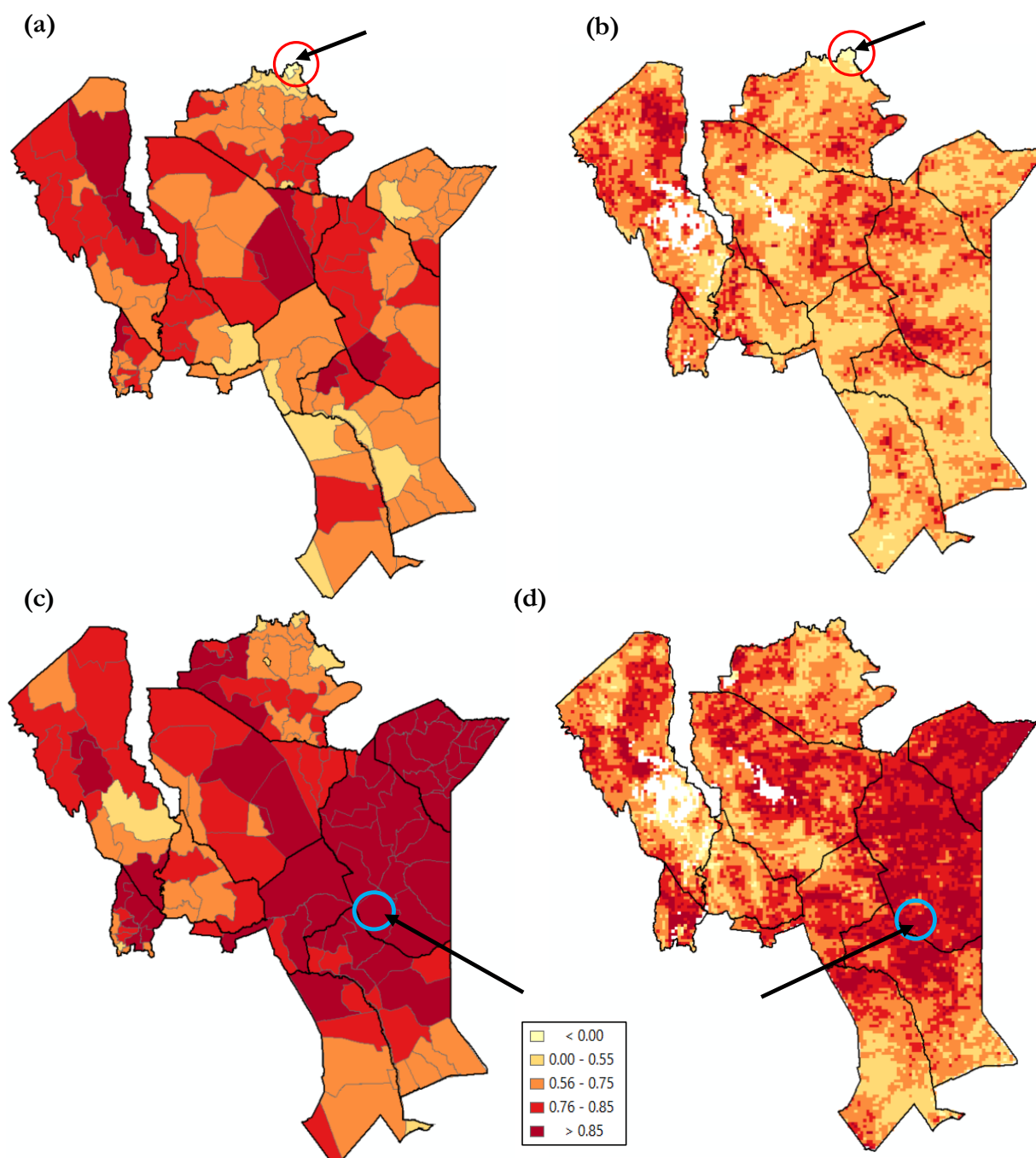


Figure 11 : Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the CHIRPS based SPI and the ZNDVI (a) for the long rain season per unit, (b) at CHIRPS raster cell; with the red circle showing Melka Soda in Borana, (c) for the short rain season per unit, (d) at CHIRPS raster cell; with blue circle showing Habaswein in Wajir.

For comparison, the Pearson correlation coefficients between the unit level seasonal SPI from TAMSAT and ZNDVI (Figure 12) similarly suggests that in general a positive relationship exists across the study area with 27% of the units in the long rain and 67% of the units in short rain season having a correlation coefficient larger than 0.75. The spatial pattern of the correlation coefficients across the study area is comparable to that of CHIRPS, with a better ZNDVI-SPI agreement in the short rain season. However, the results of the CHIRPS drought index suggest a stronger relationship with the forage scarcity index as evident by a much larger percentage of areas having high positive correlation coefficients.

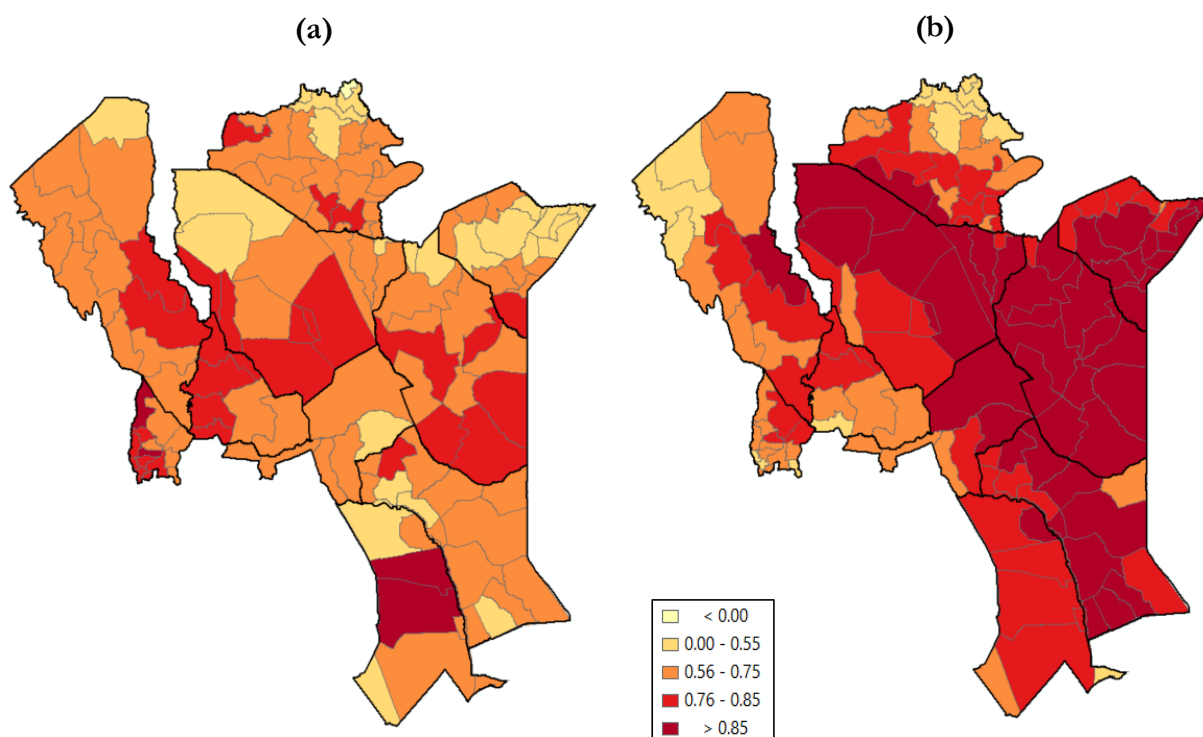
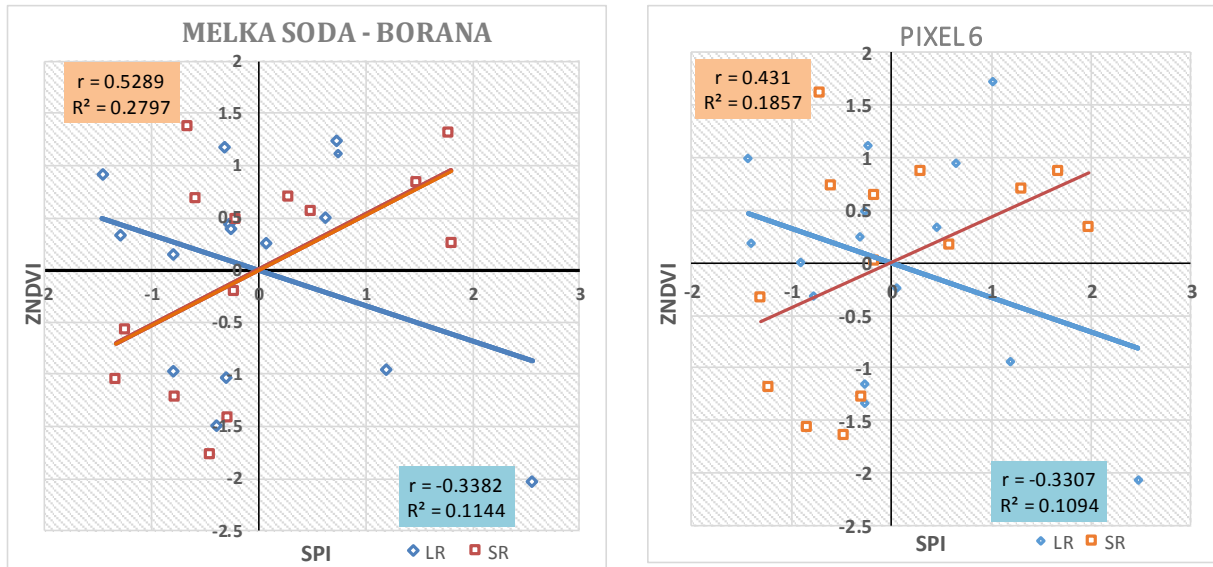


Figure 12: Pearson correlation coefficient that expresses the agreement of the inter-annual variability between the TAMSAT derived SPI and the ZNDVI (a) in the long rains (b) in the short rain season.

Figure 13 shows the corresponding scatter plots of the seasonal CHIRPS derived SPI and the ZNDVI, for units and sample pixels (within these units), that provide important insights into the relationship between these indices. For example, Habaswein in Wajir marked in a “blue circle” over the short rain season (Figure 11c, d), has a coefficient of determination (R^2) larger than 0.85 (Figure 13b) meaning that in this area the SPI can predict up to 85% of the inter-annual variability in the ZNDVI. This suggests that forage conditions over this area are highly influenced by rainfall.

From Figure 13a, the SPI and ZNDVI tend to disagree (i.e. have a negative slope value), in Melka Soda area in Borana marked in a “red circle” in (Figure 11a, b), a possible explanation may be due to the changes in seasonal rainfall distribution patterns, given that it is located in a transition zone between rainfall regimes, as shown in Herrmann and Mohr (2011). A closer look at points in the scatter plot (Figure 13a) also reveals disagreements between the ZNDVI and SPI in the year 2013 and 2003 in the long rain season. It is also comes across that the drier Habaswein in Wajir has a better correlation relationship compared to the wetter Melka-Soda in Borana.

(a)



(b)

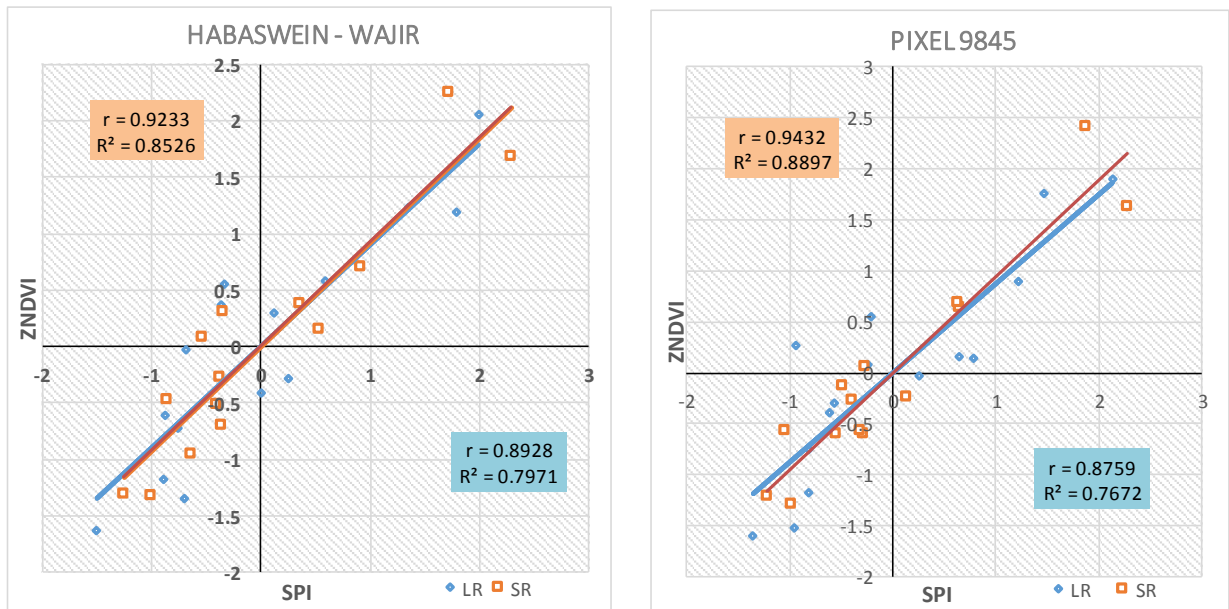


Figure 13: The scatter plots showing the seasonal SPI derived from CHIRPS against ZNDVI at both the units and corresponding sample pixels in (a) Melka Soda: weak agreement between the indices (b) Habaswein: strong agreement between the indices.

4.3.2. Temporal relationship between the SPI and ZNDVI

Inter- comparison between TAMSAT and CHIRPS derived drought indices with the ZNDVI based on Spearman rank correlation analysis (Appendix II), shows that similar to Pearson correlation analyses (Figure 11 and 12) a stronger agreement exists between CHIRPS derived SPI and ZNDVI compared to the TAMSAT derived SPI. Ranking analysis (Table 3) done between the forage scarcity index from eMODIS and the drought indices from TAMSAT and CHIRPS, reveals that generally over the four-year threshold, the seasonal SPIs and the ZNDVI agree on major drought events across the study area. However it is also evident that in most cases, CHIRPS derived SPI outperforms the TAMSAT derived SPI in terms of the agreement with the ZNDVI.

For example, in Central Wajir, three out of the four drought years from CHIRPS derived SPI, in both the long and short rains season agree with those from the ZNDVI. This indicates a fairly good agreement between the two indices. In cases where indices select the same drought years, such as for short rain season in Mogadashe – Garissa. Such an agreement (ranking coefficient of *1) could raise confidence in the current ZNDVI and further in the CHIRPS derived SPI as a reliable alternative. Nonetheless, this is not always true for other locations such as in Melka Soda in Borana where the ranking coefficients are consistently low in both seasons.

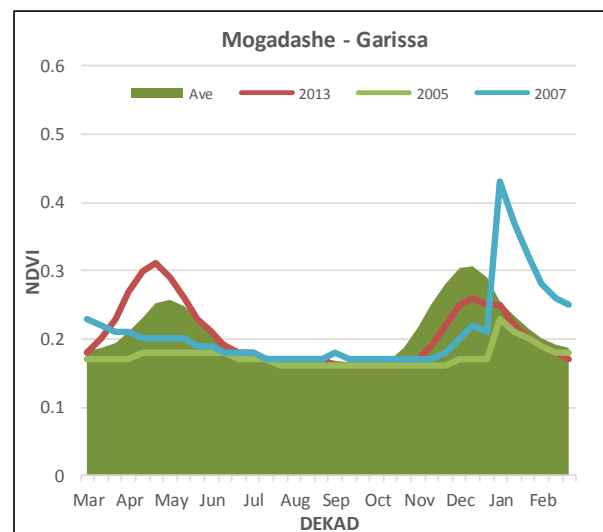
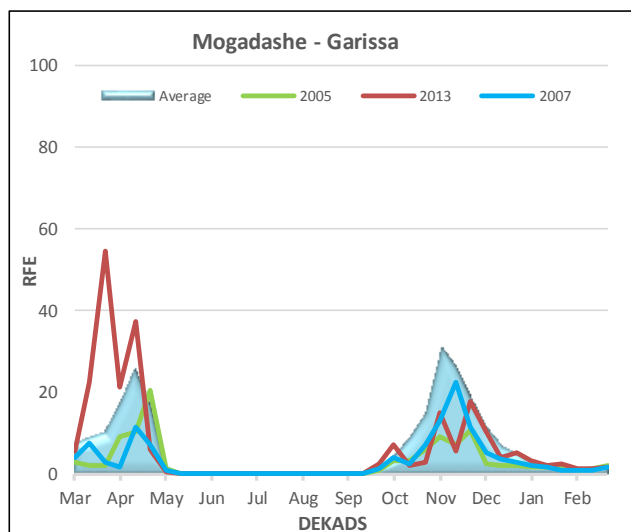
Table 3: The ranking coefficient indicates which proportion of the four years with the lowest forage scarcity index are also among the four years with the lowest drought index for the long and short rains seasons.

CENTRAL - WAJIR (LR)				MELKA SODA -BORANA(LR)				MODOGASHE-GARISSA (LR)			
Index	NDVI	CHIRPS	TAMSAT	Index	NDVI	CHIRPS	TAMSAT	Index	NDVI	CHIRPS	TAMSAT
BEST ↓ WORST	2002	2003	2013	BEST ↓ WORST	2010	2013	2013	BEST ↓ WORST	2002	2002	2013
	2008	2002	2002		2014	2003	2003		2010	2013	2003
	2003	2013	2003		2005	2005	2012		2015	2015	2015
	2004	2006	2015		2008	2010	2005		2003	2003	2002
	2010	2014	2010		2012	2012	2010		2008	2010	2008
	2013	2010	2006		2006	2015	2006		2013	2008	2012
	2015	2015	2001		2009	2009	2015		2001	2014	2001
	2006	2004	2012		2004	2006	2007		2014	2006	2010
	2012	2001	2004		2015	2007	2009		2012	2012	2004
	2007	2012	2007		2002	2014	2014		2007	2004	2006
	2014	2007	2005		2003	2011	2004		2006	2001	2009
	2001	2008	2009		2001	2002	2001		2004	2009	2014
	2005	2009	2014		2007	2001	2011		2009	2005	2005
	2009	2005	2008		2011	2004	2002		2005	2007	2007
	2011	2011	2011		2013	2008	2008		2011	2011	2011
Ranking coefficient	1	0.75	0.5	Ranking coefficient	1	0.25	0.5	Ranking coefficient	1	0.75	0.5

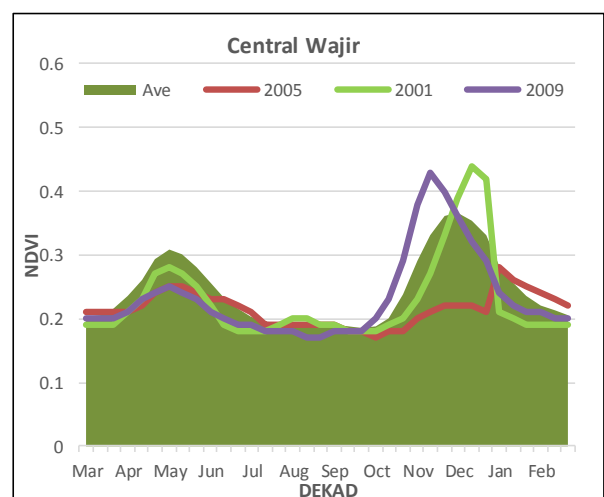
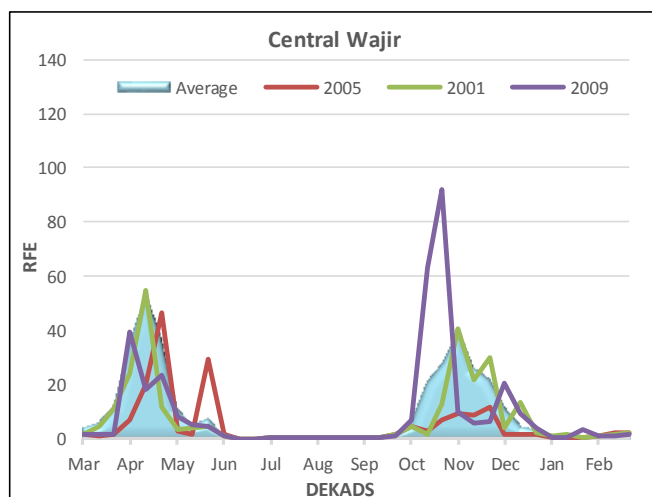
CENTRAL WAJIR (SR)				MELKA SODA -BORANA (SR)				MODOGASHE-GARISSA (SR)			
Index	NDVI	CHIRPS	TAMSAT	Index	NDVI	CHIRPS	TAMSAT	Index	NDVI	CHIRPS	TAMSAT
BEST ↓ WORST	2011	2011	2011	BEST ↓ WORST	2002	2008	2008	BEST ↓ WORST	2006	2011	2011
	2006	2006	2006		2013	2013	2013		2011	2006	2006
	2004	2009	2004		2011	2011	2011		2002	2002	2002
	2003	2004	2009		2006	2012	2004		2001	2001	2009
	2009	2002	2002		2005	2006	2012		2003	2009	2003
	2007	2014	2003		2012	2004	2002		2009	2004	2004
	2001	2007	2008		2004	2001	2014		2004	2014	2014
	2002	2008	2007		2008	2007	2007		2008	2012	2001
	2008	2003	2013		2001	2009	2009		2014	2003	2012
	2013	2001	2014		2003	2005	2001		2012	2008	2007
	2012	2013	2001		2010	2002	2005		2013	2007	2008
	2014	2012	2012		2014	2014	2003		2007	2013	2013
	2005	2010	2010		2007	2003	2010		2010	2010	2010
	2010	2005	2005		2009	2010	2006		2005	2005	2005
Ranking coefficient	1	0.75	0.75	Ranking coefficient	1	0.5	0.25	Ranking coefficient	1	1	0.75

The temporal graphs (Figure 14) help to explore the dynamic temporal properties of the data. A drought year occurs when an annual profile stays under the average annual profiles for a significant part of the season, for example in Mogadashe – Garissa drought years are detected in 2005 and 2007 over the long rains, and in 2005 and 2013 for the short rains season (Table 3). The distribution of rainfall within the season for Mogadashe (Figure 14a) links up well with that of the NDVI patterns, however, this is not the case for all locations. Melka Soda –Borana (Figure 14c) illustrates a case where the temporal profiles of NDVI and rainfall do not agree, in 2013 and 2003 rainfall profiles in the long rains season indicate a fairly good season, whereas the NDVI profiles pick them out as drought years. Central Wajir (Figure 14b) is comparable to Mogadashe although the seasons there are much wetter. Further, judging visually from the NDVI profiles, the short rains on average have a better forage development as indicated by higher NDVI profiles peaks as compared to the long rains seasons.

(a)



(b)



(c)

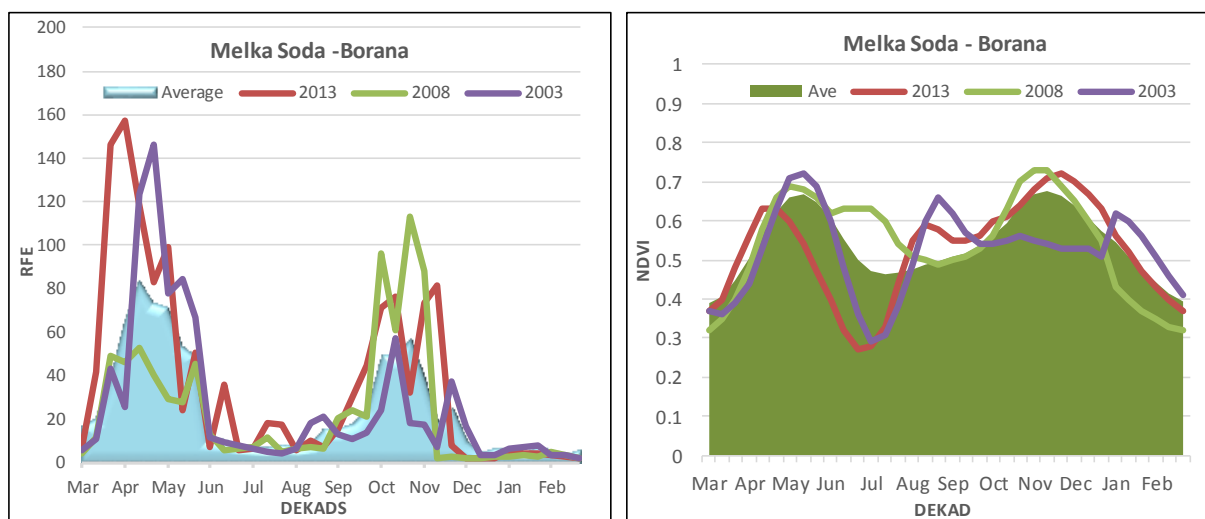


Figure 14: Temporal graphs showing for the drought years the annual profiles against the long term annual average profiles for rainfall and NDVI in (a) Mogadashe –Garissa (b) Central Wajir (c) Melka Soda – Borana (Ethiopia)

5. DISCUSSION

5.1. Spatial patterns of rainfall seasonality

Precipitation has a primary influence on vegetation growth and consequently on NDVI, particularly for the arid and semi-arid areas (J. Wang et al., 2003). Evaluation of the contrast in seasonal rainfall distribution across the study area suggests that a bi-modal seasonal pattern is dominant across the study area (Appendix I). These findings compare well with previous studies of seasonality analyses from NDVI time series data by Vrieling et al. (2016). In the arid areas of Turkana and higher elevation zones of Baringo, a mix of unimodal and bimodal seasonality is presented to be common, this is echoed in rainfall based seasonality analyses that similarly indicate a complex spatial pattern of unimodal and bimodal seasonality in this regions (Herrmann & Mohr, 2011).

In regions such as Wajir, Mandera, Isiolo, Garissa, Marsabit, northern Tana River and southern Borana where a clear seasonality regime was established, the Liebmann seasonality rule could effectively retrieve season–start and –end dates to be used as the temporal integration periods for calculating a seasonal SPI. However, for some parts of Baringo and western Turkana that were identified as having complex rainfall distribution patterns (i.e. with no clear seasonality regime), the NDVI-derived long-term average SOS_N/EOS_N were used, and to acknowledge the fact that rainfall precedes vegetation green-up (Udelhoven et al., 2009; Herrmann & Anyamba, 2005) a lag period was factored into the SOS_N/EOS_N . Although the lag is a complicated phenomenon, as a general rule from the analysis of regions with clear seasonality, a lag period of one dekad was found to be dominant in the start of season and five dekads in the end of season regardless of whether the short or long rains season. To account for the inter-annual variability while limiting the chance of overlap between the seasons, half a standard deviation is subtracted from the average SOS dates and half a standard deviation is added to the average EOS dates per pixel/per unit.

The long rains season, on average span from early March to early June while the short rains span from early September to late December, similarly the long rain growing season from NDVI phenological analyses extends from early April to early July and the short rains from mid-October to late January (Vrieling et al., 2016). This on average corresponds to an average of one to two months lag between the SOS_R/EOS_R and the SOS_N/EOS_N . This lag period is confirmed by analyses done by Davenport and Nicholson (1993) and Eklundh (1998) in East Africa. It is, however, important to note that despite having obtained spatially consistent estimates of SOS_R and EOS_R from rainfall estimates, some temporal error is inherent in using the 10- day, cumulative rainfall data as opposed to the actual daily observations for deriving seasonality. This is because cumulating the rainfall over the defined period tends to disregard the erratic day to day changes in rainfall that may have an influence on vegetation development during the growing season.

5.2. Spatio-temporal responses of ZNDVI to SPI.

The comparative analyses to a great extent revealed typical characteristics of vegetation response to rainfall in arid and semi-arid areas. The positive linear correlation coefficients between the ZNDVI and SPI from both TAMSAT and CHIRPS, generally indicate that vegetation growth is linearly responsive to inter-annual variability of rainfall across the study area. This relationship was also found to be better in the short rains than long rains season, studies show that the short rains are more reliable in terms of the amount of rainfall and vegetation development compared to the long rains season (Shisanya, 2011). Furthermore, it is evident that better relationships exist in drier regions of the study area such as Mandera, Wajir and

northern Garissa compared to the wetter regions such as Borana, and Baringo, probably because the vegetation is more sensitive to rainfall than in the drier regions compared to wetter regions.

However, from the correlation maps, some disparities are evident in the relationships between the ZNDVI and SPI. For example in Melka Soda –Borana in the long rains, the scatter plots (Figure 13a) and the ranking analyses in (Table 3), reveal that the SPI for the long rain season of 2003 and 2013 suggested a fairly good season with $SPI > 1.0$, whereas this was not reflected for the same years by the ZNDVI that had values below -0.5. A plausible explanation for this negative relationship between the indices may be linked to the issues of excess or intense rainfall concentrated over a short period of time that more often than not, manifest as increase in run-off resulting in rainfall that is ineffective for vegetation development as also documented by Leblois and Quirion (2013).

Studies have shown that the time scale over which SPI is calculated may be too coarse to capture short term or erratic changes in rainfall distribution (Thavorntam et al., 2015). For example, in the present study, rainfall was cumulated over the SOS_R and EOS_R dates meaning that dry spells that occur within the season are unaccounted for. Given that vegetation in the arid and semi-arid areas is highly sensitive to rain, occurrence of the dry spells may negatively affect or stunt forage development during the growing season, resulting in the observed differences in inter-annual variability between the SPI and ZNDVI. Furthermore, even though the SPI is computationally equivalent to the ZNDVI as they both indicate the number of standard deviations an observed variable is above or below the long-term mean in the present study, these variables represent different aspects of drought. Whereas the SPI is an indicator of meteorological drought and is based solely on precipitation, the ZNDVI is an indicator of agricultural drought that relates to vegetation growth. The fact that vegetation growth does not solely rely on precipitation for growth, influences the way NDVI responds to rainfall and may negatively affect the ZNDVI-SPI relationship.

Besides precipitation other factors that may possibly affect the ZNDVI-SPI relationship are, physical environmental factors such as temperature, evapotranspiration and soil types. The climate in the study area is largely arid and semi-arid, characterized by high temperatures with high rates of potential evapotranspiration. Temperature has a direct influence on plant growth because it influences water balance causing changes in soil moisture regime, which in turn influences growth as also documented by Jue Wang et al. (2001) and J. Wang et al. (2003). Studies have also shown that NDVI response to rainfall is largely controlled by soil types and especially their water retention capabilities that links to soil moisture availability (Nicholas & Farrar, 1994; Farrar et al., 1994). Soil moisture is the component of precipitation that it is directly associated with plant dynamics such as photosynthesis and largely stimulates vegetation growth. In the study area, high temperatures coupled with poor shallow soils result in low water retention rates and consequently affect forage development.

This study found that CHIRPS-based SPI showed a better agreement with ZNDVI as compared to TAMSAT-based SPI. A possible explanation for this is that CHIRPS has a higher accuracy than TAMSAT, which is confirmed by studies in East Africa that compared both products against station data (Dinku, 2014). Nevertheless, it is important to note that satellite rainfall estimates display large systematic and random errors. Systematic errors such as, bias errors might be propagated throughout the analyses leading to over- or under-estimation of rainfall values, therefore it is recommended that such errors in rainfall products should be assessed and adjustments done using weather station reference data before any applications are made (Dinku et al., 2008; Habib et al., 2014).

The current insurance units contain large internal variability, in terms of rainfall distribution, vegetation cover, soil types and elevation which could negatively affect the ZNDVI-SPI relationship. In an effort to address the issue of within unit spatial variability and to reduce the error inherent in using such aggregation, the CHIRPS raster cell was also used in the analyses. The results from the CHIRPS raster cell indicated that the spatial pattern of the relationship between the SPI-ZNDVI were comparable to those from the units across the study area. However a better agreement was shown at the unit level compared to the pixel level of aggregation, this is probably because coarser aggregations tend to smooth out the data and remove artefacts that may otherwise negatively interfere with the ZNDVI-SPI relationship.

5.3. Operational implementation and future outlook

In as much as the drought and forage scarcity index agree in some regions, it is quite evident that the SPI cannot be entirely relied upon as an alternative to the currently used ZNDVI. This is largely because of the discrepancies revealed between them, in most parts of the study area. Nonetheless, the research findings provide some important insights, and should not rule out the possibility of using the drought and forage scarcity index in such a way that optimizes information that each provides. This is especially given that the insured pastoralists more often than not, perceive drought and subsequently livestock mortality as being linked to rainfall shortages.

As with many index insurance schemes, success lies to a great extent in having a low basis risk i.e. the difference between insurable losses and indemnity payments (Miranda & Farrin, 2012; Barnett, 2004). To assess the potential of the insurance while using either the NDVI or RFE derived index, then the reliability and accuracy of the index should be further investigated through ground validation exercises. It is highly likely that the disparities between the indices could be partly explained by detailed ground information. Notably, as a step towards minimizing spatial basis risk, IBLI has been putting efforts in place for validating and evaluating the current forage scarcity index. Potential validation data sources include:

- (i) Local ground measurements of biomass (Roumigué et al., 2015) for validating the correspondence between the NDVI time series data and the existing forage conditions,
- (ii) In-situ weather station measurements for validating and calibration of the rainfall estimates (Dinku et al., 2007)
- (iii) Crowdsourcing information from locals; this can be in the form of drought recall exercises or focus group discussions that utilize the pastoralists experiences on past drought events. For example, in areas such as Turkana where the indices disagree the local pastoralists might help to highlight the reasons for this discrepancy because they are well versed with the environment. Recently with the advancement in technology, this information can also be obtained through mobile phone communication or applications such as the IBLI Percentile Calculator available on play store on android phones,
- (iv) Household level time series data such as livestock mortality time series data to assess the accuracy of the indices (Vrieling et al., 2016).

Nonetheless, it is important to note that some ground validation data are not readily available, nor are they likely to become available especially in large area monitoring situation. This coupled with huge financial implications that might be beyond the capacity of the project, necessitate the use of clever alternatives for validation. As in the case in the present study, efforts to use the RFE derived SPI can also be taken as a step to validate the accuracy of the existing NDVI derived ZNDVI especially in areas such as Wajir, Mandera and Isiolo where the agreement was found to be relatively strong. However for this to be a viable

option for IBLI, the key lies in obtaining a portfolio of the drought and forage scarcity indices and understanding the weaknesses and strengths of the sources used to obtain them as well as the indices themselves, considering that each provides an important piece of information.

One important simplification in the research and in the current IBLI design is the use of insurance units for the contract design. Even though drought is a covariate risk, assuming a homogenous risk for pastoralists within a particular insurance unit may not be entirely accurate as the degree of risk between each pastoralist varies within the unit depending on factors such as their decision-making characteristics. On the other hand, in as much as using the CHIRPS grid cells provides a good assessment of the interactions in the study area, it is neither a practical nor scalable solution for the design of a contract for livestock insurance, especially given the migratory lifestyle of the pastoralists. For this reasons, IBLI has over the years, implemented continuous improvements in the current spatial units, with an aim of reflecting the agro-ecological conditions and rangeland utilization while incorporating the cultural heritage and customary institutions of the pastoralists.

In as far as the use of the SPI, as a drought index is justified, especially by the fact that vegetation in the study area is mostly rain-fed, with an exception of few places where agricultural practices such as irrigation are practiced. The research has presented some uncertainties between rainfall and vegetation development (as indicated by NDVI). In some cases these disparities have been linked to soil moisture availability, which is the proportion of precipitation that reaches the plant roots and is considered effective for growth. It would be interesting to evaluate how well vegetation responds to soil moisture availability and if the relationship is better than with rainfall. Therefore, further studies could involve the use of soil water balance models, which simulates how much water reaches the roots and is effective for vegetation development after making adjustments for run-off and evapotranspiration (Cooley & Robertson, 1984; Wilcox et al., 2003). It is foreseen that the soil moisture availability would lead to being a better indicator of the forage production in the study area and hence provide a much improved index for insurance of livestock mortality.

6. CONCLUSION

In retrospect, the present study has provided important insights on the extent to which rainfall distribution patterns influence the spatial and temporal dynamics of vegetation, in the arid and semi-arid areas of Kenya and Southern Ethiopia. The analyses of seasonality from rainfall estimates are reproducible and adaptable to other areas that aim to cover risk based on precipitation time series data. The results reveal that a bimodal seasonality is dominant across the study area. The SOS_R/EOS_R from Liebmann's rule were assumed to correspond to the period during which rainfall is effective for forage development, and formed the basis for temporal integration in calculating the SPI.

It has been found that the CHIRPS derived SPI displays a relatively good agreement with the currently used ZNDVI, as compared to the TAMSAT derived SPI. Generally vegetation development is responsive to inter-annual variability of rainfall, with a better relationship shown for the short rains compared to the long rains season. Nonetheless, the unexplained differences between the ZNDVI-SPI relationships suggest that rainfall estimates cannot be entirely used as a substitute to NDVI in insuring livestock mortality across the study area.

The decision on how to spatially aggregate data is not a trivial issue, in the present research the current insurance units and the CHIRPS raster cell aggregations were both used. This was done with an aim to strike a compromise between the scientific and practical approach to the contract design. Ideally, data should be aggregated within units that are representative of the grazing area used by a given group of pastoralists. The current insurance units capture aspects such as the migratory lifestyle of the pastoralists, regulation of the contract in terms of where and how to allocate premiums and pay outs, scalability of the contract and reduction of conflicts that may arise where clear boundaries are not set out. However, the issue of index accuracy and reduction of basis risk has not been well captured by the current insurance units. In light of this, IBLI has been continuously working in liaison with the local communities on improving these units. Scientifically there exists a potentially large number of ways that could be argued on how to aggregate data, in the research CHIRPS raster cells aggregation was used to capture the spatial variability in the study areas, and provide a basis for discussion and comparison with the coarser, unit level aggregates.

Finally, the importance of carrying out continuous ground validation exercises must be prioritized if ever the IBLI insurance is to be considered a sustainable solution to the pastoralists. Ground validation exercises would be a positive step towards raising the confidence of the involved stakeholders on the quality of a particular index by revealing and quantifying its weak and strong points. Furthermore, this would lead to an increase in the uptake of the policy as well as continued engagement in the contract. However in circumstances where ground data for validation are missing, as in the present research, a workaround could be to construct a portfolio of complementary drought and forage scarcity indices as a means of validating each other, considering that each might provide an important piece of information.

REFERENCES

- ARC. (2012). African Risk Capacity Overview: Sovereign Disaster Risk Solutions. *A Specialized Agency of the African Union*.
- Barnett, B. J. (2004). Agricultural index insurance products: Strengths and limitations. In *Agricultural Outlook Forum*. Retrieved from <http://purl.umn.edu/32971>
- Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty Traps and Index-Based Risk Transfer Products. *World Development*, 36(10), 1766–1785. <http://doi.org/10.1016/j.worlddev.2007.10.016>
- Belal, A.-A., El-Ramady, H. R., Mohamed, E. S., & Saleh, A. M. (2012). Drought risk assessment using remote sensing and GIS techniques. *Arabian Journal of Geosciences*, 35–53. <http://doi.org/10.1007/s12517-012-0707-2>
- Bell, A. R., Osgood, D. E., Cook, B. I., Anchukaitis, K. J., McCarney, G. R., Greene, A. M., ... Cook, E. R. (2013). Paleoclimate histories improve access and sustainability in index insurance programs. *Global Environmental Change*, 23(4), 774–781. <http://doi.org/10.1016/j.gloenvcha.2013.03.003>
- Boru, D., Schwartz, M., Kam, M., & Degen, A. A. (2014). Cattle reduction and livestock diversification among Borana pastoralists in southern Ethiopia. *Nomadic Peoples*, 18(1), 115–145.
- Boschetti, M., Nutini, F., Brivio, P. A., Bartholomé, E., Stroppiana, D., & Hoscilo, A. (2013). Identification of environmental anomaly hot spots in West Africa from time series of NDVI and rainfall. *ISPRS Journal of Photogrammetry and Remote Sensing*, 78, 26–40. <http://doi.org/10.1016/j.isprsjprs.2013.01.003>
- Brown, M. E., & de Beurs, K. M. (2008). Evaluation of multi-sensor semi-arid crop season parameters based on NDVI and rainfall. *Remote Sensing of Environment*, 112(5), 2261–2271. <http://doi.org/10.1016/j.rse.2007.10.008>
- Ceglar, A., Črepinšek, Z., & Kajfež-bogataj, L. (2008). Analysis of meteorological drought in Slovenia with two drought indices. *Methods*, (August), 1–10.
- Chantararat, S., Mude, A. G., Barrett, C. B., & Carter, M. R. (2013). Designing Index-Based Livestock Insurance for Managing Asset Risk in Northern Kenya. *Journal of Risk and Insurance*, 80(1), 205–237. <http://doi.org/10.1111/j.1539-6975.2012.01463.x>
- Chopra, P. (2006). *Drought Risk Assessment Using Remote Sensing and GIS: A Case Study of Gujarat*. Retrieved from http://www.itc.nl/library/papers_2006/msc/iirs/chopra.pdf
- Conway, D., Allison, E., Felstead, R., Goulden, M., & a, P. T. R. S. (2005). Rainfall variability in East Africa : implications for natural resources management and livelihoods Rainfall variability in East Africa : *Phil. Trans. R. Soc. A*, (363), 49–54. <http://doi.org/10.1098/rsta.2004.1475>
- Cooley, K. R., & Robertson, D. C. (1984). Evaluating Soil Water Models on Western Rangelands, 37(November), 529–534.
- Coppock, D. L. (1994). *The Borana Plateau of Southern Ethiopia : The Borana Plateau of Southern Ethiopia : Synthesis of pastoral research , development and Change 1980-91*.
- Dai, A. (2011). Drought under global warming: a review. *Wiley Interdisciplinary Reviews: Climate Change*, 2(1), 45–65. <http://doi.org/10.1002/wcc.81>

- Davenport, M. L., & Nicholson, S. E. (1993). On the relation between rainfall and the Normalized Difference Vegetation Index for diverse vegetation types in East Africa. *International Journal of Remote Sensing*. <http://doi.org/10.1080/01431169308954042>
- De Beurs, K. M., & Henebry, G. M. (2010). Spatial-Temporal Statistics Methods for Modelling Land Surface Phenology. In *Media* (pp. 147–158). <http://doi.org/10.1007/978-90-481-3335-2>
- De Leeuw, J., Vrieling, A., Shee, A., Atzberger, C., Hadgu, K., Biradar, C., ... Turvey, C. (2014). The Potential and Uptake of Remote Sensing in Insurance: A Review. *Remote Sensing*, 6(11), 10888–10912. <http://doi.org/10.3390/rs61110888>
- Dinku, T. (2014). *Validation of the chirps satellite rainfall estimate. Seasonal Prediction of Hydro-climatic Extremes in the Greater Horn of Africa (GHA)*.
- Dinku, T., Ceccato, P., Grover-Kopec, E., Lemma, M., Connor, S. J., & Ropelewski, C. F. (2007). Validation of satellite rainfall products over East Africa's complex topography. *International Journal of Remote Sensing*, 28(7), 1503–1526. <http://doi.org/10.1080/01431160600954688>
- Dinku, T., Chidzambwa, S., Ceccato, P., Connor, S. J., & Ropelewski, C. F. (2008). Validation of high-resolution satellite rainfall products over complex terrain. *International Journal of Remote Sensing*, 29(14), 4097–4110. <http://doi.org/10.1080/01431160701772526>
- Doesken, N. J., & McKee, T. B. (1991). Development of a surface water supply index for the western United States, 84.
- Edwards, D. . (1940). A vegetation map of Kenya with particular reference to Grassland types. *Journal of Ecology*, 28(2), 377–385.
- Eklund, L., & Seaquist, J. (2015). Meteorological, agricultural and socioeconomic drought in the Duhok Governorate, Iraqi Kurdistan. *Natural Hazards*, 76(1), 421–441. <http://doi.org/10.1007/s11069-014-1504-x>
- Eklundh, L. (1998). Estimating relations between AVHRR NDVI and rainfall in East Africa at 10-day and monthly time scales. *International Journal of Remote Sensing*, 19(3), 563–570. <http://doi.org/10.1080/014311698216198>
- Farrar, T., Nicholas, S., & Lare, A. (1994). The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana. II. NDVI response to soil moisture. *Remote Sensing of Environment*, 50(2), 121–133. [http://doi.org/10.1016/0034-4257\(94\)90039-6](http://doi.org/10.1016/0034-4257(94)90039-6)
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2, 150066. <http://doi.org/10.1038/sdata.2015.66>
- Gessner, U., Naeimi, V., Klein, I., Kuenzer, C., Klein, D., & Dech, S. (2013). The relationship between precipitation anomalies and satellite-derived vegetation activity in Central Asia. *Global and Planetary Change*, 110, 74–87. <http://doi.org/10.1016/j.gloplacha.2012.09.007>
- Guttman, N. B. (1998). Comparing the Palmer Drought Index and the Standardized Precipitation Index: ties of the PDSI and its variations have been the referenced studies show that the intended. *Journal Of The American Water Resources Association*, 34(1). <http://doi.org/10.1111/j.1752-1688.1998.tb05964.x>

- Guttman, N. B. (1999). Accepting the Standardized Precipitation Index: a Calculation Algorithm1. *JAWRA Journal of the American Water Resources Association*, 35(2), 311–322. <http://doi.org/10.1111/j.1752-1688.1999.tb03592.x>
- Habib, E., Haile, A., Sazib, N., Zhang, Y., & Rientjes, T. (2014). Effect of Bias Correction of Satellite - Rainfall Estimates on Runoff Simulations at the Source of the Upper Blue Nile. *Remote Sensing*, 6(7), 6688–6708. <http://doi.org/10.3390/rs6076688>
- Hayes, M. J., Svoboda, M. D., Wilhite, D. a., & Vanyarkho, O. V. (1999). Monitoring the 1996 Drought Using the Standardized Precipitation Index. *Bulletin of the American Meteorological Society*, 80(3), 429–438. [http://doi.org/10.1175/1520-0477\(1999\)080<0429:MTDUTS>2.0.CO;2](http://doi.org/10.1175/1520-0477(1999)080<0429:MTDUTS>2.0.CO;2)
- Heim, R. (2002). A Review of Twentieth-Century Drought Indices Used in the United States, (August), 1149–1165.
- Herrmann, S., & Anyamba, A. (2005). Exploring relationship between rainfall and vegetation dynamics in the Sahel using coarse resolution satellite data. *Proceedings of International Symposium on Remote Sensing of Environment. June 20-24.*, 118. <http://doi.org/10.1016/j.gloenvcha.2005.08.004>
- Herrmann, S., & Mohr, K. (2011). A continental-scale classification of rainfall seasonality regimes in Africa based on gridded precipitation and land surface temperature products. *Journal of Applied Meteorology and Climatology*, 50(12), 2504–2513. <http://doi.org/10.1175/JAMC-D-11-024.1>
- Hewitt, K. (1997). *Regions of risk : A Geographical introduction to disasters*. Harlow: Longman.
- Indeje, M., Semazzi, F. H. M., & Ogallo, L. J. (2000). Enso Signals in East African Rainfall Seasons, 46, 19–46.
- IRI Report. (2014). Using Satellites to Make Index Insurance Scalable: Final IRI Report to the ILO Microinsurance Innovation Facility.
- Jenkerson, C. B., Scientist, S., Schmidt, G. L., Engineer, S. S., & Falls, S. (2008). eMODIS product access for large scale monitoring eMODIS rationale. *Contractor*.
- Ji, L., & Peters, A. J. (2003). Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. *Remote Sensing of Environment*, 87(1), 85–98. [http://doi.org/10.1016/S0034-4257\(03\)00174-3](http://doi.org/10.1016/S0034-4257(03)00174-3)
- Johnson, L. (2013). Agricultural index insurance through remote sensing: Experiences from east Africa. Retrieved August 10, 2015, from <http://www.slideshare.net/CIMMYT/1-johnson-sfsa-remote-sensing-public>
- Kidd, C., & Levizzani, V. (2011). Status of satellite precipitation retrievals. *Hydrology and Earth System Sciences*, 15(4), 1109–1116. <http://doi.org/10.5194/hess-15-1109-2011>
- Leblois, a., & Quirion, P. (2013). Agricultural insurances based on meteorological indices: Realizations, Methods and research challenges. *Meteorological Applications*, 20(1), 1–9. <http://doi.org/10.1002/met.303>
- Liebmann, B., Bladé, I., Kiladis, G. N., Carvalho, L. M. V, Senay, G. B., Allured, D., ... Funk, C. (2012). Seasonality of African precipitation from 1996 to 2009. *Journal of Climate*, 25(12), 4304–4322. <http://doi.org/10.1175/JCLI-D-11-00157.1>

- Loucks, D. P., Beek, E. Van, Stedinger, J. R., Dijkman, J. P. M., & Monique T. Villars. (2005). Drought Management. *Water Resources Systems Planning and Management. An Introduction to Methods, Models and Applications*, 581–599.
- Mahul, & Skees. (2007). *Managing Agricultural Risk At The Country Level : The Case Of Index-Based Livestock Insurance In Mongolia. Policy Research Working Papers*. The World Bank. <http://doi.org/doi:10.1596/1813-9450-4325>
- Maidment, R., Grimes, D., Allan, R., Tarnavsky, E., & Stringer, M. (2014). Journal of Geophysical Research: Atmospheres And Time series (TARCAT) data set. *Journal of Geophysical Research: Atmospheres*, 119, 10619–10644. <http://doi.org/10.1002/2014JD021927>. Received
- Mayaux, P., Bartholomeu, A., Cabral, M., Cherlet, P., & Di Gregorio, A. (2003). The Land Cover Map for Africa in the Year 2000, 2003. Retrieved from <http://www-gem.jrc.it/glc2000>
- McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Water*, 179(January), 17–22. <http://doi.org/citeulike-article-id:10490403>
- McSweeney, C., New, M., & Lizcano, G. (2009). UNDP Climate change country profile: Kenya, pp 26. Retrieved from <http://ncsp.undp.org/sites/default/files/Kenya.oxford.report.pdf>
- Megersa, B., Markemann, A., Angassa, A., Ogutu, J. O., Piepho, H.-P., & Valle Zárate, A. (2014). Livestock Diversification: an Adaptive Strategy to Climate and Rangeland Ecosystem Changes in Southern Ethiopia. *Human Ecology*, 42(4), 509–520. <http://doi.org/10.1007/s10745-014-9668-2>
- Meroni, M., Verstraete, M. M., Rembold, F., Urbano, F., & Kayitakire, F. (2014). A phenology-based method to derive biomass production anomalies for food security monitoring in the Horn of Africa. *International Journal of Remote Sensing*, 35(7), 2472–2492. <http://doi.org/10.1080/01431161.2014.883090>
- Miranda, M. J., & Farrin, K. (2012). Index insurance for developing countries. *Applied Economic Perspectives and Policy*, 34(3), 391–427. <http://doi.org/10.1093/aep/pps031>
- Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, 391(1-2), 202–216. <http://doi.org/10.1016/j.jhydrol.2010.07.012>
- Mude, A., Barrett, C. B., Carter, M. R., Chantarat, S., & Ikegami, M. (2010). *Index Based Livestock Insurance For Northern Kenya's Arid And Semi-Arid Lands: The Marsabit Pilot*.
- Mutai, C. C., Ward, M. N., & Colman, a W. (1998). Towards the prediction of the East Africa short rains based on sea-surface temperature-atmosphere coupling. *International Journal of Climatology*, 18(9), 975–997. [http://doi.org/10.1002/\(SICI\)1097-0088\(199807\)18:9<975::AID-JOC259>3.3.CO;2-L](http://doi.org/10.1002/(SICI)1097-0088(199807)18:9<975::AID-JOC259>3.3.CO;2-L)
- Muthuwatta, L. P., Ahmad, M.-D., Bos, M. G., & Rientjes, T. H. M. (2010). Assessment of Water Availability and Consumption in the Karkheh River Basin, Iran—Using Remote Sensing and Geo-statistics. *Water Resources Management*, 24(3), 459–484. <http://doi.org/10.1007/s11269-009-9455-9>
- Nicholas, S., & Farrar, T. (1994). The influence of soil type on the relationships between NDVI, rainfall, and soil moisture in semiarid Botswana. I. NDVI response to rainfall. *Remote Sensing of Environment*, 50(2), 107–120. [http://doi.org/10.1016/0034-4257\(94\)90038-8](http://doi.org/10.1016/0034-4257(94)90038-8)

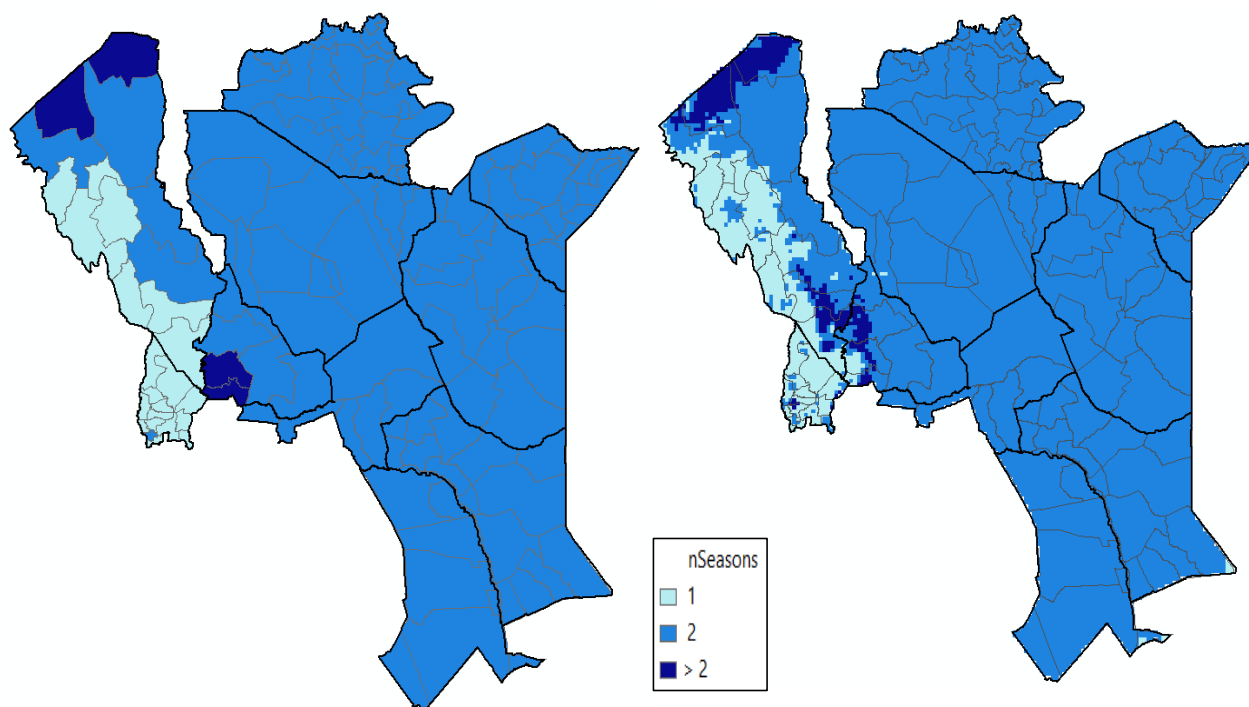
- Onono, J. O., Wieland, B., & Rushton, J. (2012). Productivity in different cattle production systems in Kenya. *Tropical Animal Health and Production*, 45(1), 423–430. <http://doi.org/10.1007/s11250-012-0233-y>
- Palmer, W. . (1965). Meteorological Drought. *Research Paper*. Retrieved from <http://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf>
- Rientjes, T., Haile, A. T., & Fenta, A. A. (2012). Diurnal rainfall variability over the Upper Blue Nile Basin: A remote sensing based approach. *International Journal of Applied Earth Observation and Geoinformation*, 21(1), 311–325. <http://doi.org/10.1016/j.jag.2012.07.009>
- Roumiguié, A., Jacquin, A., Sigel, G., Poilvé, H., Lepoivre, B., & Hagolle, O. (2015). Development of an index-based insurance product: validation of a forage production index derived from medium spatial resolution fCover time series. *GIScience & Remote Sensing*, 52(1), 94–113. <http://doi.org/10.1080/15481603.2014.993010>
- Shisanya, C. a. (2011). Rainfall Variability and Its Impact on Normalized Difference Vegetation Index in Arid and Semi-Arid Lands of Kenya. *International Journal of Geosciences*, 02(01), 36–47. <http://doi.org/10.4236/ijg.2011.21004>
- Sivakumar, M. V. . . (1988). Predicting rainy season potential from the onset of rains in Southern Sahelian and Sudanian climatic zones of West-Africa. *Agricultural and Forest Meteorology*, 42(4), 295–305.
- Smith, V., & Watts, M. (2009). Index based agricultural insurance in developing countries: Feasibility, scalability and sustainability. *Gates Foundation*. Retrieved from <https://www.agriskmanagementforum.org/sites/agriskmanagementforum.org/files/Documents/vs-mith-index-insurance.pdf>
- Swets, D. ., Reed, B. C., Rowland, J. D., & Marko, S. E. (1999). A Weighted Least-Squares Approach to Temporal NDVI Smoothing. *Proceedings of the 1999 ASPRS Annual Conference*, (Figure 1), 526–536.
- Tapiador, F. J., Turk, F. J., Petersen, W., Hou, A. Y., García-Ortega, E., Machado, L. a. T., ... de Castro, M. (2012). Global precipitation measurement: Methods, datasets and applications. *Atmospheric Research*, 104-105, 70–97. <http://doi.org/10.1016/j.atmosres.2011.10.021>
- Thavornntam, W., Tantemsapya, N., & Armstrong, L. (2015). A combination of meteorological and satellite-based drought indices in a better drought assessment and forecasting in Northeast Thailand. *Natural Hazards*, 77(3), 1453–1474. <http://doi.org/10.1007/s11069-014-1501-0>
- The Government of Kenya. (2010). The GoK's National Policy for Sustainable Development of Arid and Semi Arid Lands, (10), 48–91.
- The Republic of Kenya. (2011). Vision 2030 Development Strategy for Northern Kenya and other Arid Lands, (August).
- Tolo, C. U., Majule, E. A., & Lejju, J. B. (2014). Satellite Rainfall Products and Their Reliability in the Blue Nile Basin (pp. 451–473). <http://doi.org/10.1007/978-3-319-02720-3>
- Toté, C., Patricio, D., Boogaard, H., van der Wijngaart, R., Tarnavsky, E., & Funk, C. (2015). Evaluation of Satellite Rainfall Estimates for Drought and Flood Monitoring in Mozambique. *Remote Sensing*, 7(2), 1758–1776. <http://doi.org/10.3390/rs70201758>

- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150. [http://doi.org/10.1016/0034-4257\(79\)90013-0](http://doi.org/10.1016/0034-4257(79)90013-0)
- Udelhoven, T., Stellmes, M., del Barrio, G., & Hill, J. (2009). Assessment of rainfall and NDVI anomalies in Spain (1989–1999) using distributed lag models. *International Journal of Remote Sensing*, 30(8), 1961–1976. <http://doi.org/10.1080/01431160802546829>
- UN General, S. (1994). Intergovernmental negotiating committee for the elaboration of an international Convention to Combat Desertification in those countries experiencing serious drought and desertification, particularly in Africa., (June), 58. <http://doi.org/Accessed online: http://www.unccd.int/convention/menu.php>
- Vicente-Serrano, S. M., Cuadrat-Prats, J. M., & Romo, a. (2006). Aridity influence on vegetation patterns in the middle Ebro Valley (Spain): Evaluation by means of AVHRR images and climate interpolation techniques. *Journal of Arid Environments*, 66(2), 353–375. <http://doi.org/10.1016/j.jaridenv.2005.10.021>
- Vrieling, A., de Beurs, K. M., & Brown, M. E. (2011). Variability of African farming systems from phenological analysis of NDVI time series. *Climatic Change*, 109(3-4), 455–477. <http://doi.org/10.1007/s10584-011-0049-1>
- Vrieling, A., De Leeuw, J., & Said, M. Y. (2013). Length of growing period over africa: Variability and trends from 30 years of NDVI time series. *Remote Sensing*, 5(2), 982–1000. <http://doi.org/10.3390/rs5020982>
- Vrieling, A., Meroni, M., & Mude, A. (2015). Determining optimal seasonal integration times of NDVI series for Index-Based Livestock Insurance In East Africa.
- Vrieling, A., Meroni, M., Mude, A. G., Chantararat, S., & Caroline, C. (2016). Early assessment of seasonal forage availability for mitigating the impact of drought on East African pastoralists. *Remote Sensing of Environment*, 174(May 2015), 44–55. <http://doi.org/10.1016/j.rse.2015.12.003>
- Vrieling, A., Meroni, M., Shee, A., Mude, A. G., Woodard, J., de Bie, C. a J. M., & Rembold, F. (2014). Historical extension of operational NDVI products for livestock insurance in Kenya. *International Journal of Applied Earth Observation and Geoinformation*, 28(1), 238–251. <http://doi.org/10.1016/j.jag.2013.12.010>
- Walsh, R. P. D., & Lawler, D. M. (1981). Rainfall Seasonality: Description, Spatial Patterns and Change Through Time. *Weather*, 36(7), 201–208. <http://doi.org/10.1002/j.1477-8696.1981.tb05400.x>
- Wang, J., Price, K. P., & Rich, P. M. (2001). Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains. *International Journal of Remote Sensing*, 22(18), 3827–3844. <http://doi.org/10.1080/01431160010007033>
- Wang, J., Rich, P. M., & Price, K. P. (2003). Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. *International Journal of Remote Sensing*, 24(11), 2345–2364. <http://doi.org/10.1080/01431160210154812>
- White, M. a., de Beurs, K. M., Didan, K., Inouye, D. W., Richardson, A. D., Jensen, O. P., ... Lauenroth, W. K. (2009). Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982–2006. *Global Change Biology*, 15(10), 2335–2359. <http://doi.org/10.1111/j.1365-2486.2009.01910.x>

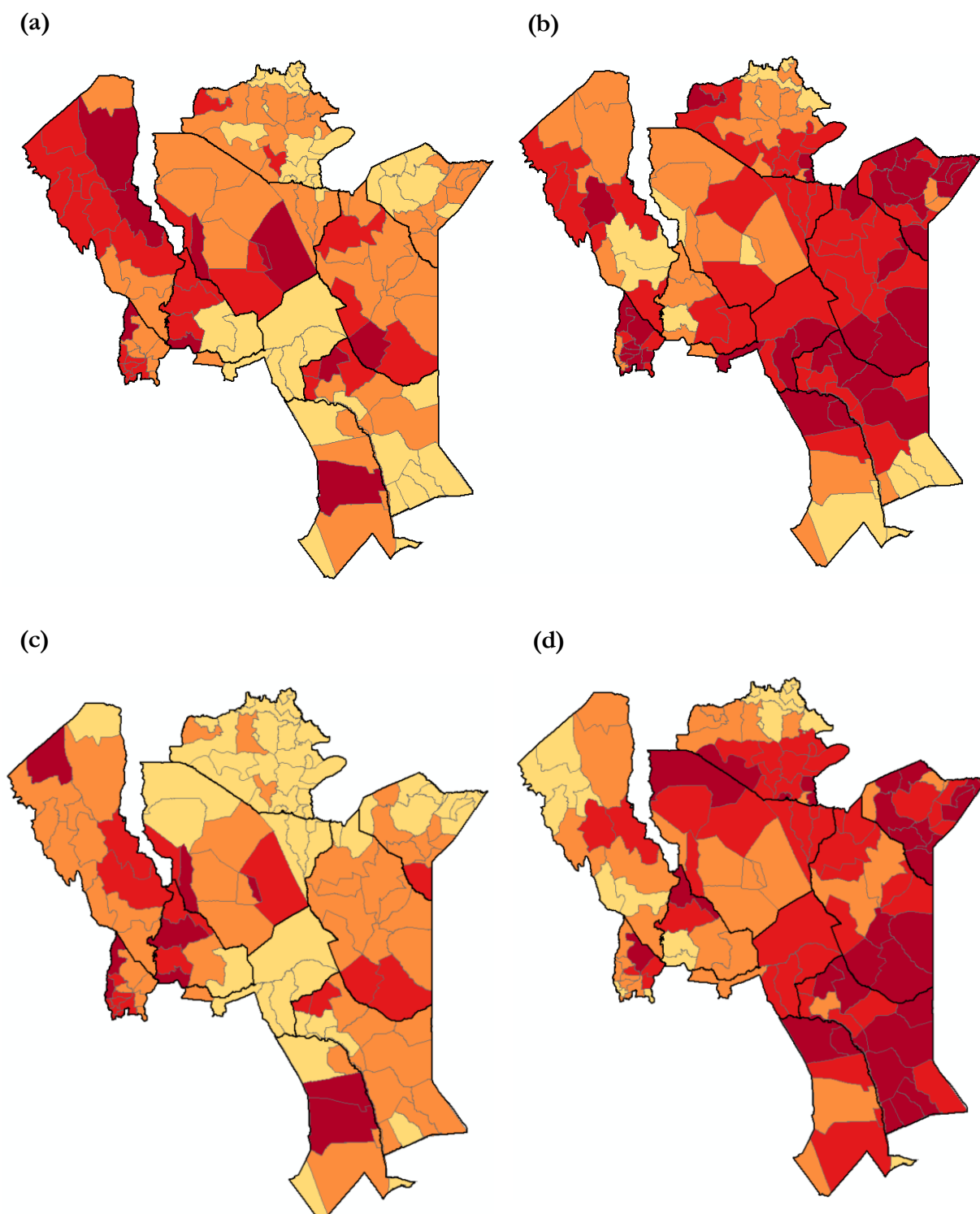
- Wilcox, B. P., Breshears, D. D., & Seyfried, M. S. (2003). Rangelands , Water Balance on. <http://doi.org/10.1081/E-EWS>
- Wilhite, D. (1996). A methodology for drought preparedness. *Natural Hazards*, 13(3), 229–252. <http://doi.org/10.1007/BF00215817>
- Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, 19(NA), 333–349. <http://doi.org/10.1139/a11-013>

APPENDICES

Appendix I: The Number of seasons over the study area



The number of seasons across the study area as retrieved from Liebmanns seasonality rule from CHIRPS data (a) per insurance unit (b) Per pixel over the study area.

Appendix II: The Spearman correlation coefficients

Spearman correlation coefficient that rank how well the unit level drought indices perform against the forage scarcity index in (a) the long rain (b) short rain season from CHIRPS data (c) the long rain (d) short rain season for TAMSAT data.