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Spatial Evaluation of Droughts Using Selected Satellite-based Indices in the Upper Tana River Watershed, Kenya

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Authors' contributions

This work was carried out in collaboration among all authors. Author HAO designed the study, retrieved and analysed the data and wrote the first draft of the manuscript. Author FKN assisted in data collection, analysis and interpretation and also managed literature searches and author JMO verified that the objectives of the study were met. The final manuscript was read and approved by all authors.

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ABSTRACT

Aims: To identify the most appropriate drought indices for the identification and monitoring of historical meteorological and agricultural drought incidences and to explore the spatial characteristics of these droughts.
Study design: GIS-based empirical research design.
Place and Duration of Study: Upper Tana River Watershed, Kenya drought analysis covering a period of 1981 to 2013.
Methodology: National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) provided raster maps for Normalized Difference Vegetation Index (NDVI) agricultural drought index, while GeoClim databased through Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) was used for retrieval of raster maps for Standardized Precipitation Index (SPI) meteorological drought index. ArcGIS version 10.3.1 facilitated image enhancement and correction for better visualization and interpretation.
Results: Agricultural drought years were in 1983, 1987, 1993, 1996, 2000, 2004, 2005, 2008, and

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2009 while meteorological drought years were in 1983, 1984, 1992, 1996, 1999, 2002, 2003, and 2011.
Conclusion: Meteorological drought triggered events of agricultural drought. Both droughts showed a widespread pattern and were found to manifest at relatively same intervals during the study period.

Keywords: Drought; spatial; GIS; remote sensing; SPI, NDVI.

1. INTRODUCTION

Human beings are often encountered with the challenge of having either too much water (flooding) or too little water (drought) due to the extreme hydrological and climatic phenomena [1, 2]. All types of climate experience drought and this phenomenon not only occurs in arid regions but also the humid regions [3,4]. Mahmoudi et al. [5], defined drought as a period of prolonged water shortages that disrupts growth, development and the environmental-human relationship. Due to its adverse impacts on food security, ecosystem functions and services, and the economy at large, much greater attention has been given to drought all around the world [6,7,5,8].

Drought continues to modify the agricultural sector and land-use-land-cover [9]. Moreover, the inconsistency between water supply and water demand is projected to be harsher in regions with warm climates [10]. Many countries in Africa have continuously faced drought [2]. The 2011 East-African drought caused dire situations across several countries and led to widespread and costly famine in the region [11]. It is expected that, as a result of drought, there will be a relative decline in water availability in the future in this region [12]. There has been evidence of increased drought frequencies in Kenya over the last three decades affecting the aquatic ecosystems and human resources [13, 14]. For instance, the 1999-2000 drought led to massive water level fluctuations in several rivers, dams, reservoirs and aquifers in the Tana River Basin [15]. The water imbalance in precipitation, evapotranspiration, runoff and water storage in the basin calls for heightened monitoring of droughts with regards to water resources [16].

There are three main types of drought that have been widely featured in the scientific literature [17]. First is the meteorological drought that is primarily as a result of prolonged periods of abnormally dry weather patterns dominating an area leading to prolonged below-normal precipitation and a rise in the air temperatures [18,19]. Not only can this deficit in precipitation quickly develop, but also abruptly halt [20,8]. The primary indicators of this category of drought are rainfall and temperature fluxes [21]. This drought type triggers the other two types of drought [22]. The second type is the hydrological drought that can be defined as a reduction in the actual streamflow levels, lakes levels, water levels in reservoirs and groundwater levels, below a threshold level [23]. Hydrological droughts persist for a longer time as compared to meteorological droughts since shortages in precipitation often translate to deficits in other hydrologic variables with significant time-lapses [24]. The last type is agricultural drought that is characterised by reduced precipitation and extreme evapotranspiration leading to a decline in the soil moisture content in the root zone. A deficit in the soil moisture is critical because crop yields can be heavily affected due to water deficiencies during the growing seasons [25,8]. The main indicator of this drought is crop water stress that aids the characterisation of vegetation responses during drought and non-drought periods [26].

Monitoring of drought can be achieved through the application of drought indices from either remote sensing or classical climatic indices of drought [27]. Drought indices based on Remote Sensing (RS) and Geographical Information System (GIS) tools produce near-real-time estimations of climatic parameters and have facilitated the monitoring and evaluation of spatial patterns of drought incidences [28]. On the other hand, classical climatic drought indices such as the Palmer Drought Severity Index (PDSI) and the Palmer Moisture Anomaly Index (the z-index) use data records from in-situ climatic and weather stations together with ground measurements, and they depend on these records to monitor and evaluate drought occurrences [29,30]. An advantage of these classical climatic drought indices over the RS based indices is that they give long-term records of data that facilitates long-term drought assessment and evaluation [31,32]. However, since drought monitoring and evaluation requires high temporal and spatial resolution of data, the new generation RS indices such as the

Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI) and Crop Water Severity Index (CWSI) have been used in many scientific studies to study drought incidences over large areas and different landscape levels since the climatic stations are sparse in many areas [33, 34,35,30].

Evaluation of spatial characteristics of drought is an exceptionally convoluted task [22]. Moreover, the complexity of drought spatial patterns and the vast climatic transitions resulting from the intricacy of atmospheric influences makes this task even more complicated [36]. A comprehensive evaluation of drought spatial characteristics is vital for drought assessment and early warning systems [37,38,39]. The spatial analysis takes into account aspects like drought severity, intensity, drought centroid and affected areas [40]. This facilitates the identification and monitoring of the onset, extension and end of a drought episode. The coverage area of a drought event is useful in determining its spatial characteristics [41].

The Upper Tana Watershed provides a wide range of ecosystem services but the extreme weather events, drought, in particular, has continuously become a threat to the watershed functions. The catchment is one of the most agriculturally productive regions in the country and additionally, due to the increased competition for water in terms of hydro-power, horticulture, irrigation, rice schemes and domestic uses, it is thus imperative to study the historical drought characteristics in the catchment. Although there have been studies of drought in the region, most of these studies applied the classical climatic drought indices such as PDSI and Soil Moisture Severity Index (SMSI). Therefore, this study used the modern and unique sensor-based data to give a comprehensive understanding of the spatial characteristics of drought that influences its severity, intensity and the affected area coverage is vital for modelling, prediction, mitigation and management of these droughts together with planning of activities such as water withdrawals in the watershed and for the sustainability of the watershed.

Therefore, to identify the most appropriate drought indices for the identification and monitoring of historical (1981 to 2013) meteorological and agricultural drought incidences and to explore drought spatial characteristics were the key objectives of this study.

2. MATERIALS AND METHODS

2.1 Study Region

The Upper Tana River Watershed covers six counties that are inclusive of Meru, Embu, Murang'a, Nyeri, Kirinyaga and Tharaka with Meru County having the highest population density of 1,356,301 while Tharaka having the lowest population density of 365,330 according to KNBS, 2010. Ecological factors, climatic conditions, food availability and type of farming influence the settling patterns in the watershed. The watershed has large protected areas such as national parks and forested areas. Moreover, large farm scales like Kakuzi, Delmonte, and Mwea rice fields and ranches such as Ngariama and Solio ranches have minimal settlements. The strong linkage to the environment is the main cause of poverty across the watershed in that changes in environmental condition has resulted to a decline in agricultural production which is the major source of livelihood to a majority of the people in the watershed.

The climate in the region is largely influenced by the inter-tropical convergence and the Mt. Kenya and Aberdare Ranges reliefs. The precipitation experienced is bimodal with the short rains between October and December and the long ones between March and June. Precipitation increases with an increase in altitude, as areas around Mt. Kenya and Aberdare ranges have an average annual amount around 2,700 mm whereas areas with lower altitudes experience average annual precipitation of 410 mm. The lower regions have a mean annual temperature that ranges from 26° to 30ºC and average annual potential evaporation of 2,300 mm while in high altitude areas, the mean annual temperatures range between 14° to 18ºC. The average annual potential evaporation of the watershed is 1,200 mm [42].

The soils in the region are grouped into four broad classes. In areas with altitudes above 4,000m, the soils are characterised by shallow dark loams with low bulk densities and high organic matter content; these are the Leptosols, Greysols and Regosols. Areas with altitudes between 2,400 to 4,000 m have soils characterised by high organic matter content, low bulk density and are primarily formed from pyroclastic rocks; these are the Histosols, Regosols and Andosols. In the lower areas with altitudes below 2,600 m have red soils with significant clay content and are mainly the Andosols, Nitisols and Cambisols.

Vegetation cover in the study region is divided into seven categories dependent on the altitude, precipitation and temperature. The Mt. Kenya catchment has the forest zone, the tea zone, the coffee zone and the Lower zone. The Aberdare Ranges catchment has the Aberdare conservation area inclusive of the national park, the middle zones inclusive of farming areas and the lower arid and semi-arid zones.

Fig. 1. Map of the Upper Tana River Watershed

2.2 Data

2.2.1 Drought indices

2.2.1.1 Normalized Difference Vegetation Index (NDVI)

The spatial characterisation of the agricultural drought were achieved using long-term NDVI. NDVI is a useful indicator for biomass estimation and production pattern and is calculated as in equation 1. Many researchers have successfully used this index to monitor vegetation phenology and mapping of vegetation cover [43,44,45].

$$NDVI = (NIR - VIS)/(NIR + VIS) \quad (1)$$

Where NIR is the near-infrared band and VIS is the visible red band of the electromagnetic spectrum. NDVI values for this study range from +1.00 to -1.00 but for this study, a range of 1 to 0 was selected for reasonability (Table 1) with values closer to 1 depicting non-drought conditions and values closer to 0 representing drought conditions.

NDVI images were retrieved from the Near-Infrared and Visible bands, which are the widely used vegetation index. Raster images of NDVI for the Upper Tana River Watershed were downloaded as GeoTiff files from the National Oceanic and Atmospheric Administration-Very High Radiometric Resolution (NOAA AVHRR) satellite using the NOAA CDR NDVI dataset from USGS Earth Explorer from 1981 to 2013. April and November were the months of interest for this study since they correspond to the rainy seasons in the study region. The raster images were then enhanced and corrected using the ArcGIS 10.3.1 for enhanced visualisation and interpretation of the spatial extents of drought. Using the ArcToolBox, the raster maps Upper Tana River watershed were extracted from their corresponding NDVI Africa raster maps using the extraction by polygon option in the extraction tool under the spatial analyst tool. The extracted raster map was then converted to point data to enable interpolation. Interpolation by kriging was selected. The output map was then classified into six classes that correspond to the NDVI spectral range in Table 1.

2.2.1.2 Standardized precipitation index (SPI)

The calculation of this index is based on long-term precipitation data [46,47]. Precipitation amounts are summed over *n* months (accumulation period) and then normalised to the standard normal distribution (μ=0, σ=1). The non-exceedance probabilities are calculated by fitting a parametric statistical distribution to the time of the year using a reference period. It is therefore easy to make objective and relative comparisons across different locations by interpreting the number of standard deviations from the normal conditions for a given time of the year [48,46].

For this study, 32 years, 1981 to 2013, was the reference period and SPI for 1, 2, 3, 6, 9, 12, 24 months was the standard period. The SPI-12, which corresponds to a 12 month accumulation period, was selected. The index values range (Table 2) was used where positive values of SPI represent wetter-than-average conditions, while negative values indicate drier-than-average conditions [9,8].

The GeoClim geodatabase was used to calculate SPI-12 and the output raster data imported and corrected in the ArcGIS10.3.1 for spatial analysis. From yearly raster images of Kenya, the image was resampled from a 0.05 to 0.005 cell size using the bilinear resampling technique in the resample option under the raster processing in the data management tools in the ArcToolBox. The Upper Tana River watershed was extracted from these resampled raster images. The raster maps were then converted to point data for ease of interpolation. The kriging interpolation method was used and the image was classified to seven classes as per the SPI scale range in Table 2.

Table 1. NDVI spectral range and interpretation

NDVI	Interpretation	Abbreviation
≥1.00	Very wet	VW
0.80 to 0.99	Moderately wet	MW
0.60 to 0.79	Near normal	NN
0.40 to 0.59	Moderately dry (moderate drought)	MD
0.20 to 0.39	Severely dry (severe drought)	SD
0.00 to 0.19	Extremely dry (extreme drought)	ED

Table 2. Interpretation of SPI values

SPI value	Interpretation	Abbreviation
≥ 2.00	Extremely wet	EW
1.50 to 1.99	Very wet	VW
1.00 to 1.49	Moderately wet	MD
0.99 to -0.99	Near normal	NN
-1.00 to -1.49	Moderately dry	MD
-1.50 to -1.99	Severely dry	SD
≤ -2.00	Extremely dry	ED

3. RESULTS AND DISCUSSION

3.1 SPI

The Upper Tana Watershed is a relatively wet region since most of the SPI values range from 1.00 to 1.49. Thus any anomaly in precipitation is a good indicator for a dry period. Additionally, the lowlands are drier as compared to the highlands with most values ranging from -1.00 to -1.99 and 0.99 to 1.49, respectively. Drought years in the region as a whole were in 1983, 1987, 1993, 1996, 2000, 2004, 2005, 2007, 2008, and 2009 with the driest year being in 2000. The most intense drought period was experienced from 2007 to 2009. Drought years in the highlands were in 1987, 1991, 1996, 2000, 2004, 2005, 2008, and 2009. Alternatively, drought years in the lowlands were in 1983, 1984, 1987, 1992, 1993, 1996, 1999, 2000, 2004, 2005, 2007, 2008, 2009 and 2013 (Fig. 2.). From the maps, drought trend can be identified. The cycle of moderate droughts from 1981 to 2013 is two to three years while for severe drought is four years from 2000 to 2013 since there was no severe drought since then. Before year 2000, the drought cycle was after longer as compared to the drought cycle from 2000 to 2013 which has evidently become shorter. SPI has successfully been used and is a good index when depicting drought severity [49,50]. From the maps, it was clear that more drought episodes occurred in the lowlands than in the highlands. When the mapping of dry events in the region using the Soil Water Supply Index, [51] made similar observations. Correspondingly, using the [52], also observed the same.

3.2 NDVI

From the results, drought years were across the entire watershed were in November 1982, April 1983, November 1987, April 1994, November 1994, November 1995, April 1998, November 2000, April 2003, November 2004, November 2005, November 2007, November 2011, April 2012 and November 2013. Between the two rainy seasons, drought was more prevalent in November than in April. The same case was seen in the highlands where agro-droughts were experienced in April 1994, November 1994, November 1995, April 1998, November 2000, April 2003, November 2004, November 2005, November 2007, November 2011, April 2012, and November 2013. On the other hand, in the lowlands, November 1994, November 1995, April 1998, November 2000, April 2003, April 2004, April 2005, April 2007, November 2007, April 2012 and November 2013 were the drought years (Fig. 3 a & b). April showed more drought susceptibility and changes in NDVI than in November. The most intense agricultural drought was in 1994

The NDVI is a numerical sign used for evaluation of vegetation. By measuring the deviations of the present NDVI from the normal conditions, the drought severity can be expressed since the values by themselves are not a reflection of drought or non-drought conditions [53]. From the NDVI maps, it is evident that during drought periods, the coverage area was widespread. This is consistent with the findings of [54]. There is a limited correlation between NDVI as an agricultural drought index and SPI as a meteorological drought index since other factors such as temperature, soil moisture content and humidity influence vegetation [55]. This is explained by the time lag that exists between meteorological drought and agricultural drought. For instance, despite the normal precipitation in 1994 and 1995, the vegetation in the region during those two years was not reestablished back to their normal conditions. [56] Made a similar observation, although a good agreement between three-month precipitation and peak NDVI has been observed [54,57].

Overall, the results show that the drought cycle changed in recent years. Drought events have become more frequent with a 2 to 3 years return period [14,58]. This gives no time for the study region to recover from the impacts of drought. The highlands showed more resilience to drought than the lowlands that seemed to be more susceptible to drought since the highlands are characterised by humid and semi-humid climate and the lowlands are categorised as semi-arid climate [51,52]. This is evident with the increasing trends of moderate to severe droughts from SPI and NDVI values in the lowlands [3]. Made a similar observation.

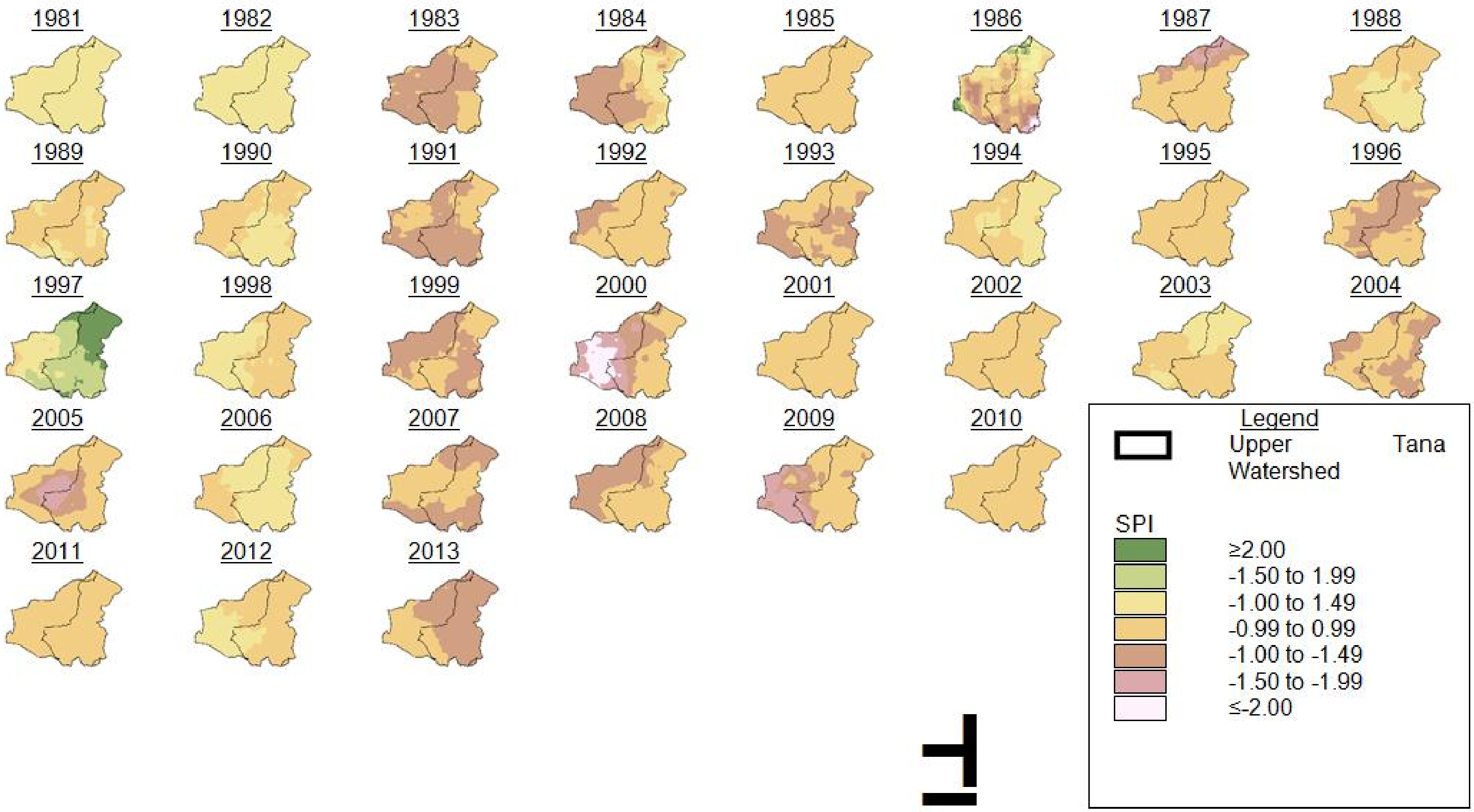

Fig. 2. Yearly SPI maps of the Upper Tana Watershed from 1981 to 2013

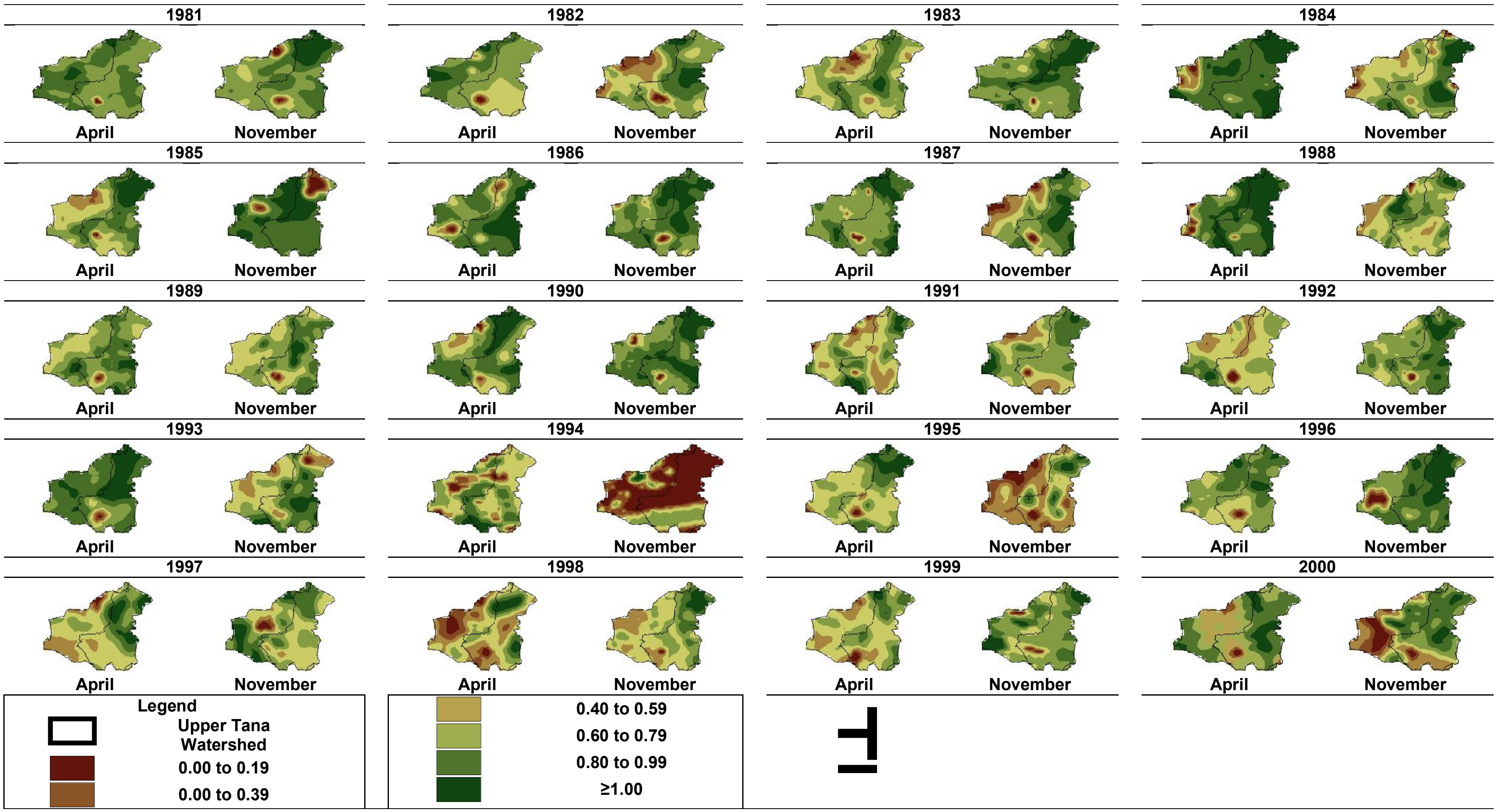

Fig. 1(a). NDVI maps of the Upper Tana River Watershed from 1981 to 2000

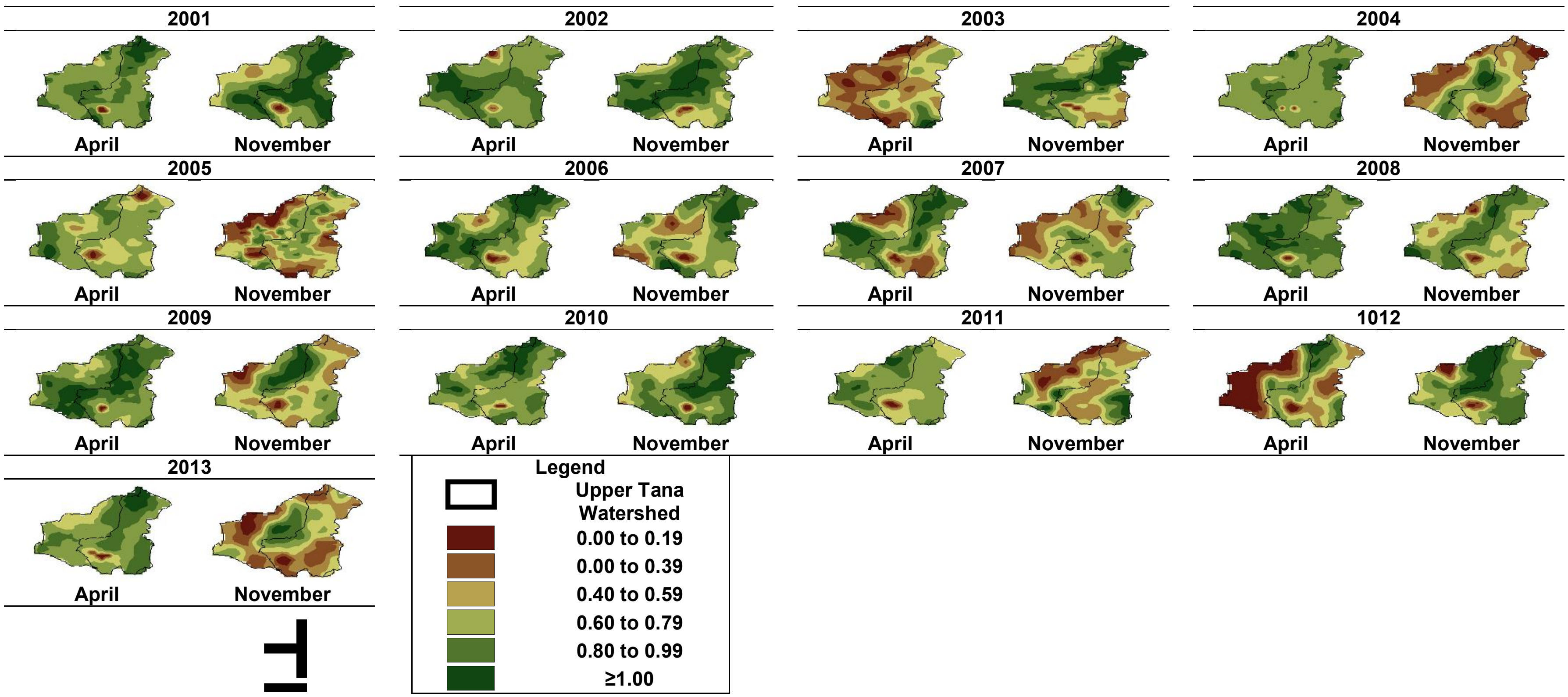

Fig. 3(b). NDVI maps of the Upper Tana River Watershed from 2001 to 2013

4. CONCLUSION

Overall, agricultural and meteorological droughts in the have been experienced in a relatively same interval during the study period. However, the lowlands were hit more by meteorological drought as compared to the highlands. Both the highland and the lowlands experienced the same drought periods for agricultural drought across the study period. The most severe meteorological drought was experienced in 2007-2009 while for agricultural drought was in 1994-1995. Meteorological drought hits first and then followed by agricultural drought as per the results in the study. Additionally, the cycle of both droughts is short since the manifestation of these droughts occurs one after the other.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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