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


## 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) and Tropical Rainfall Measuring Mission (TRMM) 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 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]). [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. MATERIAL 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 30° C and average annual potential evaporation of 2,300 mm while in high altitude areas, the mean annual temperatures range between 14° to 18° C. The average annual potential evaporation of the watershed is 1,200mm [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 4,000m 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 2,600m 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.


**Figure 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].

$$NDVI = (NIR - VIS)/(NIR + VIS) \qquad \text{Equation 1}$$

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.

**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 |

#### *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 ($\mu$=0, $\sigma$=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.

**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 (Figure 2.). 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 (Figure 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].

In recent years, the results show that the drought cycle changed. 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.

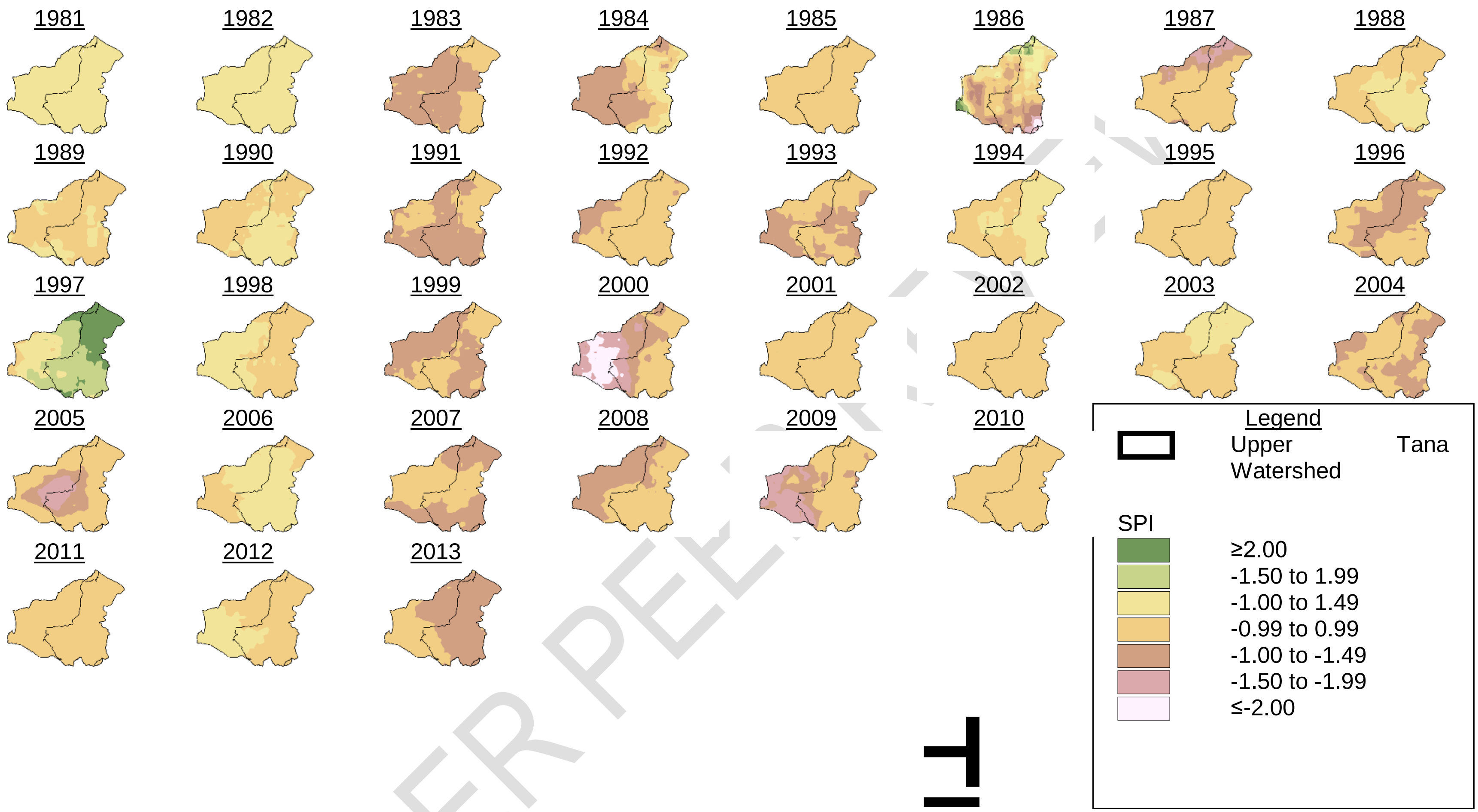


**Figure 2. Yearly SPI maps of the Upper Tana Watershed from 1981 to 2013**

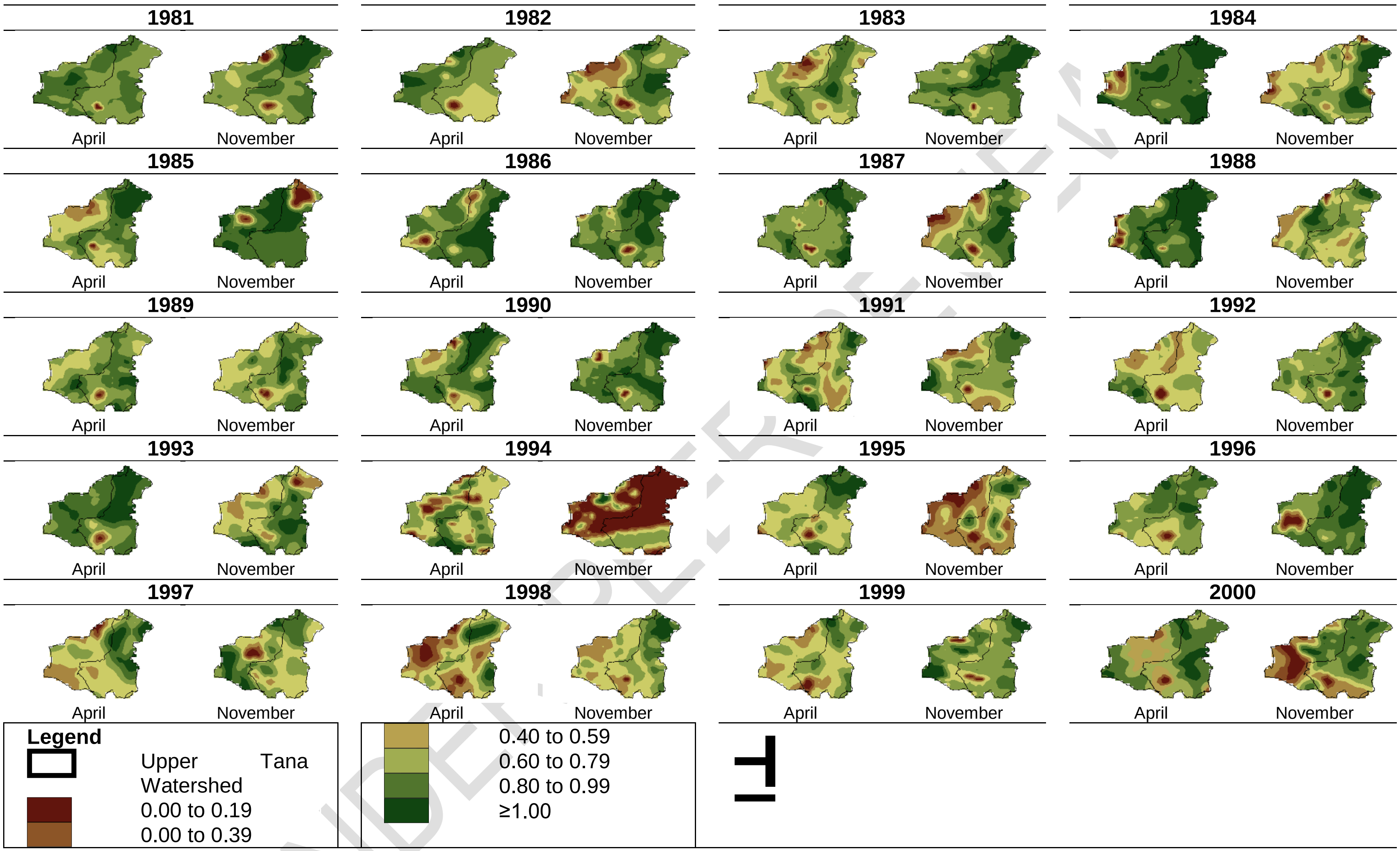


**Figure 3(a) NDVI maps of the Upper Tana River Watershed from 1981 to 2000**

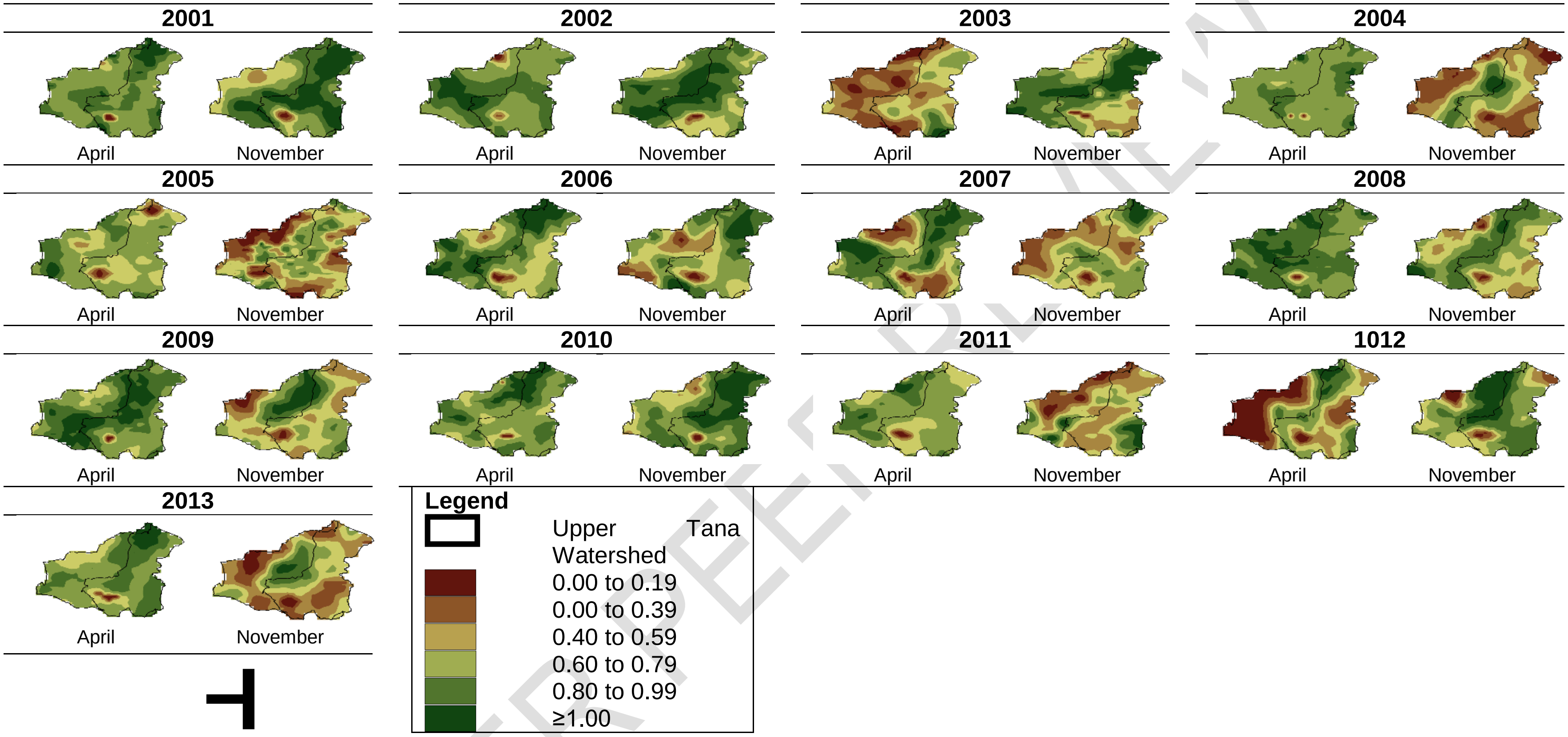


**Figure 3(b) NDVI maps of the Upper Tana River Watershed from 2001 to 2013**

## 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.



## REFERENCES


1. Sugirtharam M, Venuthasan T. Farmers' Awareness on Climate Change Related Issues at Some Irrigable Areas of Batticaloa District, Sri Lanka, I. Res. J. Environmen Sci.;1(2):29-32.

2. Agwata JF. Spatial characteristics of drought duration and severity in the Upper Tana Basin, Kenya. International Research Journal of Environment Sciences. 2014; 3.

3. Merabti A, Martins DS, Meddi M, Pereira LS. Spatial and time variability of drought based on SPI and RDI with various time scales. Water resources management. 2018; 32(3):1087-100.

4. Zhong R, Chen X, Lai C, Wang Z, Lian Y, Yu H, Wu X. Drought monitoring utility of satellite-based precipitation products across mainland China. Journal of hydrology. 2019; 568:343-59.

5. Mahmoudi P, Rigi A, Kamak MM. A comparative study of precipitation-based drought indices with the aim of selecting the best index for drought monitoring in Iran. Theoretical and Applied Climatology. 2019: 1-6.

6. Yan H, Wang SQ, Wang JB, Lu HQ, Guo AH, Zhu ZC, Myneni RB, Shugart HH. Assessing spatiotemporal variation of drought in China and its impact on agriculture during 1982–2011 by using PDSI indices and agriculture drought survey data. Journal of Geophysical Research: Atmospheres. 2016; 121(5):2283-98.

7. Li X, He B, Quan X, Liao Z, Bai X. Use of the standardized precipitation evapotranspiration index (SPEI) to characterize the drying trend in southwest China from 1982–2012. Remote Sensing. 2015; 7(8):10917-37.

8. Mallya G, Tripathi S, Govindaraju RS. An Analysis of Spatio-Temporal Changes in Drought Characteristics over India. InHydrology in a Changing World 2019; 23-71.

9. Surendran U, Anagha B, Raja P, Kumar V, Rajan K, Jayakumar M. Analysis of Drought from Humid, Semi-Arid and Arid Regions of India Using DrinC Model with Different Drought Indices. Water resources management. 2019; 33(4):1521-40.

10. Raja MU, Mukhtar T, Shaheen FA, Bodlah I, Jamal A, Fatima B, Ismail M, Shah I. Climate Change and its Impact on Plant Health: A Pakistan's Prospective. Plant Protection. 2018; 2(02):51-6.

11. Mwangi E, Wetterhall F, Dutra E, Di Giuseppe F, Pappenberger F. Forecasting droughts in East Africa. Hydrology and Earth System Sciences. 2014; 18(2):611-20.

12. AghaKouchak A. A multivariate approach for persistence-based drought prediction: Application to the 2010–2011 East Africa drought. Journal of Hydrology. 2015; 526:127-35.

13.Huho JM, Kosonei RC. The opportunities and challenges for mitigating climate change through drought adaptive strategies: The case of Laikipia County, Kenya. Academic Research International. 2013; 4(3):453.

14.Karanja A, Ondimu K, Recha C. Analysis of Temporal Drought Characteristic Using SPI Drought Index Based on Rainfall Data in Laikipia West Sub-County, Kenya. Open Access Library Journal. 2017; 4(10):1.

15. UNEP/GoK. Devastating Drought in Kenya: Environmental Impacts and Responses. I. UNEP, Nairobi. 2000; 76.

16.Kerandi NM, Laux P, Arnault J, Kunstmann H. Performance of the WRF model to simulate the seasonal and interannual variability of hydrometeorological variables in East Africa: a case study for the Tana River basin in Kenya. Theoretical and Applied Climatology. 2017; 130(1-2):401-18.

17.Mishra AK, Singh VP. A review of drought concepts. Journal of hydrology. 2010; 391(1-2):202-16.

18.Meresa H, Osuch M, Romanowicz R. Hydro-meteorological drought projections into the 21-st century for selected Polish catchments. Water. 2016; 8(5):206.

19.Wang L, Yuan X, Xie Z, Wu P, Li Y. Increasing flash droughts over China during the recent global warming hiatus. Scientific reports. 2016; 6:30571.

20.Hameed M, Ahmadalipour A, Moradkhani H. Apprehensive drought characteristics over Iraq: results of a multidecadal spatiotemporal assessment. Geosciences. 2018; 8(2):58.

21. Bandyopadhyay N, Bhuiyan C, Saha AK. Heat waves, temperature extremes and their impacts on monsoon rainfall and meteorological drought in Gujarat, India. Natural Hazards. 2016; 82(1):367-88.

22.El Hajj M, Zribi M, Baghdadi N, Le Page M. Mapping of Drought. QGIS and Applications in Water and Risks. 2018; 4:185-214.

23. Agwata JF, Wamicha WN, Ondieki CN. Analysis of Hydrological Drought Events in the Upper Tana Basin of Kenya. Analysis. 2015; 5:2.

24.Van Loon AF. Hydrological drought explained. Wiley Interdisciplinary Reviews: Water. 2015; 4:359-92.

25.Mishra AK, Ines AV, Das NN, Khedun CP, Singh VP, Sivakumar B, Hansen JW. Anatomy of a local-scale drought: Application of assimilated remote sensing products, crop model, and statistical methods to an agricultural drought study. Journal of Hydrology. 2015; 526:15-29.

26.Pachauri RK, Allen MR, Barros VR, Broome J, Cramer W, Christ R, Church JA, Clarke L, Dahe Q, Dasgupta P, Dubash NK. Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. Ipcc; 2014.

27.Abbas S, Nichol J, Qamer F, Xu J. Characterization of drought development through remote sensing: a case study in Central Yunnan, China. Remote sensing. 2014; 6(6):4998-5018.

28.Zhang A, Jia G. Monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data. Remote Sensing of Environment. 2013; 134:12-23.

29.Palmer WC. Meteorological drought, Research paper no. 45. US Weather Bureau, Washington, DC. 1965; 58.

30.Zhang A, Jia G, Wang H. Improving meteorological drought monitoring capability over tropical and subtropical water-limited ecosystems: evaluation and ensemble of the Microwave Integrated Drought Index. Environmental Research Letters. 2019; 14(4):044025.

31.Huffman GJ, Bolvin DT, Nelkin EJ, Wolff DB, Adler RF, Gu G, Hong Y, Bowman KP, Stocker EF. The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. Journal of hydrometeorology. 2007; 8(1):38-55.

32.Gu Y, Brown JF, Verdin JP, Wardlow B. A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophysical Research Letters. 2007; 34(6).

33.Ashouri Talouki H. Toward Improved Understanding of Global Precipitation Variations Using Satellite-based Observations (Doctoral dissertation, UC Irvine).

34.Wambua RM, Mutua BM, Raude JM. Analysis of spatial and temporal drought variability in a tropical river basin using Palmer Drought Severity Index (PDSI). International Journal of Water Resources and Environmental Engineering. 2017; 9(8):178-90.

35.Barbosa HA, Kumar TL, Paredes F, Elliott S, Ayuga JG. Assessment of Caatinga response to drought using Meteosat-SEVIRI Normalized Difference Vegetation Index (2008–2016). ISPRS journal of photogrammetry and remote sensing. 2019; 148:235-52.

36. Mathbout S, Lopez-Bustins JA, Martin-Vide J, Bech J, Rodrigo FS. Spatial and temporal analysis of drought variability at several time scales in Syria during 1961–2012. Atmospheric Research. 2018; 200:153-68.

37.Shahid S. Spatial and temporal characteristics of droughts in the western part of Bangladesh. Hydrological Processes: An International Journal. 2008; 22(13):2235-47.

38.Xu K, Yang D, Yang H, Li Z, Qin Y, Shen Y. Spatio-temporal variation of drought in China during 1961–2012: A climatic perspective. Journal of Hydrology. 2015; 526:253-64.

39.Hao Z, Hao F, Singh VP, Ouyang W, Cheng H. An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment. Environmental modelling & software. 2017; 91:199-209.

40.Crausbay SD, Ramirez AR, Carter SL, Cross MS, Hall KR, Bathke DJ, Betancourt JL, Colt S, Cravens AE, Dalton MS, Dunham JB. Defining ecological drought for the twenty-first century. Bulletin of the American Meteorological Society. 2017; 98(12):2543-50.

41.Ayantobo OO, Li Y, Song S, Yao N. Spatial comparability of drought characteristics and related return periods in mainland China over 1961–2013. Journal of hydrology. 2017; 550:549-67.

42.Upper Tana Natural Resources Management Project. Strategic Environmental Assessment Final Report. UTaNRMP/IFAD Kenya County Office, United Nations Complex, Nairobi.2014

43.Kogan FN. Application of vegetation index and brightness temperature for drought detection. Advances in space research. 1995; 15(11):91-100.

44.Vrieling A, Meroni M, Shee A, Mude AG, Woodard J, de Bie CK, Rembold F. Historical extension of operational NDVI products for livestock insurance in Kenya. International Journal of Applied Earth Observation and Geoinformation. 2014; 28:238-51.

45. Dutta D, Kundu A, Patel NR, Saha SK, Siddiqui AR. Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). The Egyptian Journal of Remote Sensing and Space Science. 2015; 18(1):53-63.

46. Stagge JH, Tallaksen LM, Xu CY, Van Lanen HA. Standardized precipitation-evapotranspiration index (SPEI): Sensitivity to potential evapotranspiration model and parameters. Proceedings of FRIEND-water. 2014: 367-73.

47. McKee TB, Doesken NJ, Kleist J. The relationship of drought frequency and duration to time scales. InProceedings of the 8th Conference on Applied Climatology 1993; 17(22): 179-183.

48. Guttman NB. Accepting the standardized precipitation index: a calculation algorithm 1. JAWRA Journal of the American Water Resources Association. 1999; 35(2):311-22.

49. Caloiero T, Veltri S. Drought Assessment in the Sardinia Region (Italy) During 1922–2011 Using the Standardized Precipitation Index. Pure and Applied Geophysics. 2019; 176(2):925-35.

50. Bayissa Y, Tadesse T, Demisse G, Shiferaw A. Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. Remote Sensing. 2017; 9(7):669.

51. Wambua RM, Mutua BM, Raude JM. Detection of Spatial, Temporal and Trend of Meteorological Drought Using Standardized Precipitation Index (SPI) and Effective Drought Index (EDI) in the Upper Tana River Basin, Kenya. Open Journal of Modern Hydrology. 2018; 8(03):83.

52. Wambua RM. Hydrological Drought Forecasting Using Modified Surface Water Supply Index (SWSI) and Streamflow Drought Index (SDI) in Conjunction with Artificial Neural Networks (ANNs). International Journal of Service Science, Management, Engineering, and Technology (IJSSMET). 2019; 10(4):39-57..

53. Ali Z, Hussain I, Faisal M, Shoukry AM, Gani S, Ahmad I. A framework to identify homogeneous drought characterization regions. Theoretical and Applied Climatology. 2019: 1-12.

54. Nyandega IA, Krhoda GO. Drought Frequency and Persistence in the Upper River Tana Basin in Kenya. Journal of Geography, Environment and Earth Science International. 2018:1-22.

55. Ozelkan E, Chen G, Ustundag BB. Multiscale object-based drought monitoring and comparison in rainfed and irrigated agriculture from Landsat 8 OLI imagery. International Journal of Applied Earth Observation and Geoinformation. 2016; 44:159-70..

56. Bajgiran PR, Darvishsefat AA, Khalili A, Makhdoum MF. Using AVHRR-based vegetation indices for drought monitoring in the Northwest of Iran. Journal of Arid Environments. 2008; 72(6):1086-96.

57. Karabulut M. An examination of relationships between vegetation and rainfall using maximum value composite AVHRR-NDVI data. Turkish Journal of Botany. 2003; 27(2):93-101.

58. Anderson S, Mowjee T. Climate change for Agrarian Societies in dry lands Implications and Future path ways' presentation for the World Bank Social development division Conference on the human Dimensions of Climate change. World Bank, Washington DC. 66pp. 2008.