DOI:10.28974/idojaras.2024.3.1

IDŐJÁRÁS

Quarterly Journal of the HungaroMet Hungarian Meteorological Service
Vol. 128, No. 3, July – September, 2024, pp. 287–308

Standardized precipitation index analysis and drought frequency tendencies in lower eastern counties of Kenya

Peter K. Musyimi[1,2,*], **Balázs Székely**[1], **Arun Gandhi**,[3] and **Tamás Weidinger**[3]

[1] *ELTE Eötvös Loránd University,*
Faculty of Sciences Institute of Geography and Earth Sciences,
Department of Geophysics and Space Science
Budapest, Pázmány Péter sétány 1/C, Hungary

[2]*Karatina University, School of Education and Social Sciences,*
Department of Humanities and Languages
P.O.BOX 1957-10101, Karatina, Kenya

[3] *ELTE Eötvös Loránd University,*
Faculty of Sciences Institute of Geography and Earth Sciences,
Department of Meteorology, Budapest, Pázmány Péter prom 1/A, Hungary

** Corresponding Author E-mail: musyimipeter@student.elte.hu*

(Manuscript received in final form October 9, 2023)

Abstract— The standardized precipitation index (SPI) is a fundamental indicator of meteorological, hydrological, and agricultural droughts in the world. This study aims to evaluate different timescales, 3 months (SPI-3), 6 months (SPI-6), 9 months (SPI-9), and 12 months (SPI-12) indices from meteorological data in quantifying drought characterization in lower eastern counties of Kenya from 1990 to 2018 for observed data and from 1986 to 2018 for Climatic Research Unit Time Series (CRU) data. Precipitation in-situ data (annual) and high-resolution (0.5 × 0.5 degree grid) monthly-scale precipitation data were sought from Kenya Meteorological Department and CRU TS, respectively. Z-Score (SPI) was computed for each year (in-situ data) and month (CRU TS data) using the SPI algorithm, expressed as the departure from the mean in standard deviation units. Quality control of CRU TS data was done by checking outlier values and comparing the data with precipitation data obtained from the meteorological department as well as ERA5 reanalysis data. Results showed that extreme to mild drought was experienced across the Kenyan counties for both annual in-situ and monthly gridded data. Machakos county experienced a year of extreme drought, while Makueni and Taita-Taveta have had 2 and 4 years of severe droughts, respectively. The monthly SPI indices of 3, 6, 9, and 12 months showed a remarkably consistent behavioral pattern detecting extreme droughts across the counties. Considering the uncertainties, unpredictability, and shifting of the long and short rainy seasons in Kenya, results were obtained related to dry and wet episodes and to their relationship with agricultural production as well as water availability and environmental management.

Key-words: drought, Kenya, monthly scale, precipitation, SPI, CRU TS, ERA5.

1. Introduction

Drought is a complex, dynamic climatic extreme brought about by the departure of monthly to annual long-term rainfall averages (*Naumann et al.*, 2018; *AghaKouchak et al.*, 2021). It threatens a wide range of sectors from agriculture, transport, industrialization, and water resources, among others. It varies in its inception, intensity, duration, and frequency (*Masih et al.,* 2014; *Vicente-Serrano et al.,* 2014; *Azmi et al.,* 2016; *Cammalleri et al*., 2017). Droughts have become a recurrent global phenomenon (*Sheffield* and *Wood*, 2011) with expected increased trends coupled with aridity. It has threatened humanity's livelihood, for instance, causing deaths, poor crop production, food insecurity, exacerbating famine in various regions, fueling malnutrition, health-related issues, and rural migration (*Masih et al*., 2014; *Dalu et al*., 2018; *Ault*, 2020).

Africa has experienced prolonged, widespread droughts of different magnitudes of severity, for instance, in the Sahel region in the 1970s and 1980s. The continent will be affected more severely by drought than other global regions (*Yanda* and *Mubaya*, 2011; *Niang et al*., 2014; *IPCC*, 2021). For a period of over 100 years (1900–2013), 291 drought events were reported in Africa which led to the death of approximately 850,000 people, affected approximately 362.5 million people, and resulted in a continental economic loss of an estimated USD 2 billion (*Masih et al*., 2014). On a regional scale, in East Africa, the severe drought of 2016 exposed 16 million inhabitants across Somalia, Ethiopia, and Kenya to hunger, food insecurity, and water scarcity (*Nicholson,* 2016; *Von Grebmer et al*., 2016; *Yang* and *Huntingford*, 2018; *Kalisa et al*., 2020). These droughts vary depending on anomalies in the amount of precipitation received in a region. In addition, a wide meteorological phenomena range influences its occurrence and variability in East Africa. They include monsoons, the Inter-Tropical Convergence Zone (ITCZ), subtropical anticyclones, African jet streams, easterly/westerly wave perturbations, global scale systems like the El Niño /Southern Oscillation (ENSO), and regional systems in East Africa (*Alusa* and *Mushi*, 1974; *Ogallo* and *Anyamba*, 1983). These droughts have threatened the livelihood of approximately 1.4 billion people for the last two decades and led to approximately 25,000 deaths in East Africa (*CRED*, 2020).

In Kenya, drought has remained a dominant devastating extreme climate phenomenon and recurrent hazard affecting the country's population livelihoods (*Opiyo et al*., 2015; *Musyimi et al*., 2018). This has a wide range of severe effects specifically in arid and semi-arid lands (ASALs). It further causes water scarcity due to hydrological imbalances, a situation exacerbated by extreme temperatures and evapotranspiration (*Shilenje et al*., 2019). Previous studies have projected that by the year 2100, climate change is expected to increase temperatures in Kenya by approximately a maximum of 4 °C and will lead to rainfall variability by about 20% (*Awuor et al*., 2008; *Kabubo-Mariara*, 2008; *Downing, et al*., 2009; *Ajuang et. al*., 2016; *Maingey et al*., 2020) having negative impact on agricultural production, water accessibility among households in volatile ecosystems in these regions. The studies above have outlined the global, continental, and regional status and the effects of droughts. For present and future preparedness, adaptation, and mitigation of drought characterization in arid regions of Kenya is fundamental. Even though many previous studies have been carried out in Kenyan counties, few studies have compared drought tendencies among counties based on annual and different SPI scales. Thus, the present study focused on analyzing SPI as well as spatio-temporal variability of annual rainfall and drought tendencies in arid and semi-arid lands and counties of Kenya. This was done by examining the annual in-situ precipitation data as well as CRU data across lower eastern counties. This is because most uncertainties in drought characterization are driven by precipitation variation rather than temperature variation (*Borona et al*., 2021). The study provides the basis for further research on other counties, since 89% of Kenya's total land mass (29 out of 47 counties) are classified as arid and semi-arid (*Akuja* and *Kandagor*, 2019) and characterized by recurring drought events.

Ayugi et al. (2018) examined factors influencing March-May rainfall variability using monthly observed and CRU TS reanalysis rainfall datasets for the period 1971–2010. *Mutsotso et al*. (2018) investigated CRU temperature data together with Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which is a rainfall data set from 50°S to 50°N ranging from 1981 to near-present, incorporating climatology, CHPclim, 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. *Funk et al*. (2014) merged a product composed of five satellite-based and ground weather station data to compute drought characterization. CRU TS data is gridded and based on angular distance weighting of ground weather station data from national meteorological services around the world (*Harris et al*., 2020). *Sahoo et al.* (2015) applied the Tropical Rainfall Measuring Mission (TRMM) and CRU to characterize meteorological droughts at a large scale and established that CRU data indicated severe drought for SPI-6 for the year 2006. *Assamnew* and *Mengistu* (2022) also applied CRU-TS as a reference observed data when they assess ERA5 performance in East Africa with European Center for Medium-Range Weather Forecasting (ECMWF). This indicates the wide use of various climate datasets for various climatological investigations in Kenya and East Africa at large. There has been growing interest in the recent developments of drought events in Kenyan counties. Kenya has had extreme drought events, whose spatial and temporal variability has not been understood, especially at regional and sub-regional scales. None of the studies compared various annual drought severity frequencies on a monthly scale and annual scale using different datasets hence this study. Therefore, besides examining the uncertainty of drought characterization using different datasets, our investigations fill the gap of differences experienced from various drought severity frequencies on monthly and annual scales for different datasets, which are imperative for long-term and short-term agricultural activities and associated effects.

2. *Material and methods*

2.1. *Climate characterisation within the selected counties*

The investigated area was the lower part of Eastern Kenya. It comprises Machakos, Taita-Taveta, and Makueni counties (*Fig. 1*). Machakos county falls under arid and semi-arid climates. It has an elevation range from 400 m to 2100 m above sea level (*Huho*, 2017). Taita-Taveta county is semi-humid to semi-arid with a mean annual rainfall of 650 mm and average temperature of 23 °C. Makueni county is arid and semi-arid, characterized by severe water scarcity, food insecurity, and low adaptive capacity and resilience to climate change and variability (*Muema et al.*, 2018). Rainfall ranges from 800 mm to 1200 mm, while the low-lying areas receive a range of 150 mm to 650 mm per year. The data set used by this study comprised of in-situ annual precipitation amount for a period of 29 years (1990–2018) and monthly precipitation data for the three counties from the Climatic Research Unit Time-series (CRU TS), CRU TS 3.25 datasets for the period 1986–2016 (31 years) (*Harris* and *Jones*, 2017). It was sought from Machakos, Voi, and Makindu meteorological stations of the said counties, respectively. The CRU TS dataset was quality controlled by checking various annual precipitation amounts and comparing the values with observed measured datasets from the weather stations obtained from the Kenya Meteorological Department.

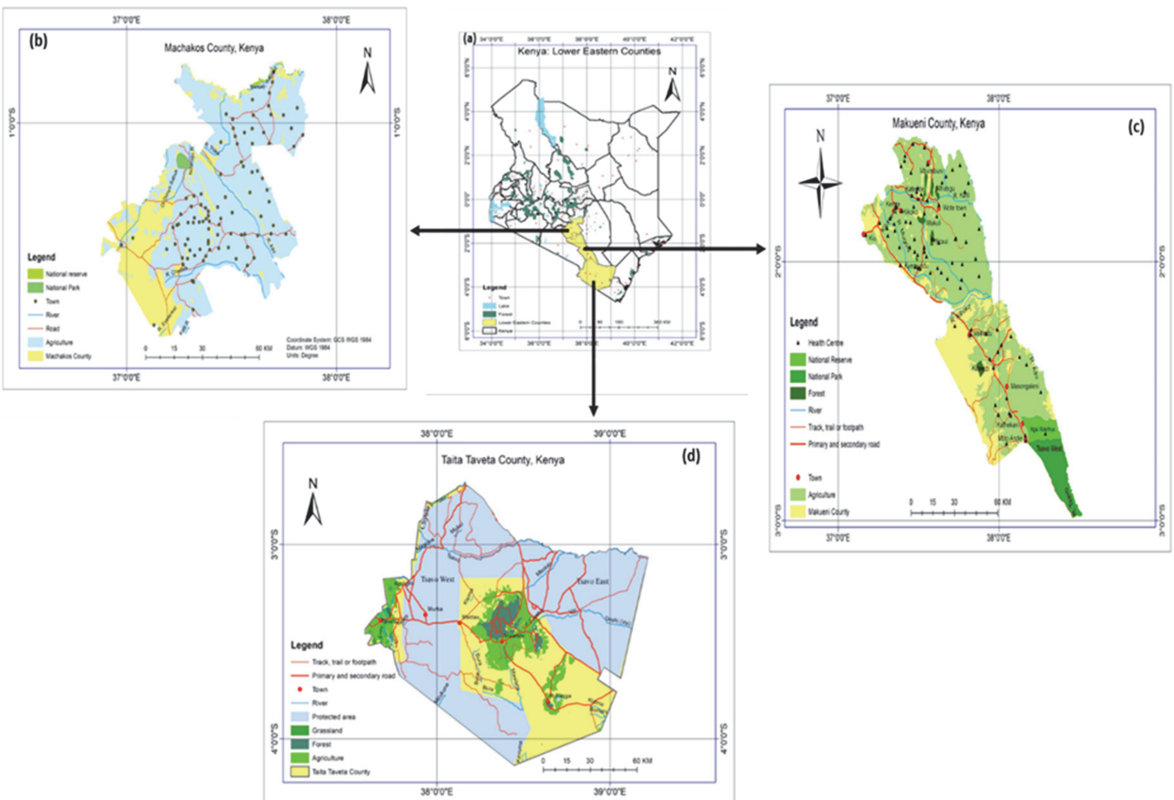

Fig. 1. Map of Kenya with the lower eastern counties under study (a), Machakos County (b), Makueni County (c), Taita-Taveta county (d).

2.2. Quality control, normality, and significance tests of the datasets

Quality control of CRU TS data (*Harris et al*., 2020) and ERA5 reanalysis data (climate reanalysis produced by ECMWF, *Hersbach et al*. (2020) was done by checking and comparing their consistency with observed in-situ data from the meteorological stations operated in Kenya. This is because most weather station time series data is quality controlled by the Kenya Meteorological Department. Few outlier (<5%) cases observed in the CRU TS dataset were harmonized based on the observed value from the meteorological station. This was to exclude their abnormality and the impacts associated with it. The quality control of gridded data differed from that of in-situ data, and therefore, CRU TS datasets underwent extensive manual quality control measures for consistency. We repeated the quality control on the ERA5 reanalysis dataset, even though there were no outlier values observed from the three stations, and compared the normality with other datasets using Shapiro and Anderson tests (*Ghasemi* and *Zahediasl,* 2012). Similar comparisons were done by *Vanella et al.* (2022) in Italy between ERA5 and ground-based agrometeorological observations and demonstrated the potential of using ERA5 reanalysis data. Further, the precipitation time series (*Fig. 2*) of the data sets were done for comparison purposes and depicted similarity in the patterns throughout the period for the three stations with an insignificant variation. The year 2005 was a drought year in Kenya as shown in Figure 2. The peak of rainfall amount in the year 2006 was as a result of 2006/2007 El Niño events which occured through out Kenya evethough low amount of rain was recieved in Makindu meteorological station as compared to ther other stations. Machakos weather station had annual mean precipitation of 679 ±198 mm, 823 ±169 mm, and 674 ±175 mm for in-situ, ERA5, and CRU TS gridded data, respectively, while Voi weather station showed annual precipitation mean of 568 ±190 mm, 590 ±140 mm, 742 ±192 mm for in-situ, ERA5, and CRU TS gridded data, respectively. Makindu weather station recorded mean annual precipitation of 521 ±192 mm, 631±162 mm, and 654 ±177 mm for in-situ, ERA5, and CRU TS gridded data, respectively. ERA5 and reanalysis datasets were obtained freely from the Climate Change Service Copernicus platform (https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset). In addition to the quality control, we carried out a normality test using Shapiro and Anderson tests of each dataset, which demonstrated that the datasets from the three stations were normal, since all the p-values from the three datasets and the three stations were $p>0.05$. An analysis of variance (ANOVA) on these datasets again yielded significant variation between datasets, for example in the Machakos weather station the F-value (variation between means/variation within the data sets) was 6.24 and the p-value was 0.003. In the Makindu weather station, the F-value was 4.56 with and p-value of 0.013 while the Voi weather station's F value was 8.15 and the p-value was 0.006. All the three p-values from the three datasets and three stations were less than 0.05, hence we concluded that there were statistical differences between the means of the three datasets.

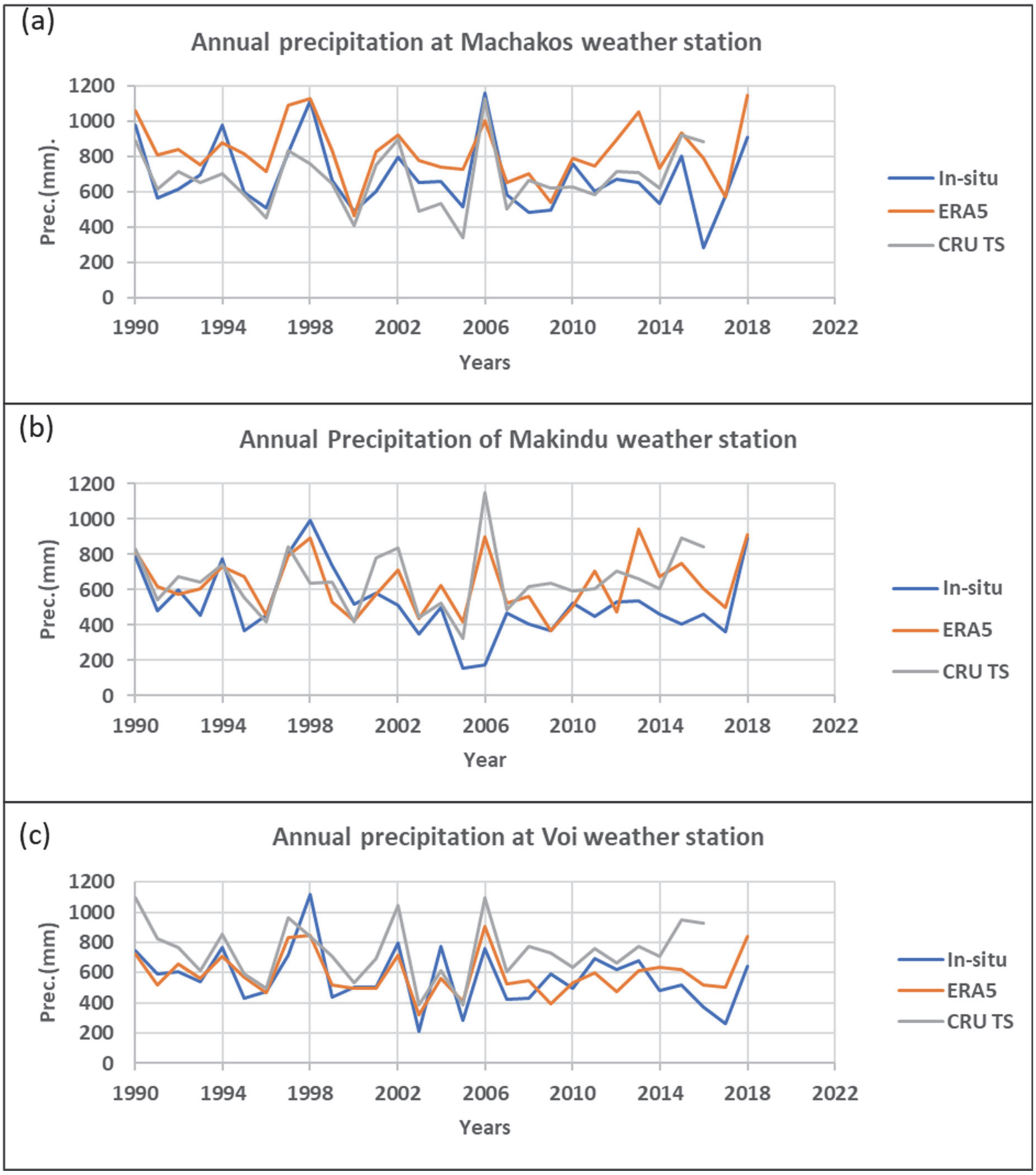

Fig. 2. Precipitation time series of in-situ, ERA5, CRU TS for (a) Machakos weather station, (b) Makindu weather station, (c) Voi weather station.

3. Methodology

The climatic parameter used for the study was the annual rainfall amount. The first set of data was obtained from three meteorological stations namely Machakos, Voi, and Makindu from three counties namely Machakos, Taita-Taveta, and Makueni, respectively. The three sets of observed rainfall data were for a period of 29 years (1990–2018), as it was the available data at the time of acquisition from the Kenya Meteorological Department. The data was used to compute annual distribution and annual variations among the counties for the different years. Further, a time series analysis was done to show the trend among different years in the counties. Ranking of the rainfall data per station was done and a serialised rank number (r) ranging from 1 to n (number of observations) given (*WMO*,1983). Rainfall data were used to compute annual totals and variations among the stations as well as probability exceedance (Eq.(1)) (*WMO,* 1983; *Raes*, 2004; *Huho,* 2017) and return period (Eq.(2)) (*Weibull*, 1939; *Olatunde* and *Adejoh*, 2017; *Kalisa et al*., 2020). The coefficient of variation (*CV*) (Eq.(3)) (*Huho*, 2017) was also applied to establish variations in annual rainfall among years and counties. It is obtained by dividing the standard deviation by the long-term mean, and it is expressed as a percentage. The second source of data was monthly-scale precipitation data for the three counties from the CRU TS, CRU TS 3.25 datasets for the period 1986–2016 (31 years) *(Harris et al*., 2020; https://catalogue.ceda.ac.uk/uuid/c311c7948e8a47b299f8f9c7ae6cb9af) which has a high spatial resolution of 0.5° and covers the period 1901−2016. Our study used 31 years to compute drought characterization as the time period recommended by *WMO* (2012) and deemed applicable in comparison with investigation from in-situ available data (1990–2018). In the present study, computation of *SPI* indices on monthly scales from the three counties was done using codes developed from the R program which was a suitable statistical analysis.

$$P_x = \frac{r-0.44}{n+0.12} * 100\ , \tag{1}$$

where P_x is the probability exceedance, n is the number of years, while r is a rank.

$$T = \frac{n+1}{m}, \tag{2}$$

where T refers to the return period in years, n is the total number of the values, and m is the rank value assigned to rainfall amount in an order from 1 to n (number of observation) (*Olatunde and Adejoh*, 2017).

$$CV = \frac{\sigma}{\bar{x}} * 100\ , \tag{3}$$

where CV is the coefficient of Variation, $\bar{x}$ and σ refer to the mean and standard deviation of precipitation, respectively.

$$SPI = \frac{x-\bar{x}}{\sigma}\ , \tag{4}$$

where x is precipitation for the period under study.

An *SPI* formula (Eq.(4)) for drought computation based on the precipitation probability was developed by *McKee et al.* (1993) and *Edwards* and *McKee* (1997) to study departures of precipitation from the long-term mean. It has received a wide range of applications globally (*Vicente-Serrano*, 2006; *Vicente-Serrano et al.*, 2010, 2012; *Guenang* and *Kamga*, 2014; *Karanja et al.,* 2017). It was used to analyze and characterize droughts of various severities in the study area. This *SPI* (*Tables 1* and *2*) drought index has been widely used and recommended over recent years to characterize and compare droughts spatio-temporarily (*Kumar et al.*, 2010; *Vicente-Serrano et al.,* 2010; *Karanja et al.,* 2017). From *Tables 1* and *2*, dry spells and meteorological drought were considered to have occurred when the *SPI* value was negative, and their absence was indicated by positive values. Droughts and dry spells were categorized as mild when the *SPI* value ranged from 0 to –0.99; moderate when values were from –1.0 to –1.49; severe when the value range was from –1.5 to –1.99; and extreme when the value range was from –2.00 and below. The index is usually negative for drought presence and positive for wet conditions. As the dry or wet conditions become more severe, the index becomes more negative or positive (https://climate.copernicus.eu/about-data-and-analysis).

Table 1. SPI values

≥2.00	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
–0.99 to 0.99	Near normal
–1.00 to –1.49	Moderately dry
–1.50 to –1.99	Severely dry
≤–2.00	Extremely dry

Sources: *Lloyd-Hughes* and *Saunders* (2002), *WMO* (2012).

3.1. Importance and preference of SPI analysis in Kenya

SPI is one of the most mentioned drought indicators in many previous studies in the world (*Kchouk, et al*., 2021), especially so in East Africa and the Horn of Africa. In Australia-Oceania, the Middle East, the North Africa (MENA), and the Sub-Saharan Africa (SSA), there are fewer studies which have used hydrological indices. As indicated by *WMO* (2012), *SPI* is a widely applied index for drought detection on a different scale (i.e., 1, 3, 6, 9, 12 months) mostly due to its versatility to space and time as well as climatic conditions. This study used total annual precipitation data (12 months) to compute *SPI* and gridded monthly scale data from CRU TS. Various studies have used combined drought index (CDI) (*Mutua* and *Balint*, 2009; *Sepulcre-*

Canto et al., 2012; *WMO*, 2012; *Shilenje et al.,* 2019), because more variables are available (temperature and vegetation). *SPI* is also widely used in India due to its adaptability, conformity to various time scales (*Shah et al.,* 2015; *Nandargi* and *Aman*, 2017), and different climatic conditions, and in Australia (*Abawi et al*., 2003) and Mexico (*Giddings et al.,* 2005) to characterize drought of various magnitudes and intensities. It has been intensely used in Kenya for drought characterization in Laikipia county and Tana River county (*Huho* and *Mugalavai*, 2010; *Ngaina et al*., 2014); Turkana county, *Opiyo, et al*. (2014) ; Laikipia county *Karanja et al*. (2017); and Makueni County *Musyimi et al*. (2018). The index is reliable to address droughts at multiple time durations for a wide range of climatic regions over the world (*Zhai et al*., 2010; *Stricevic et al*., 2011).

3.2. Limitations of SPI

SPI computation has various limitations, for instance its inability to consider and account for water deficit triggered by other processes such as evapotranspiration, deep infiltration, soil moisture content availability, and recharging abilities as well as surface runoff (*Onyango,* 2014). Better performance of the indices requires a couple of factors that influence water availability and deficiency such as the Palmer drought index. Data unavailability renders the use of other indices futile. Based on this, *Ntale* and *Gan* (2003) established that *SPI* is the most appropriate after comparing it with the Palmer drought severity index (PDSI) and Bhalme–Mooley drought index (BDI) in monitoring drought over East Africa. The probabilistic nature of the *SPI* is also a noted limitation as stated by *Agnew* (2000). Though *SPI* computation considers rainfall as the only attribute for drought characterizing, droughts need a couple of other climate parameters. They include but are not limited to soil moisture, surface runoff, and evapotranspiration. Further, in relation to different data sources, it is a challenge to compute *SPI* from long-term in-situ data from Kenya, because most weather stations do not have reliable data and so available data as well as other gridded data sources are hardly available.

4. Results and discussion

4.1. Precipitation coefficient variation (in-situ data)

The amount of precipitation received in each area varies in space and time in different climatic regions across the world (*Huho,* 2017; *Kalisa et al*., 2020). According to *Achite et al.* (2021), the coefficient of variation (*CV*) statistically measures the difference between the data values and the long-term mean value of a certain series of data. High values of *CV* indicate higher variability. In Kenya, the variation occurs mostly in the arid and semi-arid counties, which cover 89% of Kenya's total land mass (29 out of 47 counties are classified as arid or semi-arid) (*Akuja* and *Kandagor*, 2019). The lower eastern counties form part of the arid and semi-arid counties in Kenya hence the study. Purposively, *CV* was computed to establish annual precipitation variations in the lower eastern counties. Machakos station had a computed *CV* of 29%. This implies that annual precipitation varied by ±29% from its long-term average of 679 mm. Voi meteorological station had a *CV* of 34% an implication of ±34% from the long-term average of 568 mm. Makindu station recorded a *CV* of 37% indicating that precipitation varied by ±37% from the long-term average of 521 mm of the period under study. This implies that the annual precipitation reliability agriculturally was more suited for farmers in Machakos which had the smallest value of *CV* compared to the other stations in the other counties. Similar *CV* values have been recorded in previous studies in India, Africa, and Kenya (*Kisaka et al.,* 2015; *Arvind et al.,* 2017; *Muthoni et al.,* 2019; *Achite, et al*., 2021). This is fundamental in guiding farmers in agricultural decision-making on the nature and variety of crops to plant each year. In addition to this, analysis of the spatial distribution of the *CV* is vital for early warning, preparedness, and understanding of the likelihood of extreme events occurrence (*Achite et al.,* 2021). Regions that experience higher interannual variability in precipitation are highly likely to face extreme floods and severe droughts (*Halifa-Martin et al*., 2021).

4.2. Drought characterization and dry spell analysis from annual (in-situ) data

Drought is a recurrent phenomenon in most arid and semi-arid counties of Kenya as suggested by previous studies (*Huho* and *Mugalavai,* 2010; *Opiyo et al*., 2015; *Karanja et al*., 2017). Increased temperatures and precipitation variability are expected to worsen droughts as stated by *Schilling et al*. (2014) in their study from Turkana county. From this study, analysis shows that droughts ranging from mild, to severe and extreme, were experienced between 1991 and 2018 in the studied counties. Extreme drought was experienced in 2016 in Machakos county. Severe droughts occurred in 2003 and 2005 in Taita-Taveta county running from the year 2016 to 2017 (2 years). Makueni county experienced a 2-year run of severe drought from the year 2005 to 2006. Similar extreme droughts occurred in 2000, 2008, and 2009 in several counties of Kenya (*Opiyo et al*., 2015). Droughts of varied frequencies were experienced across the counties, where moderate/mild droughts were predominant for the whole period, 1990–2018 (*Table 2*). Mild droughts of varying duration and frequencies were observed from the dataset of the Kenya Meteorological Department, for instance, in Machakos county, where a 1-year drought was experienced in 2017, and 2-year droughts were experienced from 1991 to 1992 and 1995 to 1996. 3-year droughts occurred in runs from 1999 to 2001, 2003 to 2005, 2007 to 2009, and a 4-year drought period from 2011 to 2014. Similar mild drought occurrence was evident in Taita-Taveta county (Voi station) a 3-year drought that occurred from 1999 to 2001 and Makueni County (Makindu station) from the year 2002 to 2003. More than 52% (15 years) of the droughts that occurred in the counties were spatially widespread. Similar observations were made in Hungary by *Mohammed* and *Harsányi* (2019), who noted that Békéscsaba, Budapest, and Miskolc stations experienced 3-year drought events while Pápa and Siófok experienced 2-year and 5-year drought events, respectively, from 1985 to 2015.

Table 2. Frequencies (weighting by the length) of drought events in extreme, severe, and moderate /mild categories for SPI (1990–2018) (Annual droughts) Data source: Kenya Meterological Department.

County	Station	Drought category	Number of droughts	Total
Machakos	Machakos	Extreme	1	
		Severe	0	
		Moderate/mild	18	19
Makueni	Makindu	Extreme	0	
		Severe	2	
		Moderate/mild	16	18
Taita Taveta	Voi	Extreme	0	
		Severe	4	
		Moderate/mild	11	15

4.3. Probability of exceedance and return period for precipitation (in-situ data)

Probability of exceedance refers to the likelihood that the actual rainfall during a period will be equal to the estimated expected rainfall amount each year or might exceed in each period with a specific probability (*Raes*, 2004). The maximum annual amounts observed in the three stations were 1155 mm in 2006 at Machakos, 1118 mm in 1998 at Voi, and 991 mm in 1998 at Makindu. The probability of exceedance of precipitation for the three stations was 0.02. This result implies that it has a probability of 2% of occurrence in any given year for the three stations from the three counties of the available in-situ data. This also means that the amount of precipitation is likely to occur 2 times every 98 years, and it has a probability to re-occur (return period) once every 30 years. These observations are in tandem with *Olatunde* and *Adejoh* (2017), who indicated a return period of annual rainfall amount in 36 years in Lokoja, central North Nigeria. The lowest precipitation amount was received in the year 2016 with an amount of 281 mm from Machakos. Voi station recorded its lowest amount of precipitation in the year 2003 amounting to 210 mm, while Makindu had the lowest precipitation amount of 155 mm in the year 2005. The annual probability exceedance was 0.98, which meant it has a 98% probability to be equal to or exceeding in any year for the three counties. The computed values (return periods and exceedance probabilities) for precipitation amount indicated that 19 years (66%) of 29 years under study had precipitation amounts below the long-term mean of 679 mm at Machakos station, Machakos county. From Voi station, Taita-Taveta county, 15 years (52%) had precipitation below the long-term mean of 568 mm, while at Makindu station, Makueni county, 18 years (62%) had precipitation below the long-term mean of 521 mm. These results imply droughts of varied frequencies and severities, whereby moderate /mild droughts were predominant for the whole period, 1990–2018 across the three counties (*Table 2*).

4.4. Drought characterization based on different time scales of SPI from CRU dataset, 1986–2016

Based on a 3-month scale, the results indicate high drought frequency oscillations (*Fig. 3a*). This is attributed to the shortest time of analysis in which precipitation, the analyzed parameter, depicted changes at a higher speed (*Kimaru et al*., 2019; *Rascón et al*., 2021; *Wang et al*., 2022). The behavioral pattern of the 3-month *SPI* indices followed a similar pattern. The 3-month *SPI* represents short- and medium-term moisture conditions, as well as seasonal precipitation estimates and implies the accumulation of consecutive periods of three months of drought indication (*WMO*, 2012). The values ranged from –3.3 in Taita-Taveta to 3.1 in both Machakos and Makueni counties (*Table 3*). Mild to moderate drought events were more frequent in the three counties, but severe and extreme droughts interspersed throughout 31 years across the counties. The 3-month *SPI* indicates immediate effects of soil moisture reduction as stated by the *WMO* (2012) and Copernicus European Drought Observatory (*EDO*, 2020).

Table 3. Statistical summary of the *SPI* indices at different time scales from the three counties

County	Index-time scale	Mean ($\bar{x}$)	SD(σ)	Minimum	Maximum
Machakos	SPI-3 months	0.003	0.99	–3.1	3.0
Makueni		0.004	0.99	–3.3	3.1
Taita Taveta		0.005	0.99	–3.1	2.8
Machakos	SPI-6 months	0.005	0.98	–2.6	2.5
Makueni		0.007	0.97	–2.4	2.1
Taita taveta		0.004	0.98	–2.8	2.7
Machakos	SPI-9 months	0.006	0.97	–2.5	2.7
Makueni		0.008	0.95	–2.2	2.3
Taita Taveta		0.004	0.98	–2.9	2.9
Machakos	SPI-12 months	0.005	0.97	–2.5	2.7
Makueni		0.007	0.96	–2.2	2.3
Taita taveta		0.003	0.98	–2.6	2.6

The *SPI* values computed on a 6-month time scale oscillated between –2.6 and 2.5 in Machakos county, –2.4 and 2.1 in Makueni county, and –2.8 and 2.7 in Taita-Taveta county (*Fig. 3b*). 6-month *SPI* can be quite useful for displaying precipitation over several seasons. From the 6-month time scale, the severities were less compared to the 3-month time scale. Results also indicated that drought frequency in the 3- and 6-month time scales was high, and the durations were shorter conforming with a study by *Kalisa et al.,* (2020) who noted similar observations in East Africa. More variability was observed from the analysis across the counties, depicting short duration and higher frequency of droughts over years. Contrary to this, on longer time scales, a decrease in variability is observed and the frequency of droughts is less but the drought duration becomes long (*Avilés et al*., 2015). This was the observation for the 9- and 12-month *SPI* indices and longer duration as well as stability (*Figs. 3c-d*). This is caused by slowering variation of index values.

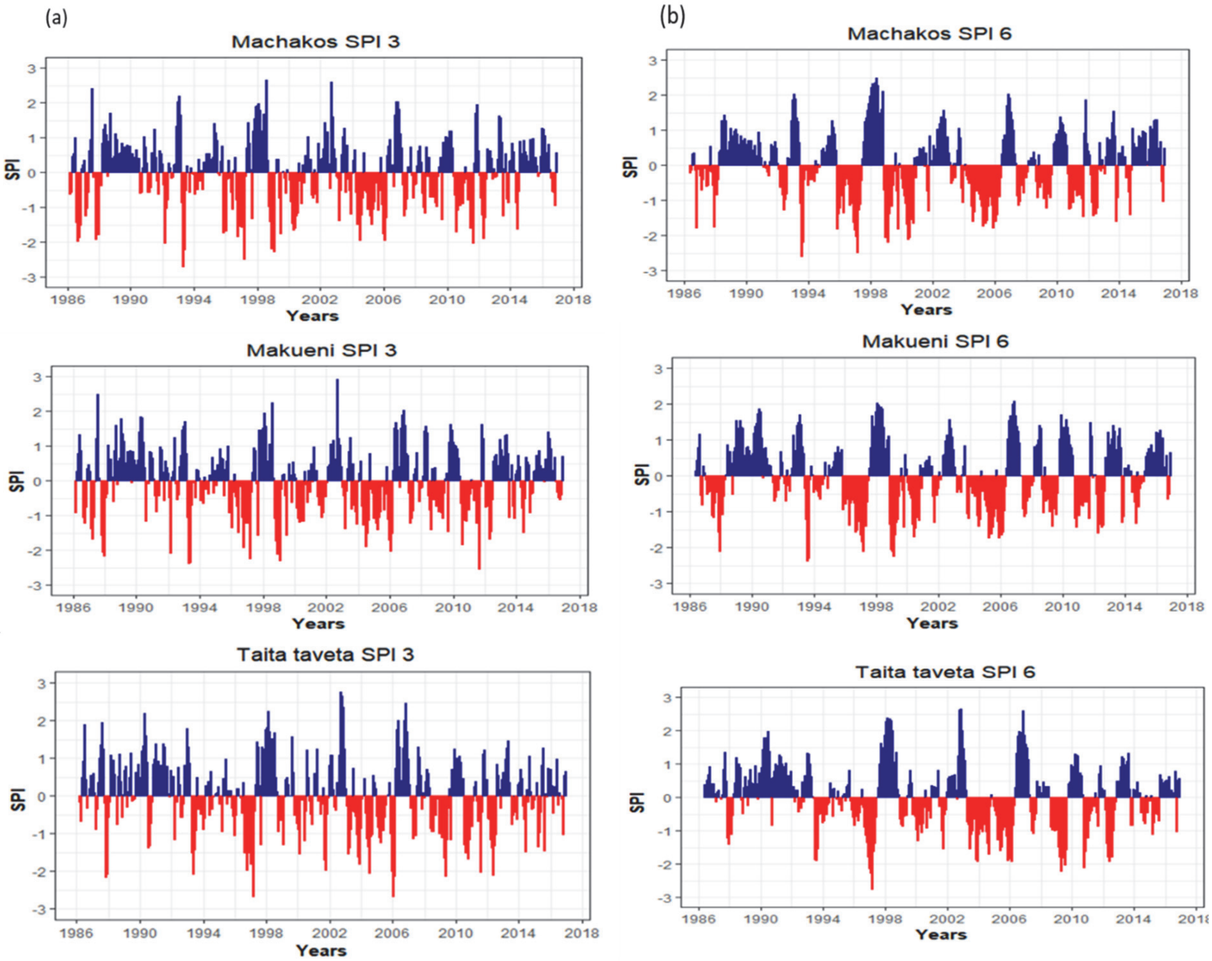

Fig. 3. 3-month *SPI* (a) and 6-month *SPI* (b) for the 1986–2016 period with mild, moderate, severe, and extreme drought severity bands as well as wet events.

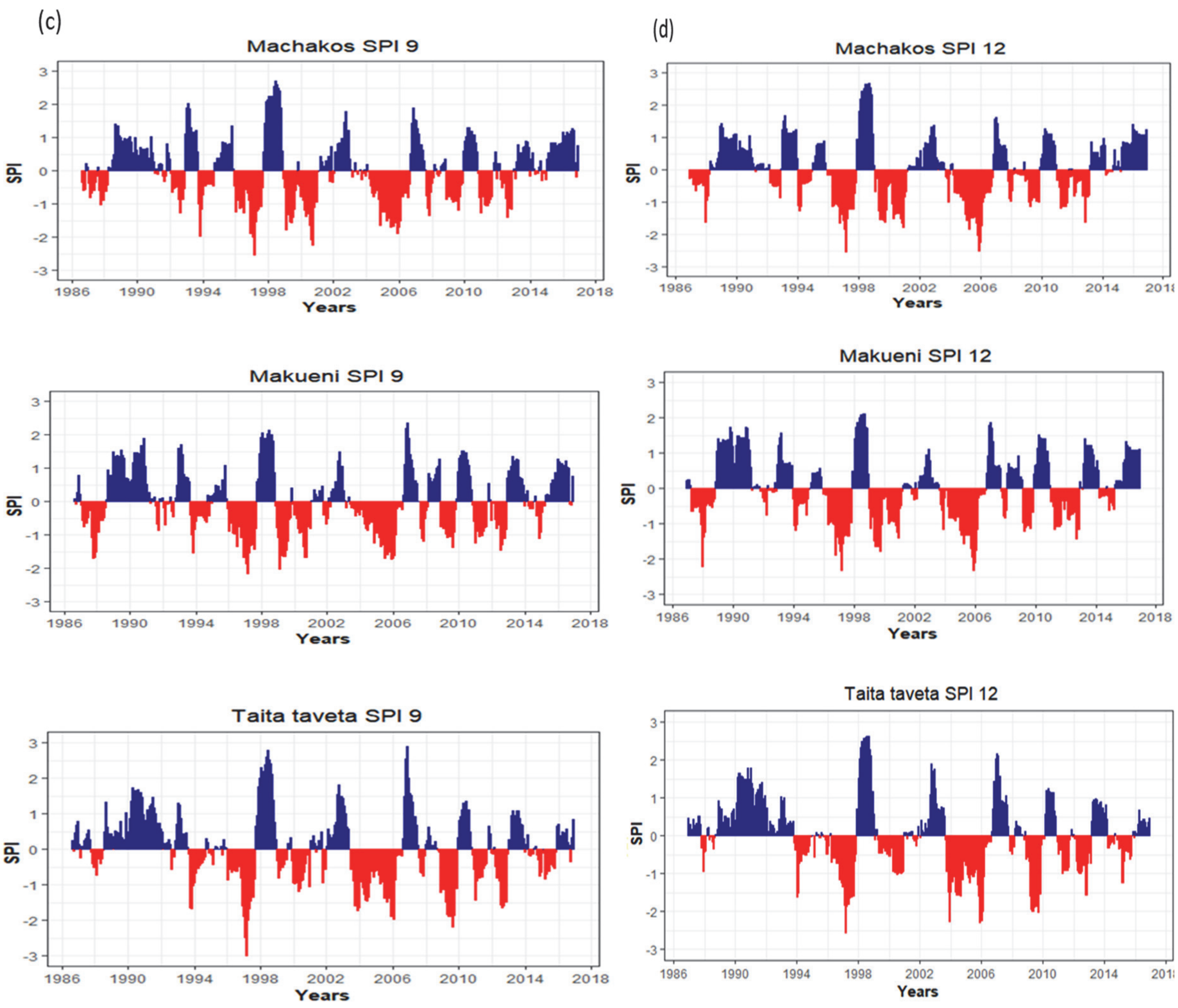

Fig. 3 (continued). 9-month *SPI* (c) and 12-month *SPI* (d) for the 1986–2016 period with mild, moderate, severe, and extreme drought severity bands as well as wet events.

The 9-month *SPI* values ranged between –2.5 and 2.7 in Machakos county, –2.2 and 2.3 in Makueni county, and –2.9 and 2.9 in Taita Taveta county. From these time scales, the *SPI* represents long-term precipitation trends. The 12-month indices were similar to the 9-month time scales for Machakos and Makueni counties, while Taita Taveta county *SPI* values ranged from –2.6 to 2.6 (*Table 3*). Droughts were more intense for the three counties between 2004 and 2005 on 9-month and 12-month time scales (*Fig. 3*). This was because as indicated earlier when the timescales are longer (9 and/or 12 months), the *SPI* values respond very slowly to changes in climate variables making the drought events less frequent but more long-lasting and, in some cases, more intense according to *Castillo-Castillo et al*., (2017). A study by *WMO* (2012) and *EDO* (2020) indicated that

SPI analysis for a longer duration, e.g., 12 months and above is a good measure for observing reduced water levels in reservoirs as well as recharging of groundwater. There existed noticeable and considerable variation in the intensity, duration, and occurrence of drought and wet episodes among the three counties (*Fig. 3*). A study by *Ahmad et al*. (2016) indicated that the variation in intensity is caused by seasonal rainfall data, and *SPI* is influenced by the amount of rainfall received in an area. In our study, the three counties experience two rainy seasons, a long-term (MAM) and a short-term (OND). This corroborates with *Kalisa et al.* (2021), who indicated that droughts vary in duration, severity, and magnitude from one region to another and through various decades.

4.5. Comparison of the annual and the 12-month SPI from the two datasets

SPI computation using annual precipitation and monthly scale precipitation data exhibited a major difference in quantifying drought and dry spell characteristics in seasonal intensity, seasonal frequency, and seasonal duration as observed. This depicts seasonal precipitation variation and identifies the driest and wettest seasons (*Hänsel et al.,* 2019), which is essential for water and agricultural planning. Results from *Fig. 3d* indicated the frequency, duration, and intensity of droughts on a 12-month scale, which was difficult to realize when annual precipitation data was used to compute *SPI* (*Fig. 4*). However, annual *SPI* computation can depict annual drought severity and year runs of brought consecutive droughts, 3-year droughts, and 4-year drought events (*Fig. 4*). This can be achieved using a 12-month time scale as well as by observing the intensity of consecutive months across the years as depicted in *Fig. 3d*. The intensities of alternating droughts, dry spells, and wet episodes are higher on minimal and shortened monthly scales. As it is indicated by *Liu* and *Liu* (2019) and *Rascón et al.* (2021), *SPI* computation uses precipitation, which is the reason behind the intensity of such alternating dry and wet episodes.

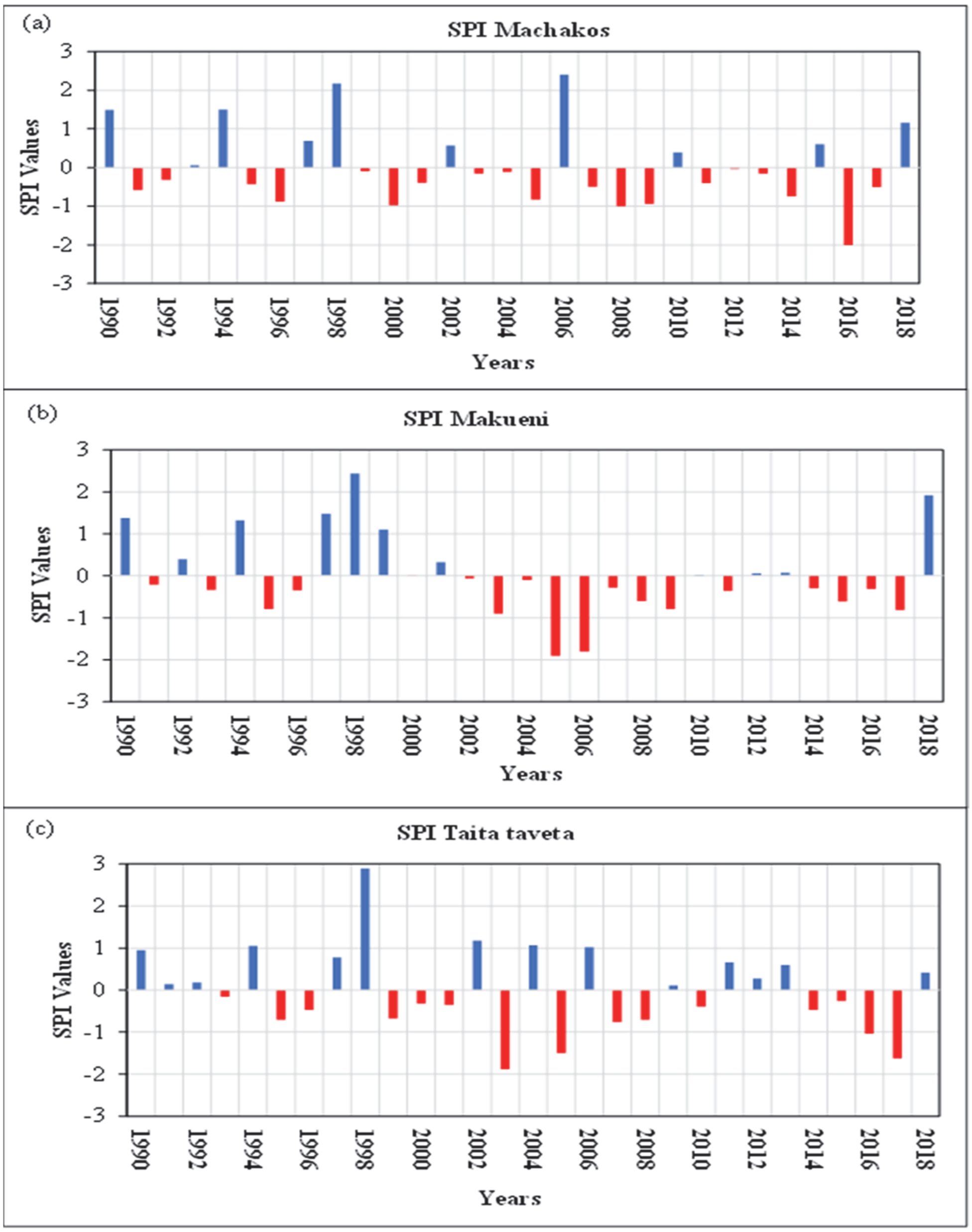

Fig. 4. Annual *SPI* values for Machakos (a), Makueni (b), and Taita-Taveta (c) counties for in-situ data from 1990 to 2018 with mild, moderate, severe, and extreme drought severity bands as well as wet episodes among years. Source of dataset: Kenya Meteorological Department.

5. Conclusions

This study analyzed monthly (3, 6, 9, and 12) *SPI* values using Climatic Research Unit Time-series (CRU TS), CRU TS 3.25 datasets for the period 1986–2016 (31 years) as well as annual *SPI* values using in-situ data for the period 1990–2018 in arid and semi-arid counties of Kenya. The results demonstrate the ability to use precipitation as a climate parameter to compare dry spells and events as well as to characterize droughts in cases of limited and /or scarcity of data. The intensity, duration, and frequency of droughts varied in different counties and regions due to the variation of precipitation received. From the results and figures of the two datasets, it can be stated that droughts of varying intensities and severities were more predominant than wet events across the three counties. From the in-situ data, an extreme drought took place in Machakos county in 2016, Makueni county experienced a 2-year run of severe drought from 2005 to 2006, while Taita-Taveta county experienced 2-year runs of severe droughts from 2016 to 2017. From the Climatic Research Unit Time-series (CRU TS), the frequency and intensity of droughts were observed and became more noticeable on the 9-month and 12-month time scales. Given the highly enormous impact of droughts in the agricultural and water sectors in Kenya and the Horn of Africa, which are fundamental for the bulging population, *SPI* analysis proves a crucial decision-making tool for the counties and the central government, agricultural and water organizations to ensure timely monitoring and adoption of mitigation measures as well as formulation of short-term (seasonal, 1-, 3-, 6-, 9-month-long) and long-time (more than 12 months) management procedures. Due to the flexibility of *SPI*, it is crucial in applications related to both short-term agricultural planning using monthly-based *SPI* frequency and long-term hydrological management using annual-based *SPI* frequency. This is fundamental for future climate variability preparedness in prone and drought risk counties, and for resilience planning in Kenya.

Acknowledgements: The authors are grateful to anonymous reviewers for useful, constructive comments and suggestions which contributed to the improvement of the quality of this scientific article. The corresponding author is also grateful to the Stipendium Hungaricum Doctoral Research Scholarship, Tempus Public Foundation of the Hungarian Government which financially supports his Ph.D. research.

References

Abawi, Y., Dutta, S., and *Ritchie, J.,* 2003: Potential use of climate forecasts in water resources management. In (eds. *Stone, R.*, and *Partridge, I.*) Science for drought: Proceedings of the National Drought Forum at Brisbane, Australia, Department of Primary Industries, Queensland, 78–81. http://doi.org/10.13140/RG.2.1.2623.1201

Achite, M., Caloiero, T., Wałęga, A., Krakauer, N., and *Hartani, T.*, 2021: Analysis of the Spatiotemporal Annual Rainfall Variability in the Wadi Cheliff Basin (Algeria) over the Period 1970 to 2018. *Water 13*(11), 1477. https://doi.org/10.3390/w13111477

AghaKouchak, A., Mirchi, A., Madani, K., Di Baldassarre, G., Nazemi, A., Alborzi, A., Anjileli, H., Azarderakhsh, M., Chiang, F., Hassanzadeh, E., Huning, L.S., Mallakpour, I., Martinez, A., Mazdiyasni, O., Moftakhari, H., Norouzi, H., Sadegh, M., Sadeqi, D., Van Loon, A.F., and *Wanders, N.,* 2021: Anthropogenic drought: Definition, challenges, and opportunities. *Rev.Geophys. 59*, e2019RG000683. https://doi.org/10.1029/2019RG000683

Agnew, C.T., 2000: Using the SPI to identify drought. *Drought Network News 12*, 6–12. https://www.researchgate.net/publication/280075154_Using_the_SPI_to_Identify_Drought

Ahmad, L., Parvaze, S., Majid, M., and *Kanth, R.H.,* 2016: Analysis of historical rainfall data for drought investigation using standard precipitation index (SPI) under temperate conditions of Srinagar Kashmir. *Pakistan J. Meteorol. 13,* 29–38. https://www.researchgate.net/publication/319058816_Analysis_of_Historical_Rainfall_Data_for_Drought_Investigation_Using_Standard_Precipitation_Index_SPI_Under_Temperate_Conditions_of_Srinagar_Kashmir

Ajuang, C.O., Abuom, P.O., Bosire, E.K., Dida, G.O., and *Anyona, D.N.,* 2016: Determinants of climate change awareness level in upper Nyakach Division, Kisumu County, Kenya. *Springer Plus 5*(1), 1015. https://doi.org/10.1186/s40064-016-2699-y

Akuja, T.E. and *Kandagor, J.,* 2019: A review of policies and agricultural productivity in the arid and semi-arid lands (ASALS), Kenya: the case of Turkana County. *J. Appl. Biosci. 140*, 14304–14315. https://doi.org/10.4314/jab.v140i1.9

Alusa, L.A. and *Mushi, M.T.*, 1974: A study of the Onset, Duration, and Cessation of the Rains in East Africa. Proceedings of the International Tropical Meteorology meeting in Nairobi, Kenya. American Meteorological Society, Boston, Massachusetts, USA, 133–140.

Avilés, A., Célleri, R., Paredes, J., and *Solera, A.,* 2015: Evaluation of Markov chain-based drought forecasts in an Andean regulated river basin using the skill scores RPS and GMSS. *Water Resour. Manage. 29*, 1949–1963. https://doi.org/10.1007/s11269-015-0921-2

Arvind, G., Ashok Kumar, P., Girish Karthi, S., and *Suribabu, C.R.*, 2017: Statistical analysis of 30 years rainfall data: a case study. IOP Conference Series: *Earth Environ. Sci. 80*, 12067. https://doi.org/10.1088/1755-1315/80/1/012067

Assamnew, A.D. and *Mengistu Tsidu, G.*, 2022: Assessing improvement in the fifth-generation ECMWF atmospheric reanalysis precipitation over East Africa. *Int. J. Climatol. 43*, 17–37. https://doi.org/10.1002/joc.7697

Ault, T.R., 2020: On the essentials of drought in a changing climate. *Science*, 368.6488: 256–260. https://doi.org/10.1126/science.aaz5492

Awuor, C.B., Orindi, V.A., and *Ochieng, A*. 2008: Climate change and coastal cities: the case of Mombasa, Kenya. *Environ. Urbanizat. 20*(1), 231–242. https://doi.org/10.1177/0956247808089158

Ayugi, B.O., Tan, G., Ongoma, V., and *Mafuru, K.B*., 2018: Circulations associated with variations in boreal spring rainfall over Kenya. *Earth Syst. Environ. 2*, 421–434. https://doi.org/10.1007/s41748-018-0074-6

Azmi, M., Rüdiger, C., and *Walker, J.P.,* 2016: A data fusion-based drought index. *Water Resour. Res. 52*, 2222–2239. https://doi.org/10.1002/2015WR017834

Borona, P., Busch, F., Krueger, T., and *Rufin, P.,* 2021: Uncertainty in Drought Identification Due to Data Choices, and the Value of Triangulation. *Water 13*, 3611. https://doi.org/10.3390/w13243611

Cammalleri, C., Vogt, J.V., Bisselink, B., and *de Roo, A.,* 2017: Comparing soil moisture anomalies from multiple independent sources over different regions across the globe. *Hydrol. Earth Syst. Sci. 21,* 6329–6343. https://doi.org/10.5194/hess-21-6329-2017

Castillo-Castillo, M., Ibáñez-Castillo, L.A., Valdés, J.B., Arteaga-Ramírez, R., and *Vázquez-Peña, M.A.,* 2017: Analysis of meteorological droughts in the Fuerte river basin, Mexico. *Water Sci. Technol. 8*(1), 35–52. https://doi.org/10.24850/j-tyca-2017-01-03

CRED, 2020: The human cost of disasters – an overview of the last 20 years 2000–2019. Technical Report. Centre for Research on the Epidemiology of Disasters (CRED) United Nations Office for Disaster Risk Reduction. https://www.undrr.org/publication/human-cost-disasters-overview-last-20-years-2000-2019

Dalu, M.T., Shackleton, C.M., and *Dalu, T.,* 2018: Influence of land cover, proximity to streams and household topographical location on flooding impact in informal settlements in the Eastern Cape, South Africa. *Int. J. Disaster Risk Reduct. 28*, 481–490. https://doi.org/10.1016/j.ijdrr.2017.12.009

Downing, T., Watkiss, P., Dyszynski, J., Butterfield, R., Devisscher, T., Pye, S., and *Sang, J.,* 2009: The economics of climate change in Kenya: Final report submitted in advance of COP15. 81 pp. SEI Stockholm Environment Institute. Project Report. Available at: https://mediamanager.sei.org/documents/Publications/SEI-ProjectReport-Downing EconomicsOfClimateChangeKenya-2009.pdf

EDO, 2020: Copernicus European Drought Observatory, 2020. EDO Indicator Factsheet, Standardized Precipitation Index (SPI), European Commission, 2020. https://drought.emergency.copernicus.eu/

Edwards, D.C. and *McKee, T.B.,* 1997: Characteristics of 20th Century Drought in the United States at Multiple Times Scales. *Atmos. Sci. Paper 634*, 1–30. http://hdl.handle.net/10217/170176

Ghasemi, A. and *Zahediasl, S.,* 2012: Normality tests for statistical analysis: a guide for non-statisticians. *Int. J. Endocrinol. Metabolism, 10*(2), 486. https://doi.org/10.5812%2Fijem.3505
Giddings, L., Soto, M., Rutherford, B.M., and *Maarouf,* A., 2005: Standardized precipitation index for Mexico. *Atmósfera 18*(1), 33–56. https://www.researchgate.net/publication/26433871_Standardized_Precipitation_Index_Zones_for_Mexico
Guenang, G.M. and *Kamga, F.M.,* 2014: Computation of the Standardized Precipitation Index (SPI) and Its Use to Assess Drought Occurrences in Cameroon over Recent Decades. *J. Appl. Meteorol. Climatol. 53*, 2310–2324. https://doi.org/10.1175/JAMC-D-14-0032.1
Hänsel, S., Ustrnul, Z., Łupikasza, E., and *Skalak, P.,* 2019. Assessing seasonal drought variations and trends over Central Europe. *Adv. Water Resour. 127,* 53–75. https://doi.org/10.1016/j.advwatres.2019.03.005
Halifa-Martin, A., Lorente-Plazas, R., Pravia-Sarabia, E., Montavez, J.P., and *Jimenez-Guerrero, P.,* 2021: Atlantic and Mediterranean influence promoting an abrupt change in winter precipitation over the southern Iberian Peninsula. *Atmos. Res. 253*, 105485. https://doi.org/10.1016/j.atmosres.2021.105485
Harris, I., Osborn, T.J., Jones, P., and *Lister, D.,* 2020: Version 4 of the CRU TS Monthly High-Resolution Gridded Multivariate Climate Dataset. *Science Data 7*, 1–18. https://doi.org/10.1038/s41597-020-0453-3
Harris, I.C. and *Jones, P.D.,* 2017: CRU TS3.25: Climatic Research Unit (CRU) Time-Series (TS) Version 3.25 of High-Resolution Gridded Data of Month-by-month Variation in Climate (Jan. 1901–Dec. 2016), Centre for Environmental Data Analysis, 05 December 2017. http://doi.org/10.5285/c311c7948e8a47b299f8f9c7ae6cb9af
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and *Thépaut, J.-N.*, 2020: The ERA5 global reanalysis. *Quart. J. Roy. Meteorol. Soc. 146*(730), 1999–2049. https://doi.org/10.1002/qj.3803
Huho, J.M., 2017: An Analysis of Rainfall Characteristics in Machakos County, Kenya. IOSR *J. Environ. Sci. Toxicol. Food Technol. 11*, 64–72. http://doi.org/10.9790/2402-1104026472
Huho, J.M. and *Mugalavai, M.E.*, 2010: The Effects of Droughts on Food Security in Kenya. *Int. J. Climate Change 2*(2), 61–72. https://doi.org/10.18848/1835-7156/CGP/v02i02/37312
Funk, C.C., Peterson, P.J., Landsfeld, M.F., Pedreros, D.H., Verdin, J.P., Rowland, J.D., Romero, B.E., Husak, G.J., Michaelsen, J.C., and *Verdin, A.P.,* 2014: A Quasi-Global Precipitation Time Series for Drought Monitoring; U.S. Geological Survey: Reston, VA, USA. *Data Series 382*, https://doi.org/10.3133/ds832
IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. [*Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T., Waterfield, T.K., Yelekçi, O., Yu, R.,* and *Zhou, B.* (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. https://doi:10.1017/9781009157896
Kabubo-Mariara, J., 2008: Climate change adaptation and livestock activity choices in Kenya: An economic analysis. *Nat. Resour. Forum 32*(1), 131–141. https://doi.org/10.1111/j.1477-8947.2008.00178.x
Kalisa, W., Igbawua, T., Ujoh, F., Aondoakaa, I.S., Namugize, J.N., and *Zhang, J.,* 2021: Spatio-temporal variability of dry and wet conditions over East Africa from 1982 to 2015 using quantile regression model. *Nat. Hazards*, *106*(3), 2047–2076. https://doi.org/10.1007/s11069-021-04530-1
Kalisa, W., Zhang, J., Igbawua, T., Ujoh, F., Ebohon, O.J., Namugize, N.J., and *Yao, F.,* 2020: Spatio-temporal analysis of drought and return periods over the East African region using Standardized Precipitation Index from 1920 to 2016. *Agric. Water Manage. 237*, 106195. https://doi.org/10.1016/j.agwat.2020.106195

Karanja, A., Ondimu, K., and *Recha, C*., 2017: Analysis of Temporal Drought Characteristic Using SPI Drought Index Based on Rainfall Data in Laikipia West Sub-County, Kenya. *Open Access Libr. J. 4*, e3765. https://doi.org/10.4236/oalib.1103765

Kimaru, A.N., Gathenya, J.M., and *Cheruiyot, C.K.,* 2019: The temporal variability of rainfall and streamflow into lake Nakuru, Kenya, assessed using SWAT and hydrometeorological indices. *Hydrology 6*, 88. https://doi.org/10.3390/hydrology6040088

Kisaka, M.O., Ngetich, F.K., Mugwe, J.N., Mugendi, D., and *Mairura, F.,* 2015. Rainfall variability, drought characterization and efficacy of rainfall data reconstruction: case of Eastern Kenya. *Adv. Meteorol. 2015,* 380404, 1–16. https://doi.org/10.1155/2015/380404

Kchouk, S., Melsen, L.A., Walker, D.W., and *van Oel, P.R*., 2021: A review of drought indices: predominance of drivers over impacts and the importance of local context. *Nat. Hazards Earth Syst. Sci. Discuss*. https://doi.org/10.5194/nhess-2021-152

Kumar, M.N., Murthy, C.S., Sesha, M.V.R., and *Roy, P.S.,* 2010: The Use of Standardized Precipitation Index (SPI) for Drought Intensity Assessment. National Remote Sensing Centre, Hyderabad, 500–625. https://doi.org/10.1002/MET.136

Liu, W. and *Liu, L.,* 2019: Analysis of dry/wet variations in the Poyang Lake basin using standardized precipitation evapotranspiration index based on two potential evapotranspiration algorithms. *Water* (Switzerland) *11*, 1380. https://doi.org/10.3390/w11071380

Lloyd-Hughes, B. and *Saunders, M.A.,* 2002: A drought climatology for Europe*. Int. J. Climatol. 22,* 1571–1592. https://doi.org/10.1002/joc.846

Maingey, Y., Ouma, G., Olago, D., and *Opondo, M.,* 2020: Trends in Climate Variables (Temperature and Rainfall) and Local Perceptions of Climate Change in Lamu, Kenya. *Geogr. Environ. Sustainab. 13*(3), 102–109. https://doi.org/10.24057/2071-9388-2020-24

Masih, I., Maskey, S., Mussá, F.E.F., and *Trambauer, P*., 2014: A review of droughts on the African continent: a geospatial and long-term perspective, *Hydrol. Earth Syst. Sci. 18*, 3635–3649. https://doi.org/10.5194/hess-18-3635-2014

McKee, T.B., Doesken, N.J., and *Kleist, J.,* 1993: The relationship of drought frequency and duration to time scale. In: Proceedings of the Eighth Conference on Applied Climatology, Anaheim, California, 17–22 January 1993. Boston, American Meteorological Society, 179–184. https://asset-pdf.scinapse.io/prod/2153179024/2153179024.pdf

Mohammed, S.A. and *Harsányi, E*. 2019: Drought cycle tracking in Hungary using Standardized Precipitation Index (SPI). *Acta Agrar. Debr. 2*, 97–101. https://doi.org/10.34101/actaagrar/2/3685

Muema, E., Mburu, J., Coulibaly, J., and *Mutune, J.,* 2018: Determinants of access and utilisation of seasonal climate information services among smallholder farmers in Makueni County, Kenya. *Heliyon 4*, 19. https://doi.org/10.1016/j.heliyon. 2018.e00889

Mutsotso, R.B., Sichangi, A.W., and *Makokha, G.O*., 2018: Spatio-Temporal Drought Characterization in Kenya from 1987 to 2016. *Advances in Remote Sensin*, *7*, 125–143. http://41.89.227.156:8080/xmlui/handle/123456789/765

Musyimi, P.K, Huho, J.M., and *Opiyo, F.E.,* 2018: Understanding Drought Characteristics and Perceived Effects on Water Sources in Kenya's Drylands: A Case Study of Makindu Sub-County. In (eds. *Fymat, A.L.* and *Kapalanga, J*) Advancing Africa's Sustainable Development: Proceedings of the 4th Conference on Science Advancement. Cambridge Scholars Publishing, Newcastle upon Tyne*,* NE6 2PA, UK, 324–349. ISBN: 1-5275-0655-X.

Muthoni, F.K., Odongo, V.O., Ochieng, J., Mugalavai, E.M., Mourice, S.K., Hoesche-Zeledon, I., Mwila, M., and *Bekunda, M.*, 2019: Long-term spatial-temporal trends and variability of rainfall over Eastern and Southern Africa. *Theor. Appl. Climatol. 137*, 1869–1882. https://doi.org/10.1007/s00704-018-2712-1

Mutua, F.M. and *Balint, Z.,* 2009: Analysis of the general climatic conditions to support drought monitoring in Somalia. Technical Report No.W-14, FAO-SWALIM Nairobi, Kenya. https://www.faoswalim.org/resources/site_files/W14%20Analysis%20of%20General%20Climatic%20Conditions%20in%20Somalia%20in%20Support%20of%20Drought%20Monitoring.pdf

Nandargi, S.S. and *Aman, K.,* 2017: Computation of the Standardized Precipitation Index (SPI) for Assessing Droughts Over India. *Int. J. Curr. Adv. Res. 6*(12), 8545–8557. http://doi.org/10.24327/ijcar.2017.8557.1383

Ngaina, J.N., Mutua, F.M., Muthama, N.J., Kirui, J.W., Sabiiti, G., Mukhala, E., Maingi, N.W., and *Mutai, B.K*., 2014: Drought monitoring in Kenya: a case of Tana River County. *Int. J. Agricult. Sci. Res. 3*(7), 126–135. http://academeresearchjournals.org/journal/ijasr

Naumann, G., Alfieri, L., Wyser, K., Mentaschi, L., Betts, R.A., Carrao, H., Spinoni, J., Vogt, J., and *Feyen, L.,* 2018: Global changes in drought conditions under different levels of warming. *Geophys. Res. Lett. 45*, 3285–3296. https://doi.org/10.1002/2017GL076521

Nicholson, S.E., 2016: An analysis of recent rainfall conditions in eastern Africa. *Int. J. Climatol. 36*(1), 526–532. https://doi.org/10.1002/joc.4358

Niang, I., Ruppel, O.C., Abdrabo, M.A., Essel, A., Lennard, C., Padgham, J., and *Urquhart*, *P.,* 2014: *Africa*. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (eds. *Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R.,* and *White, L.L.*) Cambridge University Press, Cambridge, United Kingdom, and New York, NY, USA,1199-1265. ISBN 978-1-107-05816-3.

Ntale, H.K. and *Gan, T.Y.,* 2003: Drought indices and their application to East Africa. *Int. J. Climatol. 23*, 1335–1357. https://doi.org/10.1002/joc.931

Ogallo, L.O. and *Anyamba, E.K.,* 1983: Drought of tropical, central, and eastern Africa, July-Nov, and Northern springs of 1983–84. First WMO Workshop on Medium and Long-range forecast, Maryland USA. https://doi.org/10.4172/2157-7617.1000219

Onyango, O.A., 2014: Analysis of Meteorological Drought in Northeastern Province of Kenya. *J. Earth Sci. Climat. Change 5*, 219. https://doi.org/10.4172/2157-7617.1000219

Olatunde, A.F. and *Adejoh, I.*, 2017: Annual exceedance probability and return periods of rainstorms in Lokoja. *Int. J. Soc. Sci. 11*, 40–46. https://www.researchgate.net/publication/323572900

Opiyo, F.E., Wasonga, O.V., and *Nyangito, M.M*., 2014: Measuring household vulnerability to climate-induced stresses in pastoral rangelands of Kenya: Implications for resilience programming. *Pastoralism 4*, 10. https://doi.org/10.1186/s13570-014-0010-9

Opiyo, F.E., Wasonga, O.V., Nyangito, M., Schilling, J., and *Munang, R.,* 2015: Drought Adaptation and Coping Strategies Among the Turkana Pastoralists of Northern Kenya. *Int. J. Disaster Risk Sci. 6*, 295–309. https://doi.org/10.1007/s13753-015-0063-4

Raes, D., 2004: Frequency analysis of rainfall data. International Centre for Theoretical Physics, Katholieke Universiteit Leuven, Department of Earth and Environmental Sciences Leuven. https://indico.ictp.it/event/a12165/session/21/contribution/16/material/0/0.pdf

Rascón, J., Gosgot, A.W., Quiñones, H.L., Oliva, M., and *Barrena, G.M.Á.,* 2021: Dry and Wet Events in Andean Populations of Northern Peru: A Case Study of Chachapoyas, Peru. *Frontiers Environ. Sci. 9*, 614438. https://doi.org/10.3389/fenvs.2021.614438

Sahoo, A.K., Sheffield, J., Pan, M., and *Wood, E.F.,* 2015. Evaluation of the tropical rainfall measuring mission multi-satellite precipitation analysis (TMPA) for assessment of large-scale meteorological drought. *Remote Sens. Environ. 159*, 181–193. https://doi.org/10.1016/j.rse.2014.11.032

Sepulcre-Canto, G., Horion, S., Singleton, A., Carrao H., and *Vogt, J*., 2012: Development of a combined drought indicator to detect agricultural drought in Europe. *Nat. Hazards Earth Syst. Sci. 12,* 3519–3531. https://doi.org/10.5194/nhess-12-3519-2012

Shah, R., Bharadiya, N., and *Manekar, V.,* 2015: Drought index computation using standardized precipitation index (SPI) method for Surat District, Gujarat. *Aquatic Procedia 4*, 1243–1249. https://doi.org/10.1016/j.aqpro.2015.02.162

Schilling, J., Akuno, M., Scheffran, J., and *Weinzierl, T.,* 2014: On raids and relations: Climate change, pastoral conflict, and adaptation in northwestern Kenya. In (eds. *Bronkhorst, S.* and *Bob, U.*) Conflict-sensitive adaptation to climate change in Africa? Climate Diplomacy, Berliner Wissenschafts-Verlag, Berlin 241–268. ISBN 978-3-8305-2010-8.

Sheffield, J. and *Wood, E.F*., 2011: Drought: past problems and future scenarios. London, Washington, DC, Earthscan, Routledge, 210. ISBN 978-184971-082-4.

Stricevic, R., Djurovic, N., and *Djurovic, Z., 2011*: Drought classification in Northern Serbia based on SPI and statistical pattern recognition. *Meteorol. Appl. 18*(1), 60–69. https://doi.org/10.1002/met.207

Shilenje, Z.W., Ongoma, V., and *Njagi, M*., 2019: Applicability of Combined Drought Index in drought analysis over North Eastern Kenya. *Nat. Hazards 99*(1), 379–389. https://doi.org/10.1007/s11069-019-03745-7

Vanella, D., Longo-Minnolo, G., Belfiore, O.R., Ramírez-Cuesta, J.M., Pappalardo, S., Consoli, S., D'Urso, G., Chirico, G.B., Coppola, A., Comegna, A., and *Toscano, A*., 2022. Comparing the use of ERA5 reanalysis dataset and ground-based agrometeorological data under different climates and topography in Italy. *J. Hydrology*: Regional Studies *42*, 101182. https://doi.org/10.1016/j.ejrh.2022.101182

Vicente-Serrano, S.M., 2006: Differences in Spatial Patterns of Drought on Different Time Scales: An Analysis of the Iberian Peninsula. *Water Res. Manage. 20*, 37–60. https://doi.org/10.1007/s11269-006-2974-8

Vicente-Serrano, S.M., Beguería, S., and *López-Moreno, J.I.*, 2010: A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J. Climate 23,* 1696–1718. https://doi.org/10.1175/2009JCLI2909.1

Vicente-Serrano, S.M., Beguería, S., Gimeno, L., Eklundh, L., Giuliani, G., Weston, D., El Kenawy, A., López-Moreno, J.I., Nieto, R., Ayenew, T., Konte, D., Ardö, J., and *Pegram, G.G.S*., 2012: Challenges for drought mitigation in Africa: The potential use of geospatial data and drought information systems. *Appl. Geography 34*, 471–486. https://doi.org/10.1016/j.apgeog.2012.02.001

Vicente-Serrano, S.M., Lopez-Moreno, J.-I., Beguería, S., Lorenzo-Lacruz, J., Sanchez-Lorenzo, A., García-Ruiz, J.M., Azorin-Molina, C., Morán-Tejeda, E., Revuelto, and *J., Trigo, R.*, 2014: Evidence of increasing drought severity caused by temperature rise in southern Europe, *Environ. Res. Lett. 9*(4), 9 044001. https://doi.org/10.1088/1748-9326/9/4/044001

Von Grebmer, K., Bernstein, J., Nabarro, D., Prasai, N., Amin, S., Yohannes, Y., Sonntag, A., Patterson, F., Towey, O., and *Thompson, J.*, 2016: Global Hunger Index: Getting to Zero Hunger. Welthungerhilfe, International Food Policy Research Institute, and Concern Worldwide, Bonn, Washington, DC, and Dublin. http://doi.org/10.2499/9780896292260

Wang, Q., Zhang, R., Qi, J., Zeng, J., Wu, J., Shui, W., Wu, X., and *Li, J.,* 2022: An improved daily standardized precipitation index dataset for mainland China from 1961 to 2018. *Scientific Data 9*, 124. https://doi.org/10.1038/s41597-022-01201-z

Weibull, W., 1939: A Statistical Theory of the Strength of Materials. *Generalstabens Litografiska Anstalts Förlag*, Stockholm. No. 151. https://www.worldcat.org/title/statistical-theory-of-the-strength-of-materials/oclc/873844617

WMO, 1983: Guide to climatological practices. World Meteorological Organization, *WMO – No. 100. Geneva*, Switzerland. https://www.posmet.ufv.br/wp-content/uploads/2016/09/MET-474-WMO-Guide.pdf

WMO, 2012: Standardized precipitation index user guide. No. 1090, © World Meteorological Organization, https://library.wmo.int/index.php?lvl=notice_display&id=13682#.Ykr2muhBzIU

Yanda, P.Z. and *Mubaya, C.P.* 2011: Managing a Changing Climate in Africa; Local Level Vulnerabilities and Adaptation Experiences. Dares Salaam, Mkuki wa Nyota Publishers Ltd. https://www.scirp.org/(S(351jmbntvnsjt1aadkozje))/reference/referencespapers.aspx?referenceid=2923178

Yang, H. and *Huntingford, C*., 2018: Brief communication: Drought likelihood for East Africa. *Nat. Hazards Earth Syst. Sci. 18,* 491–497. https://doi.org/10.5194/nhess-18-491-2018

Zhai, J., Su, B., Krysanova, V., Vetter, T., Gao, C., and *Jiang, T.,* 2010: Spatial variation and trends in PDSI and SPI indices and their relation to streamflow in 10 large regions of China. *J. Climatol. 23*(3), 649–663. https://doi.org/10.1175/2009JCLI2968.1