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RESEARCH ARTICLE

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Analysis of Drought Trends and Severity Using Standard Anomalies: Case of Baringo County, Kenya

R. Ochieng'

Department of Social Sciences, University of Eldoret, P.O. Box 1125 – 30100, Eldoret – Kenya; snrochieng@gmail.com

Abstract

Increased frequency, severity and duration of drought events in arid and semi-arid lands (ASALs) of Kenya increase scarcity in water and pastures that support livestock assets. This destabilizes the livelihood base dependent on livestock assets. Drought analysis can provide early warning of the drought events and inform actions to reduce vulnerability of pastoral households to drought effects. Drought studies use different methods to analyse drought events. The most commonly used methods include: Percent of normal, Deciles, Palmer drought severity index (PDSI), Surface water supply index (SWSI) and Normalised difference vegetation index (NDVI). The objective of this study was to use the estimation of standardized anomalies ($SA(t) = \{SP(t) - \mu\} \div \{\sigma\}$) to characterise trends and severity of droughts in Baringo County. Rainfall data for the period 1970 – 2013 for two rainfall stations (Nginyang and Perkerra) in the study area was collected from Kenya Meteorological Department. Through literature review, the present study confirmed that the standard anomalies method requires only rainfall data that is the most accessible meteorological data in most countries unlike other methods such as PDSI that is based on the supply and demand concept on water balance equation, SWSI that use monthly data for precipitation, reservoirs, snowpack and stream flow and NDVI that monitor rangeland conditions, desertification and changes in the land use systems. The standard anomalies method ensures that the spatial and temporal frequency of extreme events is consistent and therefore useful in establishing inter and intra-annual and seasonal drought variability across the study area. Through the use of estimation of standard anomalies, the study established that the study area experienced extreme drought events of $SA(t) < -0.9$ during the years 1972/1973. 1976, 1980, 1984, 1986, 1995/1996, 2001-2004, 2006 and 2008. These results concur with observed drought events and perceived drought/rainfall events over the study period, an indication that the method yields accurate results. The study concludes that estimation of standard anomalies is an efficient method of analysing drought events. Through time-series plots of the standard anomalies, the method deduced that the study area will generally continue to experience drought events. The study recommends use of estimation of standard anomalies in analysing drought events and a tool in decision making regarding adoption of appropriate strategies to respond to drought events such as diversification, livestock off-sets, pastoral migration among others.

Keywords: Drought, Trends, Severity, Standard Anomalies, Rainfall

INTRODUCTION

Drought risks and vulnerability have attracted assessment of drought impacts on livestock-based livelihoods to reduce the vulnerability (Chipanshi *et al.*, 2003, Wilhelmi *et al.*, 2002; Brunett *et al.*, 2002). These have involved drought monitoring and early warning (Svoboda *et al.*, 2002), drought policy and mitigation strategies (Brown, *et al.*, 2006). In detailed assessments, analysis of drought occurrences and effects use meteorological variables. These include rainfall, temperature, soil water holding capacity and other water supply indicators. The variables are useful in generating drought indices because they are considered a key element in defining a drought and deciding on the techniques for the analysis. Drought indices describe the severity of drought as compared to the long-term average on normal condition (Hayes 2003; Keyantash & Dracup 2002). Despite efforts to strengthen the adaptive capacity, livelihoods in the Arid and Semi-Arid Lands (ASALs) remains vulnerable to drought events associated with climate change and variability.

Drought studies use different methods to analyse drought events. Fleig *et al.* (2006) conducted studies using observed data useful in examining geographical differences in the statistical nature of droughts but are constrained by limited observation points hence need to use different or incorporated approaches. Sheffield & Wood (2007) used monthly drought based on simulated soil moisture data to identify the locations most prone to short, medium and long-term droughts and to examine severe past drought events on a regional basis. Dai *et al.* (2004) developed a global monthly data of Palmer Drought Severity Index while Dettinger & Diaz (2000) used monthly stream-flow series to characterize and map geographic differences in the seasonality and annual variability of stream-flow, which influences drought events globally. Lloyd-Hughes & Saunders (2002) developed grid-based climatology for Europe, which provides the time series of drought strength, the number, the mean duration of droughts of a given intensity and the trend in drought incidence based on Standardized Precipitation Index. There are several indices that can be used to analyse drought through estimation of how much precipitation for a given period has deviated from historically established norms. The most commonly used indices in drought analysis include:

i. Percent of normal: The index is computed by dividing the actual precipitation by the normal precipitation typically considered to be a 30 – year mean and multiplying by 100 ($I = (P_0 \div P_{30}) \times 100$; Values of the index less than 100 means drought conditions exist). Its main weakness is that what is normal may be perceived differently in various geographic regions (Morid, Smakhtin & Moghaddasi, 2006). The average precipitation may also nor reflect the median precipitation in a given region.

ii. Deciles: The distribution of the time series of the cumulated precipitation for a given period divided into intervals each corresponding to 10% of the total distribution (Deciles). Gibbs & Maher (1967), grouped deciles into 5 classes as shown in Table 1.

Table 1: Classes of Events

Class	**Percent**	**Period**
Deciles 1-2	20% lower	Much below normal
Deciles 3-4	20% following	Below normal
Deciles 5-6	20% medium	Near normal
Deciles 7-8	20% following	Above normal
Deciles 9-10	20% more high	Much above normal

Source: Gibbs & Maher (1967:10)

The decile index is easy to compute but requires a long-time series of data that is not readily available in most African countries (Masih *et al.*, 2014; Gibbs & Maher, 1967).

iii. Palmer drought severity index (PDSI): Developed by Palmer (1965) and Palmer (1968) and based on the supply and demand concept of the water balance equation. It measures the departure of the moisture supply for normal condition at a specific location based on precipitation and temperature data on the local available water content of the soil and other meteorological parameters. The Palmer index varies between -6.0 and +6.0 as shown in table 2. The PDSI identifies abnormality of agricultural droughts and historical aspects of prevailing situations. The method depends on soil moisture data that possess challenge to analyse over a wide geo-spatial scale (Palmer, 1965; Palmer, 1968; Masih *et al.*, 2014). The palmer indices may not identify droughts as early as standard anomalies method (Fuchs, Svoboda, Wilhite, & Hayes, 2014).

Table 2: Palmer Index Classification

PDSI	Class
4.0 or more	Extremely wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderately wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to -0.49	Mild drought
-2.0 to -2.99	Moderate drought
-3.0 to -3.99	Severe drought
-4.0 or less	Extreme drought

Source: Palmer (1965: 2)

iv. Surface water supply index (SWSI): Developed by Shafer & Dezman (1982) to complement Palmer index and designed for large topographical variations across a region and accounts for snow accumulation and subsequent runoff. The index use monthly data collected and summed for all the precipitation stations, reservoirs and snowpack/stream-flow measuring stations over the basin. The index analysis involves normalization of summed component using a long-term mean. The index is centred on zero and has a range between -4.2 and +4.2. The index is unique to specific basins and therefore not effective in comparative studies (Fuchs *et al*., 2014).

v. Normalized difference vegetation index (NDVI): This index can monitor rangeland conditions, desertification and changes in the land use systems. NDVI and forage conditions are important factors in forecasting droughts and livestock mortality. NDVI measures vegetation cover and productivity by computing the proportion of absorbed radiation from the photosynthesis process. This ratio of visible and near infrared wavebands ranges between negative one (-1) and positive one (+1) with zero or less indicating non-vegetation cover. Values close to +1 indicate a high level of green vegetation cover or biomass while bare soil cover records lower NDVI values of between 0.1 to 0.2 (Wittemyer *et al.*, 2007; Tucker *et al.*, 2005).

vi. The Standardized anomalies: Estimation of standardized anomalies is carried out using the following formula:

$SA(t) = \{SP(t) - \mu\} \div \{\sigma\}$

Where:

SA (t) = time-series of standardized anomalies

SP (t) = cumulative precipitation during the season

μ = represents mean

σ = standard deviation

Interpretation of Standard Anomalies uses World Bank (2013) definition as follows:

Anomaly lower than -0.9 = Catastrophic drought

Anomaly between -0.9 and -0.6 = Severe drought

Anomaly above -0.6 = Not severe

The standardised anomalies method is mostly preferred because it is simple to use and only requires precipitation data for computation of the indices (Zargar *et al.*, 2011). The method monitors drought parameters such as drought onset, intensity and duration (Dai, 2011; Mishra & Sing, 2010; Smakhtin & Schipper, 2008). The present study used the standardized anomalies to identify and classify droughts.

Study Area

Baringo County (Figure 1) is located within the Rift Valley of Kenya, between longitudes $35^0$30' and $36^0$30' East and between latitudes $0^0$10' South and $1^0$40' North. The County covers an area of 11,090 Km^2 with a population of 555,561 persons in 110,649 households. The Agro-ecological zones in the county are: UH 1, UH 2, LH 2, LH 3, UM 3, UM 4, UM 5, LM 4, LM 5, LM 6 and IL 6. Temperatures range from a minimum of 10 ^{0}C to a maximum of 35.0 ^{0}C with bimodal rainfall pattern of long rains of MAM and short rains of OND which range from 300 to 700 mm in the lowlands and 1200 mm in the highlands (Jaetzold *et al.*, 2011; RoK, 2010; RoK, 2013). Despite the diversity of agro-ecological zones and livelihood support system, Baringo County is classified as arid and semi-arid land and study site was limited to AEZs LM5 and IL6. The two agro-ecological zones were purposely chosen as the study targeted the extreme semi-arid and arid parts that have in the past experienced massive loss of livestock due to rainfall variability and drought events.

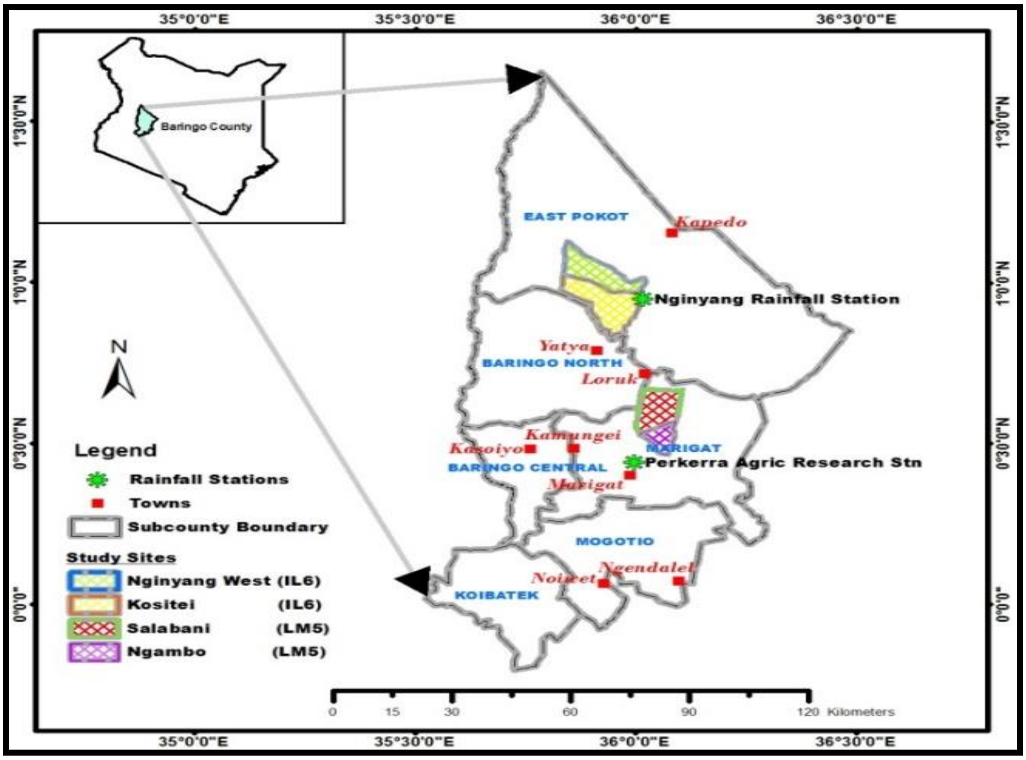

Figure 1: Map of Study Area.

MATERIALS AND METHODS

The study collected rainfall data for the period 1970-2008 and 1974-2013 from Perkerra (LM5) and Nginyang (IL6) weather stations respectively. The rainfall data from the two weather stations had missing rainfall data for which imputation method was then used to fill those missing values to eliminate gaps in the data set. This is a requirement of World Meteorological Organization for climatological analysis. In this study, multiple imputations method was used to overcome underestimation of standard errors and confidence intervals typical of single imputation (Radi *et al.*, 2015). This method replaces missing data with substituted values from the observations of rainfall (rainfall data sets) at the same station and period but in different years (Ochieng' *et al*., 2017).

The missing rainfall data Px was estimated using the following formula:

$$\mathrm{P}x = 1/n \sum_{i=1}^{i=n} \mathrm{P}i \text{…… Equation 1}$$

Where:
n = the number of rainall data sets
Pi = rainfall data from the ith data set
Px = missing rainfall data

The standardized anomalies were computed from rainfall data using the formula:

$$\mathrm{SA}\ (\mathrm{t}) = \frac{\{\mathrm{SP(t)} - \mu\}}{\{\sigma\}} \text{………………Equation 2}$$

Where:

SA (t) = time-series of standardized anomalies
SP (t) = cumulative precipitation during the season
μ = mean
σ = standard deviation

Categorisation of Standard Anomalies used World Bank (2013) definition as follows:

Anomaly lower than -0.9
Catastrophic drought

Anomaly between -0.9 and -0.6
Severe drought

Anomaly above -0.6
Not severe

RESULTS AND DISCUSSIONS

Severity of the Observed Drought Events

Figure 2 is a plot of the annual drought index for the observed drought events in LM5 and IL6 agro-ecological.

On a time-scale of 12-month (annual), for the period 1970 – 2008, four extreme catastrophic drought periods were observed in 1984, 2000, 2002 and 2004 with standard anomalies less than -0.9 (SA(t)< - 0.9) as a function of the time scales in LM5 (Figure 2a). Other noticeable catastrophic drought events were in 1972/1973, 1976, 1980, 1986, 1995/1996, 2001, 2003, 2006 and in 2008. With the exception of year 2003 and 2008, the observations concur with those of Huho and Kosonei (2014) on the occurrence of extreme climatic events in Kenya. The 2003 and 2008 cases can be attributable to locational variation in drought events in place and time. Similar findings of catastrophic droughts were recorded in Morocco, Algeria and Tunisia in 1984 and 1999-2003 (Ouassou *et al.*, 2007; Touchan *et al.*, 2008; Touchan *et al.*, 2011). These reports are indication of the spatio-temporal nature of drought events. The drought events experienced in Baringo County were also being experienced elsewhere as well in other parts of Africa. The concurrence of these findings indicate that similar drought events can be experienced in different locations and therefore the current study findings can be implemented in other ASAL regions in Kenya.

Noticeably, all the catastrophic drought events were preceded by high rainfall events (Standard Anomalies greater than 1, SA(t)>1.00) and this phenomenon takes place when the sea surface temperature in oceans increase anomaly, causing sudden heavy rainfall and thereafter rainfall decreases drastically followed by a prolonged severe dry spell (Fyfe *et al.*, 1999). For instance, the El Niño rains in 1997 - 1998 classified as the worst El Niño effect in 20th century preceded catastrophic drought event in 2000 – 2004 period. The obtained drought indices show breaks between successive drought events in the study area. The period between successive droughts provides pastoralists with an opportunity in restock or invest more in livestock. Deeper insight into the drought trends is a sure way of reducing the pastoralists' vulnerability to droughts and associated impacts.

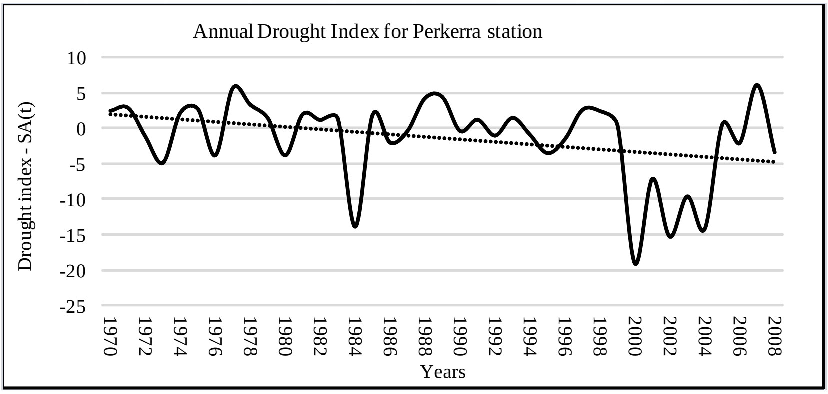

Figure 2a: Annual drought index for LM5 zone - Perkerra rainfall station.

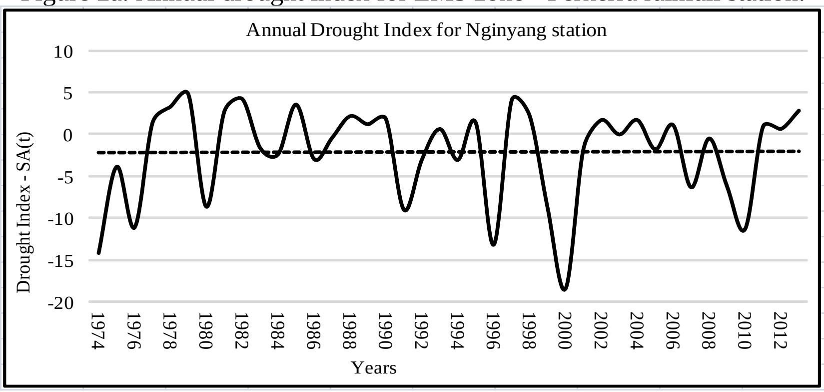

Figure 2b: Annual drought index for IL6 zone - Nginyang rainfall station.

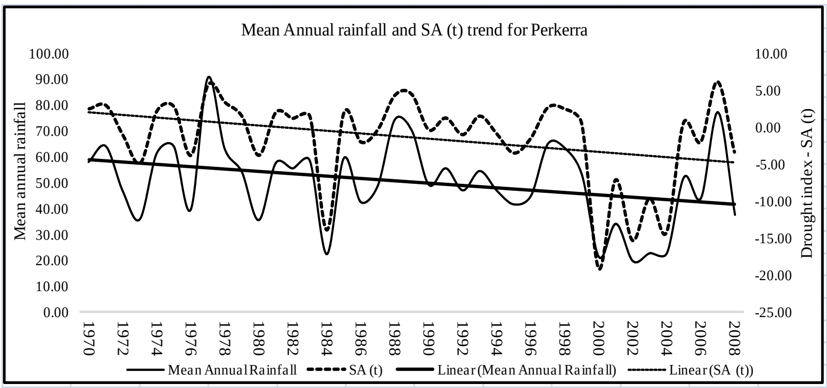

Figure 2c: Relationship between mean annual rainfall and annual drought indices for LM5 zone - Perkerra rainfall station.

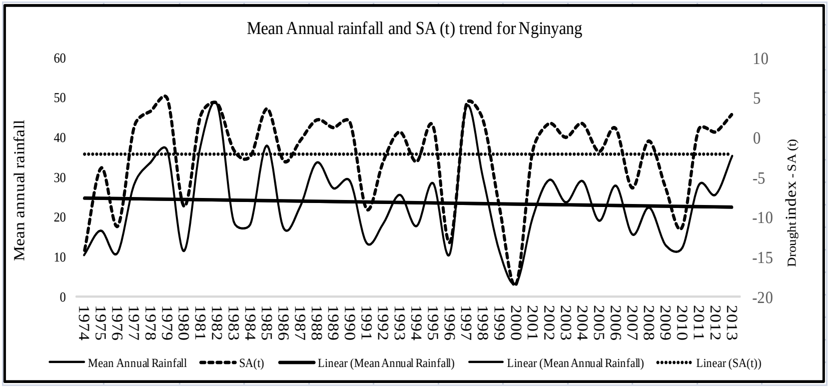

Figure 2d: Relationship between mean annual rainfall and annual drought indices for IL6 zone - Nginyang rainfall station.

In the IL6 zone - Nginyang station - data on a time scale of 12-month (annual) reveal five catastrophic drought periods in the study area observed in 1974, 1976, 1996, 2000 and 2010 period (Figure 2b) with standard anomalies less than -0.9 (SA (t)< -0.9) as a function of the time scales. The study observed noticeable severe drought events in 1980, 1999 and 1991 with standard anomalies between -0.9 and – 0.6 as a function of the time scales (Figure 2b). The drought events are likely related to shifts in warmer sea surface temperatures. Dai (2011) documented the 1970s and 1980s droughts in Western Africa – Sahel and attributed it to southward shift of the warmer sea surface temperatures in the Atlantic and warming in the Indian Ocean. Dutra *et al.* (2013) and Tierney *et al.* (2013) registered drought in the horn of Africa in 2010 while drought in Ethiopia and Somalia were attributed to Indian Ocean sea temperatures that have influence in the East African rainfall (Masih *et al.*, 2014; Dutra *et al.*, 2013; Tierney *et al.*, 2013).

The annual rainfall and the drought indices - SA(t) are negatively correlated ($r = -0.9218$, $p<0.05$) in LM5 zone - Perkerra rainfall station (Figure 2c). The plot depicts a negative correlation between the total recorded annual rainfall and the annual standardized drought anomaly indices SA(t) as illustrated in figure 2c. Similarly, correlation analysis results between the annual rainfall and the drought indices - SA (t) in Nginyang also posted a significant negative correlation ($r = - 0.6879$, $p<0.05$) (Figure 2d). This result is significant in analysing effects of drought in livestock assets for it is an indication that severity of drought increases with decrease in rainfall amount. The strong negative correlation indicates that there exists a strong significant association between rainfall amount and drought events in the study.

Estimation of Seasonal Drought Index

The seasonal drought index - SA(t) for the variation of rainfall in 1970 – 2008 periods for the two stations are plotted for the March-April-May (MAM) and October-November-December (OND) in figure 3a and 3c and over the period 1974 - 2013 in figure 3b and 3d.

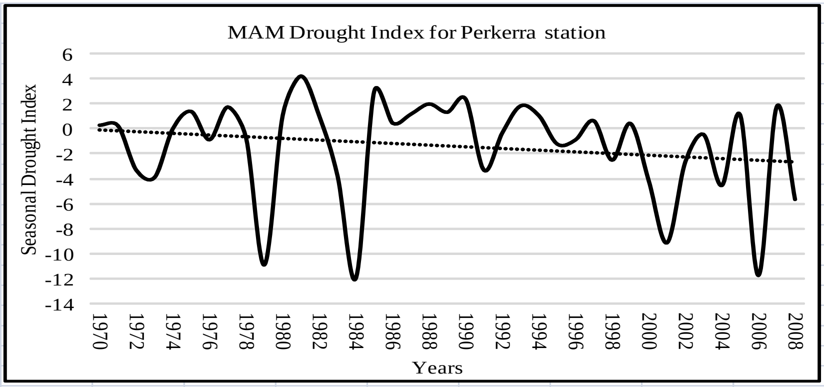

Figure 3a: March-April-May (MAM) drought index for LM5 zone - Perkerra rainfall station.

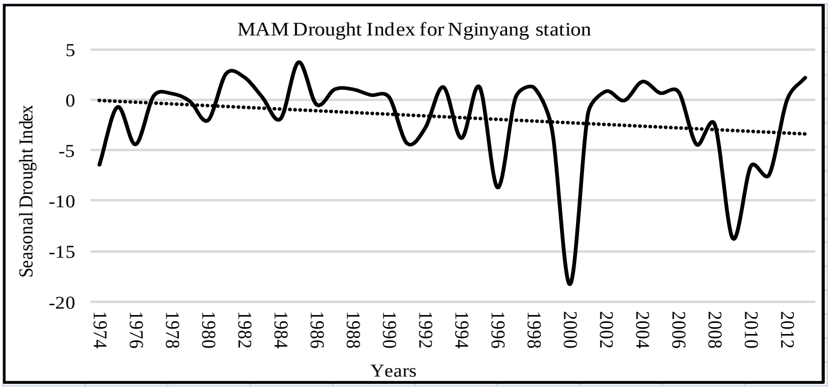

Figure 3b: March-April-May (MAM) drought index for IL6 zone - Nginyang rainfall station.

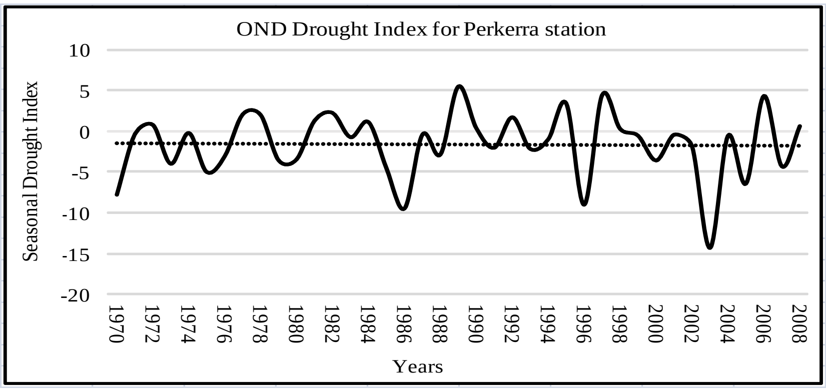

Figure 3c: Oct-Nov-Dec (OND) drought index for LM5 zone - Perkerra rainfall station.

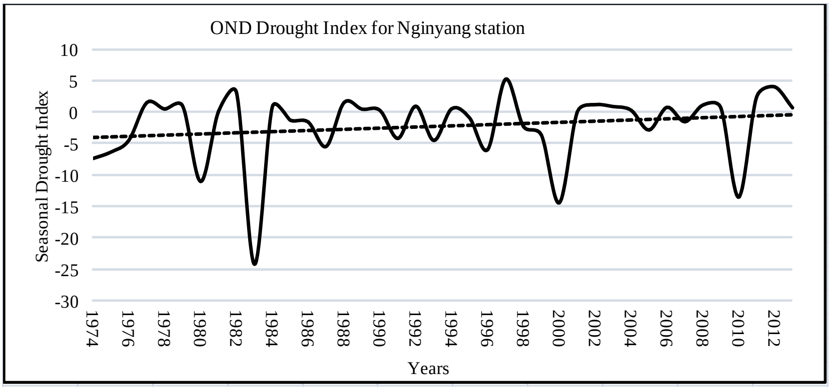

Figure 3d: Oct-Nov-Dec (OND) drought index for IL6 zone - Nginyang rainfall station.

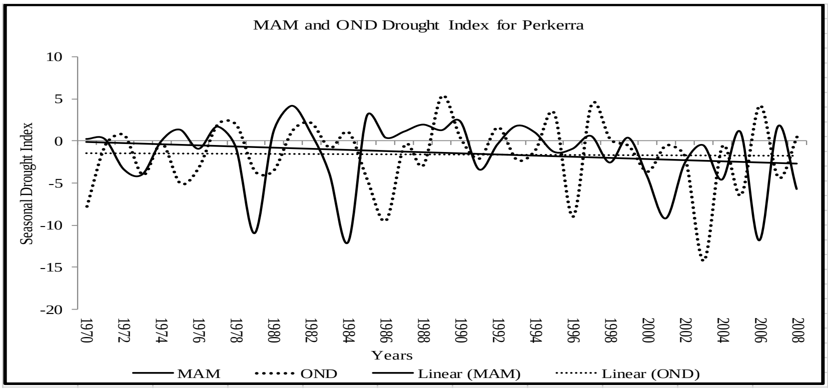

Figure 3e: March-April-May (MAM) and Oct-Nov-Dec (OND) drought index for LM5 zone – Perkerra rainfall station.

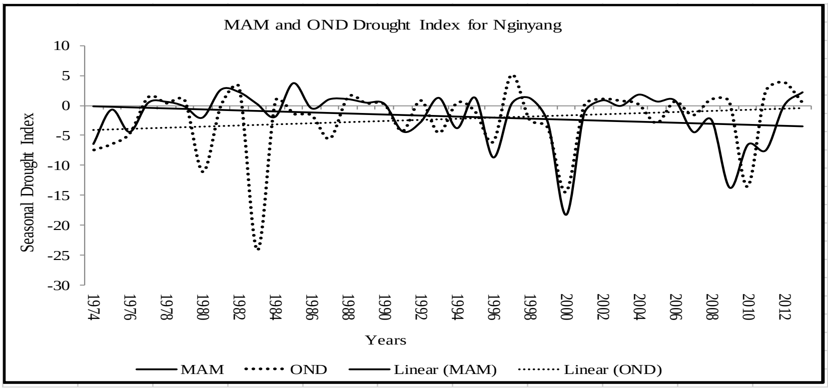

Figure 3f: March-April-May (MAM) and Oct-Nov-Dec (OND) drought index for IL6 zone – Nginyang rainfall station.

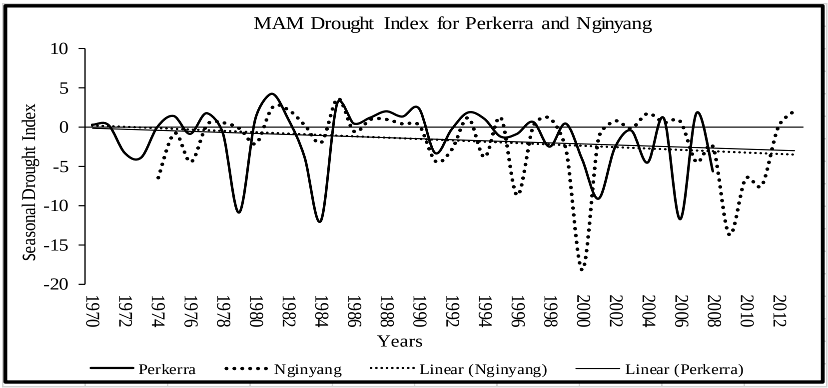

Figure 3g: March-April-May (MAM) drought index for LM5 zone – Perkerra rainfall station and IL6 zone – Nginyang rainfall station.

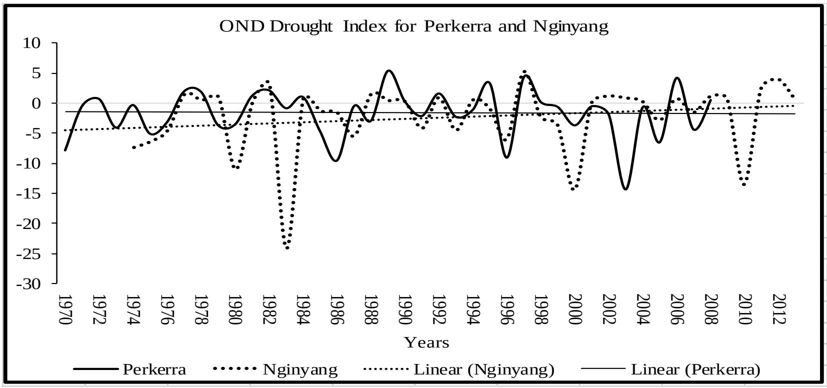

Figure 3h: Oct-Nov-Dec (OND) drought index for LM5 zone – Perkerra rainfall station and IL6 zone – Nginyang rainfall station.

The MAM seasonal drought index plot for LM5 - Perkerra rainfall station - shows intermittent trend of drought events with peaks observed in 1979, 1983, 2000 and 2005 and a declining trend indicating drier conditions, which implies that the region is vulnerable to drought events (Figure 3a and 3e). The MAM in IL6 - Nginyang station - seasonal drought index plot shows fluctuating trend of drought events with drought peaks observed in the years 2000 and 2009 and others visible in the years 1974, 1996, 2010 and 2011. The long-term MAM seasonal trend for rainfall shows a declining trend, which is an indication of drier conditions over long time scale and implies vulnerability of the region to drought (Figure 3b). This corroborates with Masih *et al.* (2014) that significant increase in drought occurred in the African continent during the 1901-2011 period.

The OND seasonal drought index plot for LM5 zone - Perkerra station - shows few drought events with the major drought event peak being observed in the years 2003 (Figure 3c) and shorter peaks in the years 1985 and 1996. Compared to the MAM seasonal drought index plot, the OND season has fewer drought events for the 39-year period for Perkerra rainfall station (Figure 3e). Noteworthy, from the OND seasonal drought index plot, the study deduced that the long-term OND seasonal trend for rainfall shows a constant trend of below mean rainfall for Perkerra rainfall station (Figure 3c). Figure 3e shows that the long-term trend for MAM in Perkerra is worsening through time as compared to the

OND trend, which displays a relatively constant situation.

On the other hand, the OND seasonal drought index plot also shows a fluctuating trend of drought events in Nginyang with catastrophic drought events being observed in years 1980, 1983, 2000 and 2010 (Figure 3d). Severe drought peaks include year 1974 and 1996. Compared to the MAM seasonal drought index plot, the OND season seems to have more catastrophic drought events for Nginyang rainfall station (Figure 3f). However, from the OND seasonal drought index plot (Figure 3d) and the combined MAM and OND plot (Figure 3f), the study observed that the long-term OND seasonal drought trend shows a gentle upward trend, an indication that the conditions are improving. The trend indicates that in IL6 zone - Nginyang station - rainfall totals with time is likely to display an upward trend with decreasing drought severity for OND season.

Comparing the two regions of Perkerra LM5 and Nginyang IL6, the MAM seasonal trend shows declining trend (Figure 3g), an indication of drier conditions compared to OND seasonal trend that displays below mean rainfall (Figure 3h). More so, the plots show a likelihood of decreasing drought severity for the OND season for Nginyang and a relatively constant trend for Perkerra. Comparing the two study locations (Figure 3g and 3f), the study areas is becoming drier over time. In confirmation of past drought situation in the study area, Mr Stanley Kibiwot of NDMA confirms said;

> Baringo County over the years has experienced drought events adversely affecting human lives and livestock assets. The drought events have become more severe calling for timely dissemination of early warnings and planning.

CONCLUSION

From the findings presented, the researcher concluded that the standardised anomalies method can effectively be used to assess and predict the severity of drought events, estimate seasonal and annual drought index, and undertake comparative drought monitoring over spatial and temporal scale. The standard anomalies can be computed for different time scales and provide early warning for drought events.

RECOMMENDATION

The study recommends wide use of standard anomalies method to monitor drought events. This is important in improving uptake of new technologies aimed at building pastoral resilience. It is also important to equip the existing meteorological stations with modern technology and trained personnel to improve acquisition and management of high-resolution climate data for application of standard anomalies to monitor drought trends and severity.

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