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Article

Characterization of meteorological drought and pluvial scenarios over Kenya, East Africa

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Abstract: This work examines drought and wet events based on Standardized Precipitation-Evapotranspiration Index (SPEI) over Kenya from 1981 to 2016. Spatiotemporal analysis of dry and wet events is conducted for 3 and 12-month SPEI. The drought incidences were observed during the period 1984, 1987, 2000, 2006, 2009, 2015, and 2016 for SPEI-3 whilst the SPEI-12 demonstrated the manifestation of drought during the year 2000 and 2006. SPEI clearly shows that the wettest period, 1997 and 1998 that coincide with the El Nino event in both time steps. SPEI -3 shows a reduction in moderate drought events while severe and extreme cases were on increase towards the end of the twentieth century. Conversely, SPEI-12 depicts an overall increase in severe drought occurrence over the study location with observed intensity of -1.54 and cumulative frequency of 64 months during the study period. The trend of wet events is upwards in the western and central highlands while the rest of the regions show increase in dry events during the study period. Moreover, moderate dry/wet events predominate whilst extreme events occur least frequent across all grid cells. It is apparent that the study area experiences mild extreme dry events in both categories although moderately severe dry events dominate most parts of the study area. High intensity and frequency of drought is noted in SPEI-3 while least occurrences of extreme events are recorded in SPEI-12. Although drought event prevails across the study area, there is evidence of extreme flood conditions over the recent decades. These findings form a good basis for next step of research that will look at projection of droughts over the study area based on regional climate models.

Keywords: Drought, SPEI, Pluvial, Severity, Frequency, Duration, Kenya.

1. Introduction

Drought remains one of the most complex natural phenomena affecting the economy, environment and society at global, regional and local level [1]. For instance, occurrences of prolonged rainfall failure remarkably alter water resources, ecosystem balance, and have adverse impact on agriculture and urban livelihoods [2, 3,]. There is growing concern following the impacts of rapidly changing climate with projections pointing to an increase in extreme events (such as droughts and floods) are expected in across many regions [4].

Consequently, with emphasis on drought, the focus of many researchers has been to infer from the intricate dynamics of drought and vulnerability impacts in a bid to establish mitigation measures [5-7]. Despite the efforts, according to World Meteorological Organization (WMO) [8], there is still limited understanding of drought evolution, frequency, and severity of occurrence from one region to another. This is due to its 'creeping phenomenon' as compared to other natural disasters [2]. For instance, drought vary by multiple dynamic dimensions including severity and duration making it difficult for scientists and policy makers to determine the exact timing of its inception or termination of either meteorological, agricultural or hydrological drought events [9-11].

Numerous studies have reported an upsurge in droughts events in many regions with noticeable increase over the recent decades, as a result of the ongoing global warming and decadal variability [4, 5, 12-14]. To illustrate this, drought has affected many countries in Europe [15, 16], North America [17-19], Asia [20-22], Australia [23, 24], and Africa [12, 25, 26]. Most significantly, Africa, southern Europe, and eastern Australia have recorded an increase in drought events, mostly attributed to precipitation decrease linked with decadal fluctuations in the Pacific and western Indian Ocean [13, 27, 28].

East Africa (EA), mainly classified as an arid and semi-arid (ASAL) region despite falling within the tropics, continues to experience unprecedented records of drought events in comparison to other natural threats such as heat waves, torrents, cold surge, and cyclones [29, 30]. Colossal records of economic losses and environmental degradation continue to be witnessed across many parts of the region [30, 31]. For example, Kenya, Uganda, Somalia, and Ethiopia experienced severe drought event in 2010-2011 [30], with an estimated 10 million people acutely impacted [31]. Furthermore, approximately 450,000 deaths were reported in Ethiopia during the 1984-1985 drought while Kenya witnessed a wide spread drought in 2005, affecting 2.5 million people in the northern region [32, 34]. This trend is likely to increase with intensification of extreme climate events towards the end of the 21st century [13, 35, 36]. Global predictions based on Palmer Drought Severity Index (PDSI) show that desiccation will become more severe and widespread over EA region with reduced precipitation and increased evaporation [13].

Kenya has been witnessing an increase in severe and frequent famine events in the recent decades, exacerbated by the recent decline in March-May (MAM) seasonal rainfall [37-40]. Numerous studies have been conducted to ascertain drought variabilities, trends and the respective

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impacts on agriculture, economy, water resources and environment over the study region [41-44]. These researchers have employed various drought indices recommended by the WMO [11]. For instance, Mutsotso et al. [43] investigated the drought occurrences in Kenya based on the combination of Standardized Precipitation-Evapotranspiration Index (SPEI) and Normalized Difference Vegetation Index (NDVI) on one-month basis and three-month basis and analyzed correlation between the two indices. On the other hand, Karanja et al. [42] used Standardized Precipitation Index (SPI) to characterize seasonal and annual droughts in Laikipia west sub-county, Kenya from 1984 to 2014. The study focused on drought events occurring during the two rain seasons, namely MAM and OND. On the other hand, Frank et al. [45] employed Effective Drought Index (EDI), as an "accurate" index in drought assessment along the Tana-River basin in Kenya. In contrast, Zargar et al. [46] reported contradictory results that EDI seemed to have weak imprecision in monitoring the inception, cessation and accumulated stress. Wambua et al. [47] applied both indices of SPI and EDI to delineate drought occurrences during 1980-2016 in the upper Tana River Basin, where nearly all agro-ecological zones of Kenya are located. Both indices demonstrated that the south-eastern basin parts were more likely to experience severe droughts as compared to the north-western parts.

The mentioned indices employed by various researchers over the study domain highlighted a glimpse of spatiotemporal variation and occurrence of historical dry/wet events from one region to another, without necessarily indicating the magnitude, severity, and duration of extreme events. Moreover, other studies for drought and flood evaluation reported a contrary occurrence of dryness/wetness events while some showed incoherence in spatial patterns of drought frequencies. Therefore, precise analysis of recent changes in drought and wet events in a complex subtropical domain is an important step in identifying mechanisms associated with these anomalous events in the era of changing climate, which still remains a challenge.

Thus, the main objective of this study is to characterize drought and pluvial events based on intensity, severity, and frequency over the Kenya, using widely accepted index, SPEI [75], from 1981 to 2016. Specifically, the study will: (1) examine the intensity, frequency and severity of drought and pluvial scenario at each grid cell over the whole study domain. The results could be useful in accurate examination of the drought and pluvial events in the study locale, thereby helping hydrologist and farmers to take timely decisions. The findings of this work form a good basis for analysis and discussion of drought projections over the region based on improved Regional Climate Models (RCM) datasets.

The remaining sections are organized as follows: Section 2 highlights characterization of the study locale, data and methodology while results and discussions are given in section 3. Finally, conclusion and recommendation are presented in part 4.

2. Materials and Methods

2.1. Study Area

The study location (Kenya) is situated in East Africa. It is bound within longitude 34° E- 42° E and latitude 5° S - 5° N (**Fig. 1**). Adjoining nations include Uganda, Tanzania and Somalia. The economy of the country is predominately anchored on rain-fed agriculture [58]. Complex geomorphological features regulating local climate are prevailing across different parts in the country. Highest altitude is in central highlands while low-lying regions characterized by ASAL ecosystems and climate occupies eastern, northwest and northeastern sides. Towards the south, lies

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Indian Ocean coastline regulating local climate whereas the western sides of the study domain have large water basin of Lake Victoria, driving land-lake breezes [48].

The rainfall of the study locale is mostly bimodal with 'long rains' experienced during March to May (MAM) while 'short rains' occur during October to December (OND) [31, 37, 39, 49]. Overall, a dry anomalous climate is experienced despite the region being situated along equatorial wet tropical belt. Circulation features over the region is extensively elaborated in past studies [33, 38, 48, 51-54].

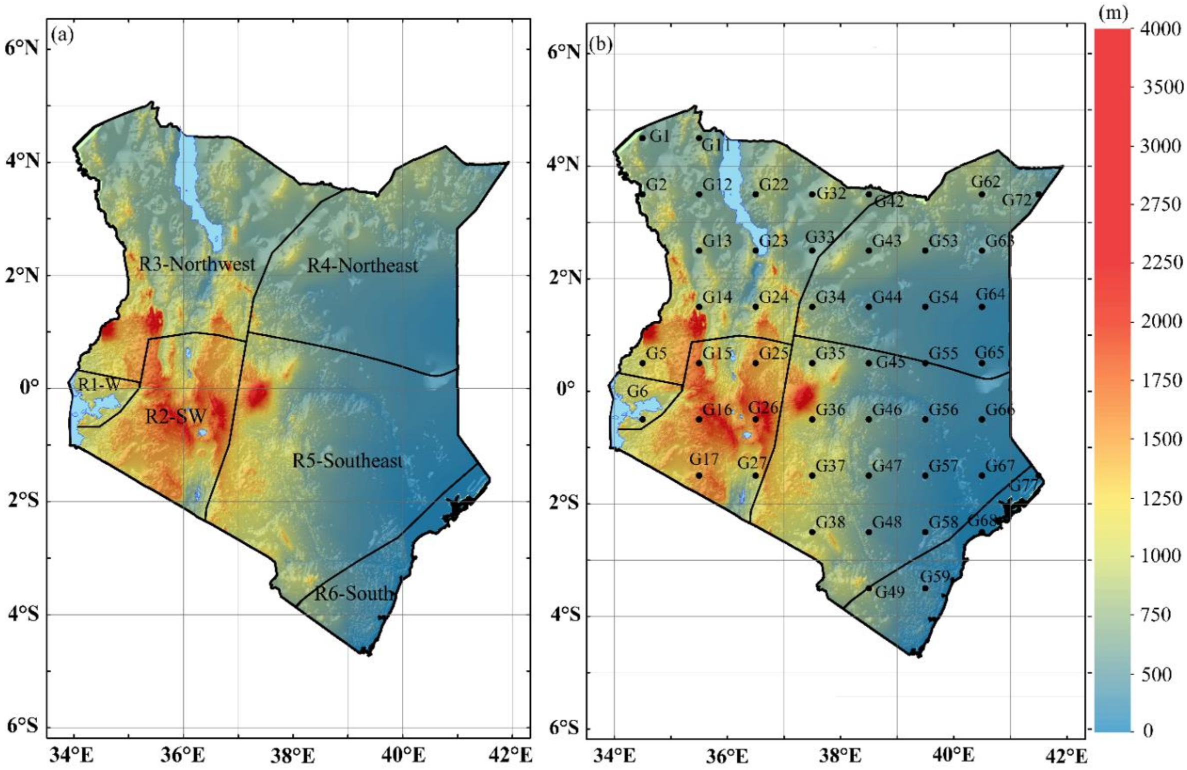

Figure 1. Elevation of the study area with distinct homogeneous locations as delineated by Indeje et al. [59] and the respective grid cells in each region.

2.2. Data Description

Comprehensive assessment of meteorological drought and pluvial events over a region involves use of a several climatic datasets. This study utilizes monthly maximum and minimum temperature datasets from Climatic Research Unit (CRU TS4.03; available from the site; https://crudata.uea.ac.uk/cru/data/hrg/ [60]) and monthly precipitation datasets obtained from Climate Hazard Group Infrared Precipitation with Station (CHIRPS; [61]).

The CHIRPS datasets were obtained through website (http://chg.geog.ucsb.edu/data/chirps/) for the years 1981-2016. The study employed latest version of CHIRPS (CHIRPS v.2), which has been produced by the CHIRPS following two steps: (i) pentad rainfall estimates, produced from cold cloud duration (CCD) based satellite data on regression model calibrated using TRMM; (ii) the stations are merged with CHIRP data to produce CHIRPS . This product has spatial resolution of

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0.05 (~ 5.3 km) with a quasi-global coverage (50° S – 50° N, 180° E – 180° W) and is existing from 1981 to present-day at pentad, decadal, and monthly temporal resolution [61].

The satellite derived precipitation datasets (CHIRPS) were recently evaluated by inferring their performance over the study domain [62]. The CHIRPS data covers the period 1981 to 2016. The CRU data with spatial resolution of ~ 50 km X 50 km was used in deriving the potential evapotranspiration (PET). In the present study, all datasets were extracted from all grid cells within the study domain (**Fig. 1**). This was derived from re-gridding of study area based on 1° x 1° spatial resolution in bid to achieve uniform grids for analysis since the gridded datasets were of varying resolutions. Analysis at each grid cell provides an insight to evolution of extreme events in region that is characterized by varying topographical features on finer horizontal resolution. This approach improves the representation of orographic features, such as elevation, land use and other surface features which might not otherwise be captured in major homogeneous regions [41].

2.3. Methods and Metrics

2.3.1*Standardized Precipitation Evapotranspiration*

The SPEI is computed using precipitation and PET to delineate the phases of anomaly of dry and wet conditions by normalizing the alteration amongst water supply (precipitation) and demand (evapotranspiration). The SPEI and SPI [71] are almost similar except that SPEI includes PET and employs various schemes to derive PET.

Consequently, the robustness of SPEI is derived from its ability to combine the various aspects of the SPI with data on evapotranspiration, qualifying it further to a substantially accurate drought index. Many evaluative studies have ranked SPEI as best performance as compared to other indices for drought assessment [70, 72]. The PET employed in the present study is based on Hargreaves scheme that relies on any available time series datasets and has superior performance similar to that of Food and Agricultural Organization (FAO) criterion of Pen-Monteith [73].

Comparative studies on different PET estimations over diverse domains concluded better performance of the PET derived from the Hargreaves equation with cautionary point regarding difference in few hundred-of-millimeter scale across different locations or characterized by unique land cover [74]. The SPEI built in R Program language version 3.4.2 (http://cran.rproject.org/web/packages/SPEI) was used to compute the SPEI. Vicente-Serrano et al. [75] expounds more details on the mathematical equation for computing SPEI.

Comparable to the original SPI, a negative value indicates dry conditions, whilst positive value depicts wet condition [92]. For instance, drought events are divided into four main categories, namely: extreme (SPEI ≤ -2.00), severe (-1.50> SPEI > -1.99), moderate (-1.00 > SPEI > -1.49), and mild (0 >SPEI > -0.99). Similarly, wet events are categorized as follows: extreme (SPEI ≤ +2.00), severe (+1.50 > SPEI > +1.99), moderate (+1.00 > SPEI > +1.49), and mild (0 > SPEI > +0.99). These values for SPEI, defines the characteristics of drought or pluvial condition in terms of severity, intensity, and

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duration of occurrence. In this study, the threshold for SPEI ≤ -1.0 was inferred to signify dry events whereas SPEI ≥ +1.0 represent wet events over the study domain.

This study defined the severity, intensity, and frequency for dry/wet event over the study domain as follows:

i) Severity is the cumulative sum of the index value based on the duration extent (Equation 1);

$$S = \sum_{i=1}^{Duration} Index \quad (1)$$

ii) Intensity of an event is the severity divided by the duration (Equation 2). Events that have shorter duration and higher severity will have large intensities.

$$I = \frac{Severity}{Duration} \quad (2)$$

iii) Frequency of occurrence (F_s) is defined in the Equation 3;

$$F_s = \frac{n_s}{N_s} x100\% \quad (3)$$

where n_s as the number of drought events (SPEI < -1.0), N_s is the total of the months for the study period, and *s* is a grid cells.

Furthermore, the duration of dryness/wetness situation is presented by the length of time (months) that the drought index is consecutively above or below a truncation value. The intensity, severity and frequency of extreme events define drought/wet episodes. The dominance of the dry/wet cases was examined for each grid cells and timescales and computed on the percentage of frequency of each incidence with reference to the total number of months. This approach was successfully employed in a recent study of drought evaluation along the major water basin in Kenya [41]. The intention of employing this approach was to categorize regions that frequently experience concurrence of extreme and severe climatic cases at corresponding periods.

The SPEI values were calculated in two-time scales namely, the average annual SPEI-3 and SPEI -12. Shorter time scale of annual SPEI-3 is derived by averaging monthly values within a year while SPEI-12 is from accumulated 12-month timescale. A timescale 3 month was chosen to denote drought/flood impacts on agriculture during the crop growing season [77, 78, 79]. On the other hand, selection of a 12-month timescale aimed to reflect hydrological consequences of drought such as energy production services

2.3.2 Empirical Cumulative Frequency

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The Empirical Cumulative Frequency [93], was adopted to compare the performance of time series for SPEI and SPI over the study region. The equation for Empirical Cumulative Frequency $(F_N(t))$ is presented as given in Equation 4;

$$F_N(t) = \frac{1}{N}\sum_{i=1}^{N} 1(x_i \le t) \qquad (4)$$

where N is the number of months in observations and $(x_i \le t)$ is the number of drought index values than the value of t. The concurrence performance of SPI and SPEI over study domain is presented in **Figure 2**. The results show that the indices share similar frequency for all drought categories as highlighted in Gozzo et al. [92]. In addition, the bimodal distribution of the SPI and SPEI is evident with the decreasing slope at 0. However, there is higher frequency of severe drought and extreme spell values (-1, to -2 and 1 to 3) as compared to near normal SPI/SPEI values (-0.99 to 0.99). Thus, the present study employed SPEI indices for historical trends synthesis of drought at each grid pixel over the study domain whereas SPI indices is recommended in situation where minimum (maximum) temperature datasets to aid in computing the evapotranspiration for SPEI index are missing or unavailable.

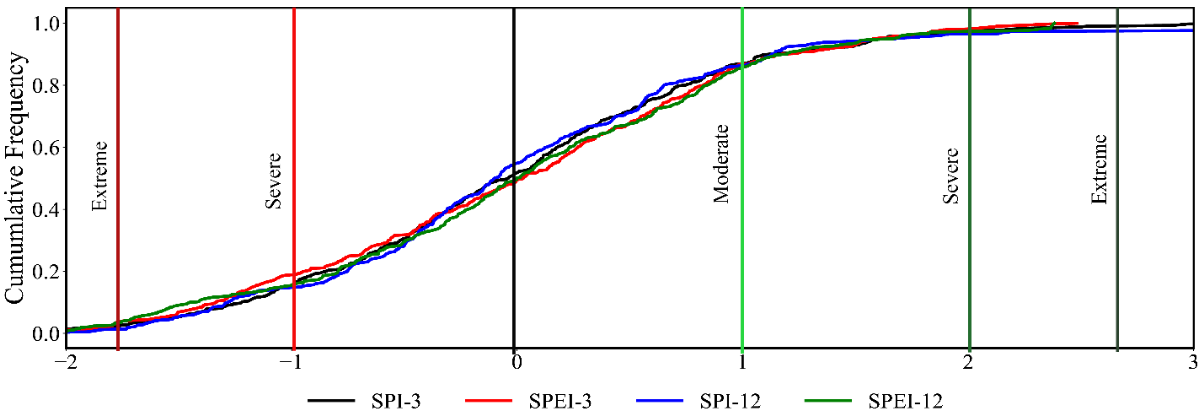

Figure 2. The empirical cumulative frequency of the monthly SPI and SPEI for Kenya region. Vertical lines represent dry spell (red) and wet spell (green) threshold classified in drought indices presented in Gozzo et al. [92].

3. Results

3.1. Temporal patterns and frequency incidences of dry/wet events

Figure 3 provides an overview of historical analysis for SPEI 3- and 12 months for the period 1981 to 2016 over Kenya. The evaluation of drought and wet events was conducted for moderate, severe and extreme frequencies [75, 76]. From the SPEI-3 results (**Figure 3a**), it can be seen that the study domain experiences moderate to severe and moderate to extreme drought cases towards the end of the twentieth century. The extreme drought incidences were observed during the period 1984, 1987, 2000, 2006, 2009, 2015, and 2016 for SPEI-3. The listed years coincide with atmospheric

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circulation changes related to SSTs variations that influence the regional rainfall patterns [27]. Further, the observed changes in drought characteristic for SPEI-3 event indicates moderate intensity phenomenon at -1.43, although the severity recorded is more intense with noted value of -111.5 over the duration of 78 months (**Table 1**). It is apparent from results presented that SPEI-3 exhibit greater temporal frequency of occurrence of wet and dry cases during the study duration.

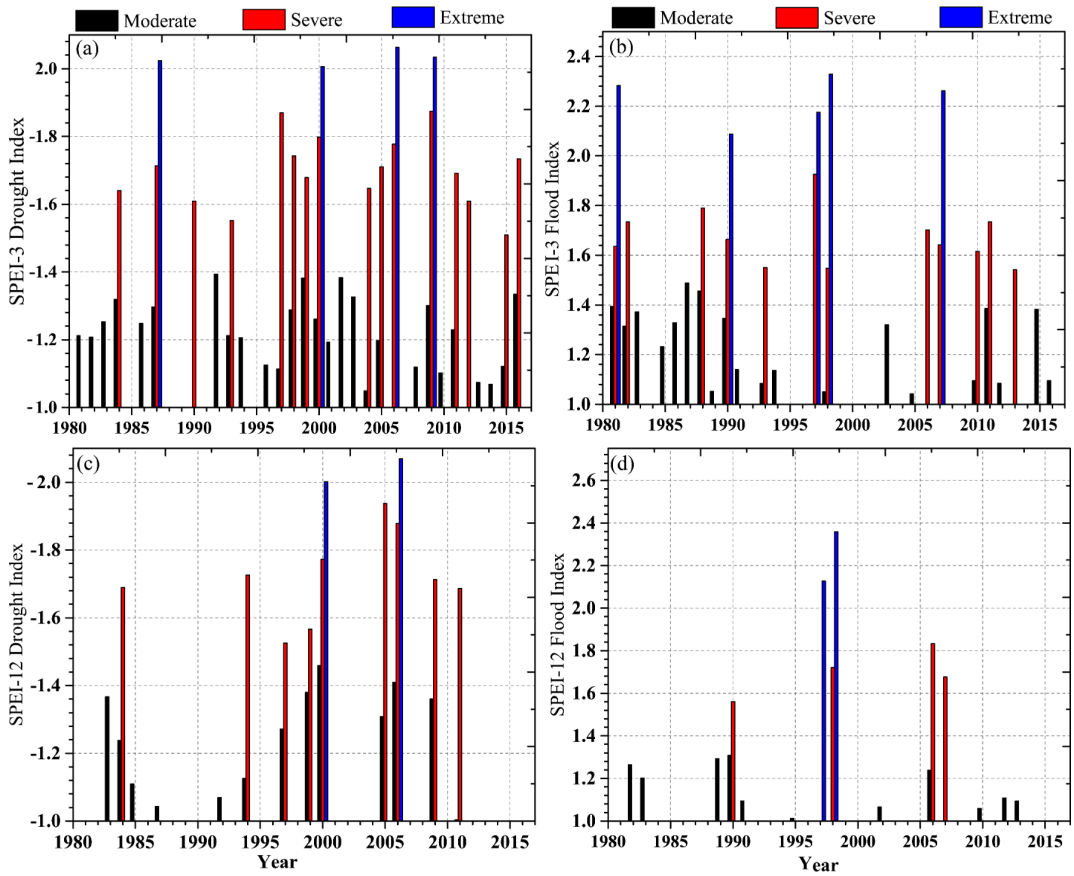

Figure 3. Evolution of the mean SPEI for 3- and 12-month timescale for moderate, severe and extreme drought and flood over Kenya showing the variation in the duration, severity and intensity of dry and wet events, 1981-2016.

The results for SPEI-12 show stability in the frequency of incidences over the study area during the period 1981-2016. This demonstrates that SPEI at elongated timescales respond more gradually and consistently to deviations in climatic variables indicating strong durations of frequent occurrences of anomalous events over the years. Subsequently, the longer timescales are most appropriate for the revealing of incidences of signature events over the region whereas shorter intervals demonstrate suitability for detecting frequent seasonal and inter-annual variations. Further analysis of drought severity (**Figure 3c**) show an overall severe drought occurrence over the study location with observed intensity of -1.54 and cumulative frequency of 64 months during the study period (**Table 1**). The extreme drought incidences were observed during the years 2000 and 2006.

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Comparison of the two indices show that SPEI-3 is characterized by severe drought occurrence while long-term drought (SPEI-12) show reduction in the extreme events over the study area. Meanwhile, the wetness episodes for both SPEI-3/12 demonstrate severe occurrence with intensity of SPEI ≥ 1.5 in all intervals. The wettest period between 1997 and 1998 during the El Nino event is well captured in both time steps, depicting a robust performance of SPEI index in capturing the underlying mechanisms of dry/wet conditions. A comparison of the two results reveals an overall moderate dry conditions occurrence while more intense wet events over the short duration of existence are experienced.

Table 1 The duration, severity, and intensity occurrence of the major dry (SPEI ≤ -1) and wet SPEI ≥ 1) events over Kenya during 1981 to 2016.

	SPEI	Duration	Severity	Intensity
Dry	**3**	78	-111.15	-1.43
	12	64	-98.70	-1.54
Wet	**3**	61	94.79	1.55
	12	61	93.31	1.53

Further evaluation for SPEI was conducted over six homogeneous climatic zones as delineated by Indeje et al. [59]. The SPEI values for each region was identified by averaging the values at grid cell as presented in **Figure 1**. The regions are as follows: R1- western sides; R2-Southwest; R3-Northwest; R4-Northeast; R5-Southeast; and R6-South coastal area. **Figures 4 and 5** demonstrate the linear trend for dry and wet events for different time scales across the six regions during the period of 1981 to 2016.It can be noted that in both timescales, the R1, and R2 depict increasing trend in wet events while the rest of the regions show increase in dry events during the study period. R1 and R2 is characterized by high elevations while R3, R4, and R5 is mostly occupied by the bare lands of arid and semi-arid climate. These regions experience below-normal rainfall and high temperature, resulting to high evapotranspiration as compared to R1 and R2 which is characterized by dense vegetation cover and raised water table. Moreover, the high terrains in R1 and R2 produce lee rain shadows and block the passing of rain bearing disturbances in other regions [88]. In-depth analysis at each grid cells along the homogenous zones was conducted based on duration, severity and magnitude of occurrences of some significant anomalous incidences. **Table 2** highlights the evolution of dry/wet events for some noteworthy cases over the study region. The dry/wet years highlighted concurred with similar years as noted over the whole area average (**Figure 3**).

The results from analyses of frequency of wet and dry events for SPEI-3 for all grids pixels across the study domain demonstrate that moderate events predominate while extreme events occur least frequent across all grid cells during the study period. It is further noted that variations of wet/dry events occur across different grid cells from one-time scale to another. This agrees with previous studies that observed similar variations of anomalous climate events across different parts

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of the study domain [42-44, 91]. For instance, the wettest event for SPEI-3 was recorded in grid cell 58 during May 1981 and the duration for occurrence lasting for 87 months. Likewise, the prolonged duration of dry event for SPEI-3 was observed in pixel 36 and 49 lasting for 83 months. Regarding the severity of below and above normal events over the study domain, **Table 2** gives locations which had experienced these abnormal climatic cases. The most severe dry event for SPEI-3 was remarked in grid cell 36. More notably, the severe wet event was experienced over similar grid cell 36 with a magnitude of 125.95. This shows that the region experiences both extremes as compared to other regions over the study domain, a feature worth further investigation.

The findings for SPEI-12 based on individual grids for the analysis of wet and dry events frequency demonstrate that moderate events prevail while extreme events occur least frequent across all grid cells during the study period. The wettest event for SPEI-12 was experienced March 1998 in grid cell 34 and 55 with the duration of occurrence persisting for 97 months. Drought analysis demonstrated prolonged duration of dry event in grid cell 7 for 82 months. Concerning the severity of below and above normal events over the study domain, **Table 2** show that most severe dry event for SPEI-12 ensued in pixel 62. On the contrary, the severe wet event was noted over grid cell 17 and 63 with a magnitude of 119. Overall, moderate intensity of both wet and dry events for SPE-3 and 12 was experienced across the study domain during the study duration except for grid cell 55 that recorded high intensity of SPEI ≥ 1.5. This agrees with previous studies conducted over various parts of the study domain or based on different indices [43, 89, 90].

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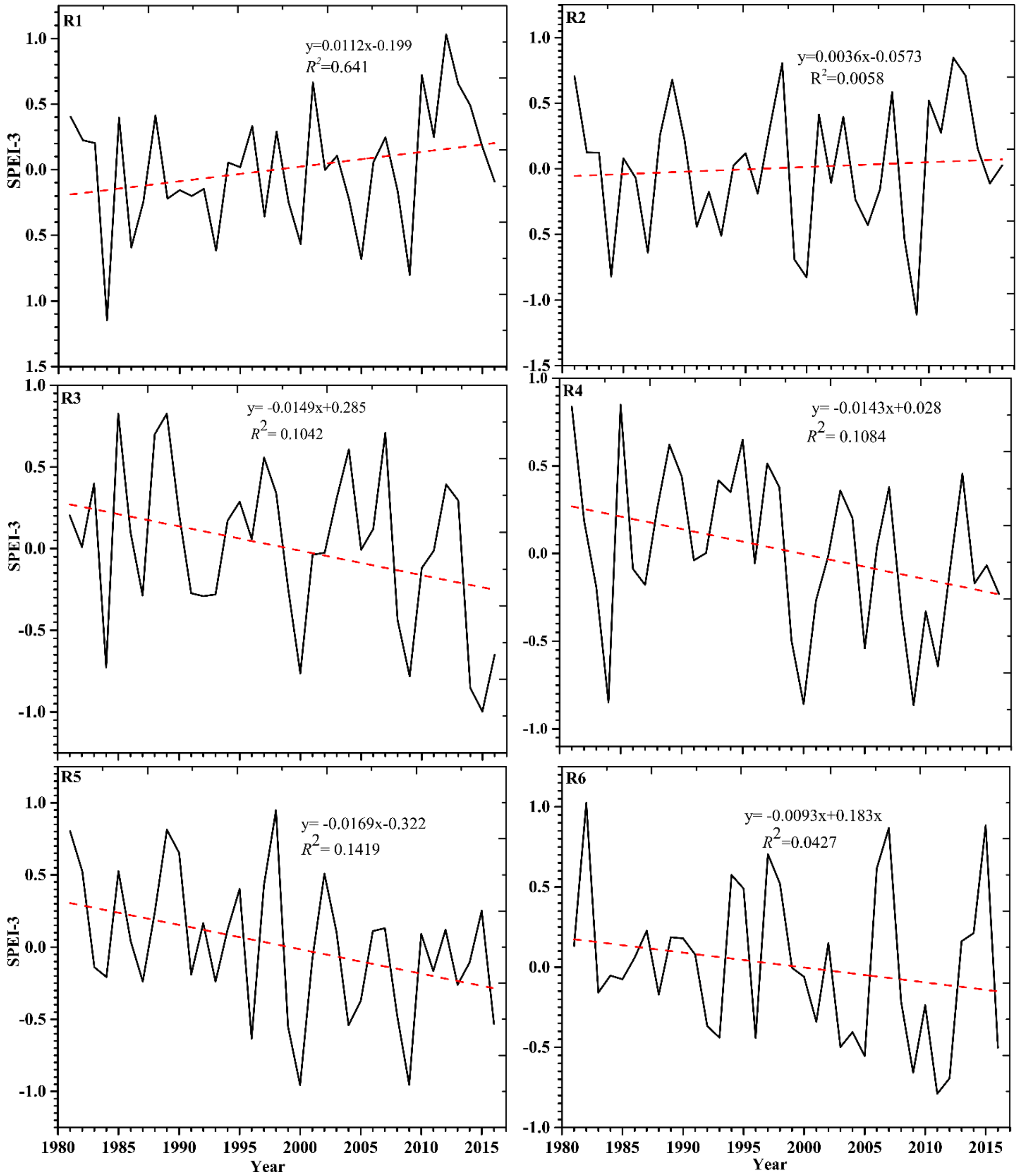

Figure 4. Linear trends of dry and wet events for SPEI-3 over six distinct climatic zones as presented in **Figure 1**

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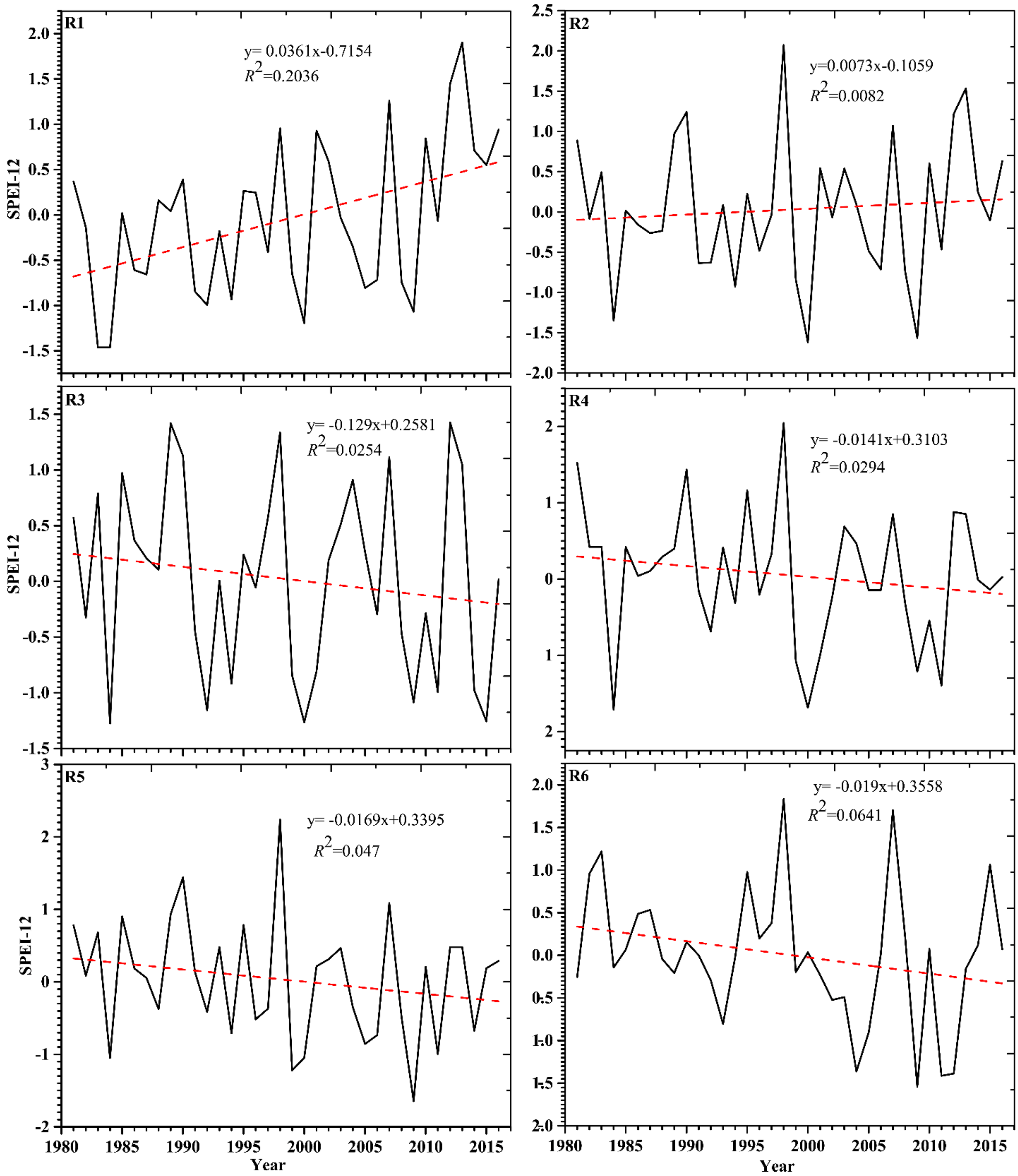

Figure 5. Linear trends of dry and wet events for SPEI-12 over six distinct climatic zones as presented in **Figure 1**

Table 2. The duration, severity and intensity of occurrence of some of the major dry and wet events (SPEI ≤ -1 SPEI ≥ +1) over each grid cell in Kenya, 1981- 2016

Grid	Duration	Severity	Intensity	Grid	Duration	Severity	Intensity
Dry event for SPEI-3				**Wet event for SPEI-3**			
4	80	-110.74	-1.38	**4**	81	115.69	1.42
15	81	-109.76	-1.35	**26**	80	117.26	1.46
16	81	-109.74	-1.35	**44**	85	121.71	1.43
27	82	-114.28	-1.39	**48**	81	117.61	1.45
36	83	-114.81	-1.38	**72**	87	125.92	1.44
49	83	-112.69	-1.35	**73**	80	119.58	1.49
67	80	-107.9	-1.34	**76**	80	116.05	1.45
Dry event for SPEI-12				**Wet event for SPEI-12**			
7	82	-112.69	-1.37	**7**	81	111.65	1.37
13	80	-112.28	-1.40	**27**	80	116.22	1.45
17	78	-110.48	-1.41	**32**	85	119.88	1.41
36	76	-107.69	-1.41	**38**	81	115.89	1.43
48	78	-108.77	-1.39	**47**	80	113.5	1.42
55	79	-108.21	-1.36	**53**	97	97.59	1.54
62	78	-113.83	-1.45	**58**	81	115.83	1.43
63	77	-112.19	-1.45	**77**	87	119.4	1.37

3.3 Spatial patterns of SPEI in the study area

The spatial pattern of frequency of severe and extreme dry (wet) cases for the SPEI-3 and 12 months period are presented in **Figures 6 and 7,** respectively. From the analysis introduced in **Figure 6**, it is apparent that the study area experiences mild extreme dry events in both categories whilst moderately severe dry events dominate the most parts of the domain. For instance, the frequency of severe dry events for SPEI-3 varied from 3.25 in grid cell 72 to 6.51 in pixel 57, suited in northeastern region. On the other hand, extreme dry events depicted uniform distribution over the study locale with low incidences during SPEI-3. The percentage occurrence ranged from 0.23 in grid cell 27 and 36 to 3.72 in grid cell 53, along northeastern area. Moreover, maximum frequency recorded in pixel 63 with percentage value of 1.86. Overall, high intensity and frequency of drought are noted during SPEI-3.

Analyses for severe and extreme wet events are presented in **Figure 7.** The pluvial events were mainly found in the western parts, extending towards southern sides and partly central areas during the severe wet events for SPEI-3 while extreme pluvial covered most parts of the study domain. The frequency of severe wet events for SPEI-3 varied from 3.25 in grid cell 59 and 50 to 7.9 in pixel 5, suited in western region. On the other hand, maximum frequency was recorded in pixel 59 with percentage value of 3.25 whereas minimum wet event observed over grid 6 with recorded value of 0.46.

Meanwhile, assessment for SPEI-12 revealed occurrence of maximum severe dry event observed in grid cell 42 (8.6) characterized by ASAL ecosystems while least severe dry scenario recorded over in grid 77 (2.09) along coastal region. Over ASAL areas, anomalous soil moisture content restraints dehydration as well as little vegetation cover results to depressed transpiration

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rates, ensuing in low mean latent heat flux as compared to over humid lands [6]. Extreme dry events depict bimodal distribution over the study locale with least occurrences of extreme events recorded during the study duration.

The severity and extreme wet events are presented in **Figure 7.** The pluvial events were mainly noted in the western parts, extending towards southern sides and partly central areas during the severe wet events while strong wetness is observed over northeastern during the SPEI-12 timescales. The frequency of severe wet events for SPEI-12 was observed in grid cell 16 (9.06) while minimum severe wet event observed over most grids namely, 64, 65, and 43 (0.23), situated along the northeastern sides. Meanwhile, extreme pluvial events had percentage occurrence ranging from 0.23 over grid cell 23 to 4.18 in grid cell 34.

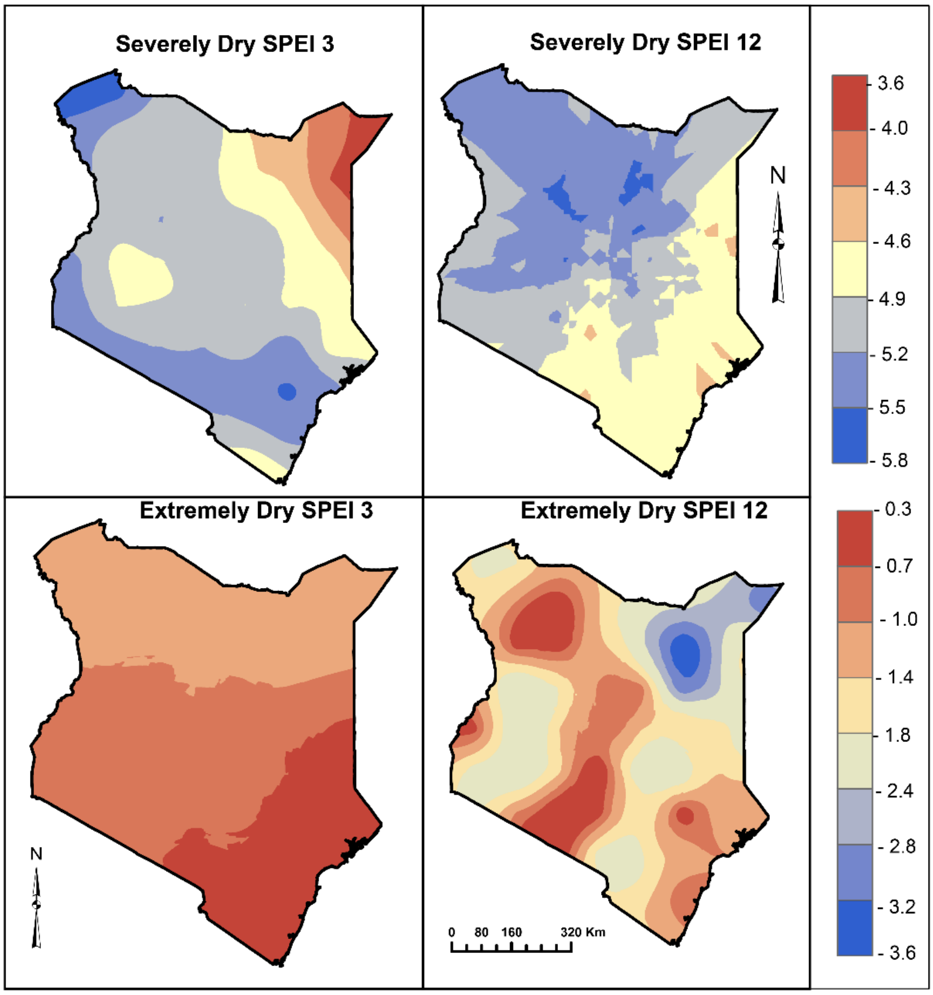

Figure 6. Frequency of severe (top) and extreme (bottom) dry events computed for the SPEI-3 and SPEI-12 month respectively over Kenya, 1981-2016.

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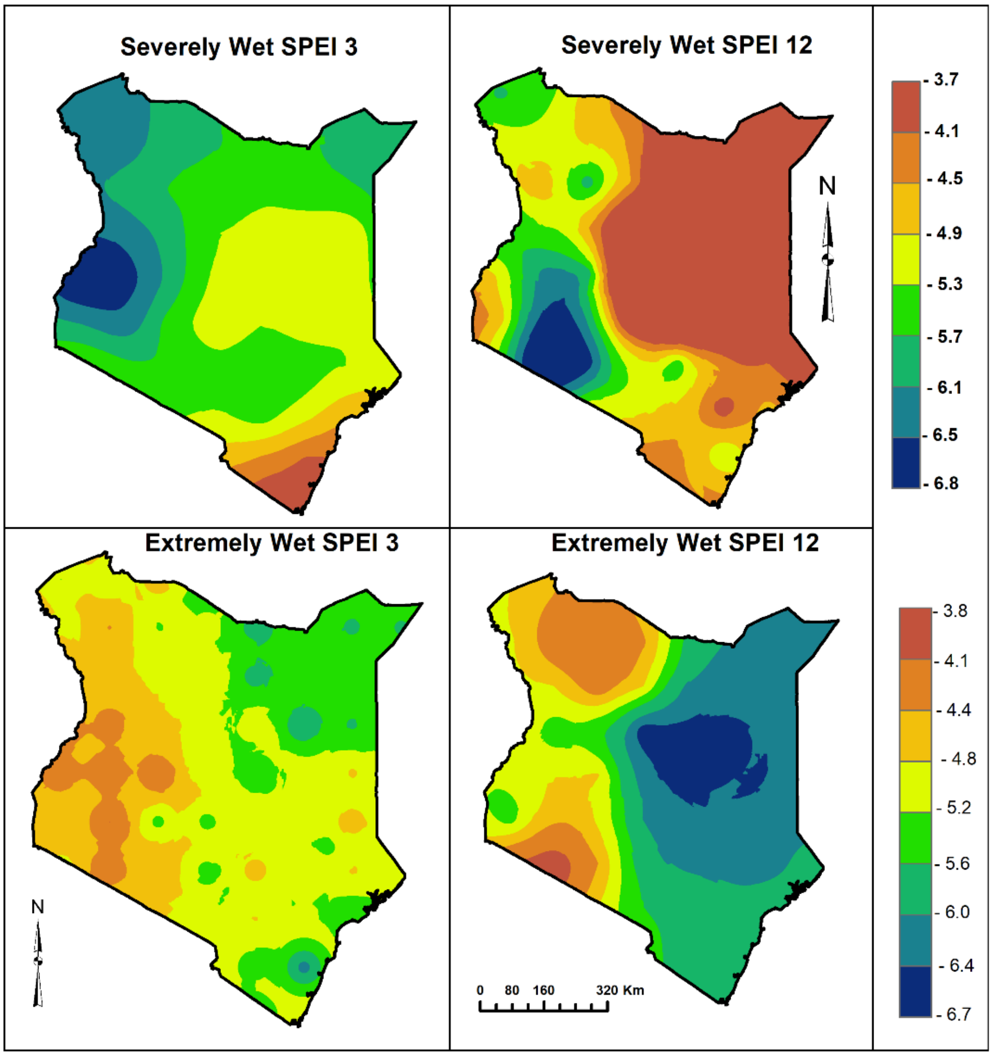

Figure 7. Frequency of severe (top) and extreme (bottom) wet events computed for the SPEI-3 and SPEI-12 month respectively over Kenya, 1981-2016

4 Discussion

Drought occurrence is a stochastic natural phenomenon that is mainly influenced from the changes in climatic variables, namely precipitation and temperature. The variability of both variables on historical perspective have been observed a number of existing literatures with sharp increase being noted, most significantly in temperature towards the end of twentieth century and beginning of twenty first century era [35]. It is worth remarking that the observed trends towards the end of 21st century are mainly as a result of GHG-induced changes and changes caused by internal variability, e.g by ENSO and the Inter-decadal Pacific Oscillation (IPO) [29, 83-85]. This is equally echoed in a recent Intergovernmental Panel on Climate Change (IPCC) report that stated unequivocal warming from 1950s across the globe, as a result of anthropogenic induced global warming [4]. The observed variability in climatic variables has profound impact in drought/flood mechanism which is influenced by ratio of precipitation and potential evapotranspiration [29, 80, 81]. For instance, increase in surface air temperature towards the end of the 21st century will

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significantly influence the PET level which characterizes the evaporative demand of the atmosphere. Other factors include the low humidity and abundant solar radiation which remains a signature feature over the study domain [82].

As a consequence of global warming, there is apprehension that increased temperature which is linked to evapotranspiration may lead to increase in drought incidences and severity across many regions [12, 13, 50]. The study domain has been experiencing rapid increase in extreme events characterized by drought and pluvial scenarios towards end of 20th century and beginning of 21st century. While drought event has prevailed, there are extreme flood conditions with devastating consequences which are equally witnessed [31]. Evidently, the severity and intensity of drought/flood, along with abrupt deviations between the extremes continues to pause a threat to the livelihoods of people. Hence, the need for continuous evaluation of drought and flood occurrences over the study domain remains paramount.

The results of this present study which examined meteorological drought and pluvial scenarios over Kenya using a robust index of SPEI during study duration, points to decreasing patterns in moderate wetting occurrences towards the end of twentieth century which also in harmony with past studies [40, 57, 86]. Moreover, the impact of drought is shown to vary from low-lying region to humid vegetative areas, mainly due to surface and atmospheric interaction dynamics. For example, the changes in wet events is mostly associated with heightened heating Sea Surface Temperatures (SST) of Indian Ocean which alters the Walker circulation anomalies contributing to drying trends [27]. On the other hand, the recent drying tendency over the study domain, mainly as result of changes in the tropical SSTs variations over Indo-Pacific [40, 50]. This may lead to substantial increase in regional aridity and drought areas [12, 13]. In addition, the large-scale atmospheric circulation changes associated with a weaker West African monsoon also have made contribution [26, 27]. Consequently, this will impact negatively on the area's economy that entirely relies on season-based farming for livelihoods and sustainability [57, 58].

This study thus highlights key features of drought and pluvial events, which remains major climatic extremes occurrence affecting people and socio-economic infrastructure [66, 67]. Understanding historical complexities and dynamics of drought and flood events build a momentum to conduct further studies on future evolution of this extreme events over study area with view of recommending appropriate and timely polices to avert damages and loss of life. This study reveals occurrences of mild extreme dry events whilst moderately severe dry events dominate over most parts of the domain. High intensity and frequency of drought are noted in SPEI-3 whereas least occurrences of extreme events are recorded in SPEI-12.

5 Conclusions

Drought remains one of the most complex natural phenomena affecting the economy, environment and society at global, regional and local level. The present study examines drought and wet events by characterizing the trends, intensity, severity and frequencies based on widely

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accepted indices of SPEI over Kenya, East Africa from 1981 to 2016. The spatial and temporal evolution of dry and wet events is captured by both 3- and 12- month SPEI. The drought incidences were observed during the period 1984, 1987, 2000, 2006, 2009, 2015, and 2016 for SPEI-3 whilst the SPEI-12 demonstrated the manifestation of drought during the years 2000 and 2006. The wettest period was noted in 1997-1998 coinciding with the El Nino event, depicting the better performance of SPEI index in capturing the underlying mechanisms of dry/wet conditions.

SPEI -3 shows an occurrence of moderate to severe and moderate to extreme drought cases towards the end of the twentieth century whilst SPEI-12 depicts an overall increase in severe drought occurrence over the study location with observed intensity of -1.54 and cumulative frequency of 64 months during the study period. Spatial patterns show that western and central highlands depict increasing trend in wet events while the rest of the regions show increase in dry events during the study period. Moreover, moderate dry/wet events are dominant while extreme events occur least frequent across all grid cells during the study period.

It is apparent that the during the study duration, the region experiences mild extreme dry events in both categories whilst moderately severe dry events dominate over most parts of the domain. High intensity and frequency of drought are noted in SPEI-3 whilst least occurrences of extreme events are recorded in SPEI-12. Whereas drought event has prevailed, there are extreme flood conditions with possible devastating consequences equally witnessed.

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