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Article

Characterization of historical trends of droughts and pluvial scenarios over Kenya, East Africa

Brian Ayugi[1], Guirong Tan[1*], Niu Rouyun[2], Dong Zeyao[3], Moses Ojara[4], Lucia Mumo[1], Hassen Babaousmail[5], Victor Ongoma[6]

[1]Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters/Key Laboratory of Meteorological Disaster, Ministry of Education, Nanjing University of Information Science and Technology, Nanjing 210044, China; ayugi.o@gmail.com (B.A)

[1]Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters/Key Laboratory of Meteorological Disaster, Ministry of Education, Nanjing University of Information Science and Technology, Nanjing 210044, China; tanguirong@nuist.edu.cn (G.T)

[2]National Meteorological Centre, China Meteorological Administration, Beijing 100081, China; niury@cma.gov.cn (N.R)

[3]NUIST-Reading Academy, Nanjing University of Information Science and Technology, Nanjing, Jiangsu 210044, China; 2166139679@qq.com (D.Z)

[4]Uganda National Meteorological Authority, Clement Hill Road, P.O. Box 7025 Kampala, Uganda; ojacksmoz@gmail.com (M.O)

[1]Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters/Key Laboratory of Meteorological Disaster, Ministry of Education, Nanjing University of Information Science and Technology, Nanjing 210044, China; mumolucia@gmail.com (M.L)

[5]School of Computer and Software, Nanjing University of Information Science and Technology, Jiangsu, Nanjing 210044, China; baw.hassan12@gmail.com (H.B)

[6]School of Geography, Earth Science and Environment, University of the South Pacific, Laucala Campus Private Bag, Suva, Fiji; victor.ongoma@gmail.com (V.O)

*Correspondence: tanguirong@nuist.edu.cn

Abstract: This work examines drought and pluvial 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 the wettest period, 1997 and 1998 coinciding 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 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

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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.

Keywords: Drought, SPEI, Pluvial, Linear trend, Mann-Kendall, Kenya.

1. Introduction

Drought remains the most complex natural phenomenon affecting the economy, environment and society at global, regional and local level [1]. For instance, the occurrence of prolonged rainfall failure remarkably alters water resources, ecosystem balance, and impact on agriculture [2, 3]. In the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC AR5), 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 [8] there is still a dearth in the understanding of drought evolution, frequency, and severity of occurrence from one region to another. This is due to its unique characteristic as compared to other natural disasters. Thus, this makes it difficult for scientists and policy makers to determine the exact timing of inception and termination of either meteorological, agricultural or hydrological drought events [9-11].

The global widespread of droughts have reported in many regions with noticeable increase over the recent decades, as a result of the ongoing global warming [4, 5, 12-14]. To illustrate, 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), classified as an arid and semi-arid (ASAL) region, 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 [31, 32]. For example, Kenya, Uganda, Somalia, and Ethiopia experienced severe drought event in 2010-2011 [33], 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]. Moreover, global predictions based on Palmer Drought Severity Index (PDSI) shows that desiccation will become more severe and widespread over EA region with reduced precipitation and increased evaporation [13].

Kenya has been witnessing 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 impacts on agriculture, economy, water resources and environment over the study region [41-44]. These researchers have employed various drought indices recommended by the World Meteorology Organization [11].

For instance, [43] investigated the severity and duration of drought in Kenya from 1987 to 2016 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

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analyzed correlation between the two indices. On the other hand, [42] used Standardized Precipitation Index (SPI), to characterize seasonal and annual droughts in Laikipia west sub-county from 1984 to 2014, focusing on drought events occurring during the two rain seasons in Kenya.

Moreover, [45] employed Effective Drought Index (EDI), as an accurate index regarding to on-set, and spatial and temporal analysis of drought along the Tana-River basin in Kenya. In contrast,[46] stated negatively that EDI seemed to have weak imprecision in monitoring the inception, cessation and accumulated stress. [47] applied both SPI and EDI to characterizing drought (1980-2016) in the upper Tana River Basin, where nearly all agro-ecological zones of Kenya are located. Both exhibited that the south-eastern basin parts were more likely to experience severe droughts as compared to the north-western parts.

The various indices employed by numerous researchers over the study domain highlight a glimpse of variation and occurrence of historical drought events one region to another, without necessarily indicating the magnitude of trends and future projections. Furthermore, some indices employed reported a contrary occurrence of dryness/wetness events while some showed incoherence in spatial patterns of drought frequencies.

Thus, there is a need to establish a drought early-warning system that provides reliable information for preparedness and mitigation to minimize the damage and loss via increasing adaptive capacity [19]. However, it is a challenge to find a universally applicable criterion for the whole country due to the complexity of landforms and meteorological conditions. So far, very few studies [42, 43] have employed a drought monitoring algorithm that is grounded on current rainfall and temperature anomaly, which can be used as a predictor of the severity and the duration of possible occurrence of extreme climatic events.

The present study examines drought and pluvial events over the study domain, characterizing the trends, intensity, severity and frequencies based on widely accepted index, SPEI (Vicente-Serrano et al., 2010), from 1981 to 2016. The remaining sections are organized as follows: Section 2 highlights characterization of the study locale, data and methodology while results and discussions are enumerated in section 3. Finally, conclusion and recommendation are presented in part 4.

2. Materials and Methods

2.1. Study Area

The study location 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. 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 a coastline of Indian Ocean regulating local climate whereas the western domain has 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) [37, 39, 49]. Overall, a dry anomalous climate is experienced despite the region being situated along equatorial wet tropical belt.

Numerous researches have examined the influencing factors regulating the rainfall variability [31, 33, 38, 50-52]. The seasonal rainfall is mainly as an influenced by oscillation of Intertropical convergence zone (ITCZ) and local mesospheric factors [53, 54] whereas interannual variability is mainly influenced by global teleconnection dynamics [55, 56].

Downward trend of long rains has been reported in many studies [29, 37, 38, 57, 58] and an opposite trend in short rains [37, 39]. This is of great concern to farmers who have for long rely on long rains season for planting purposes due to changes in climatic patterns. [54] and Camberlin (2018) elaborate more on general circulation features of the study domain.

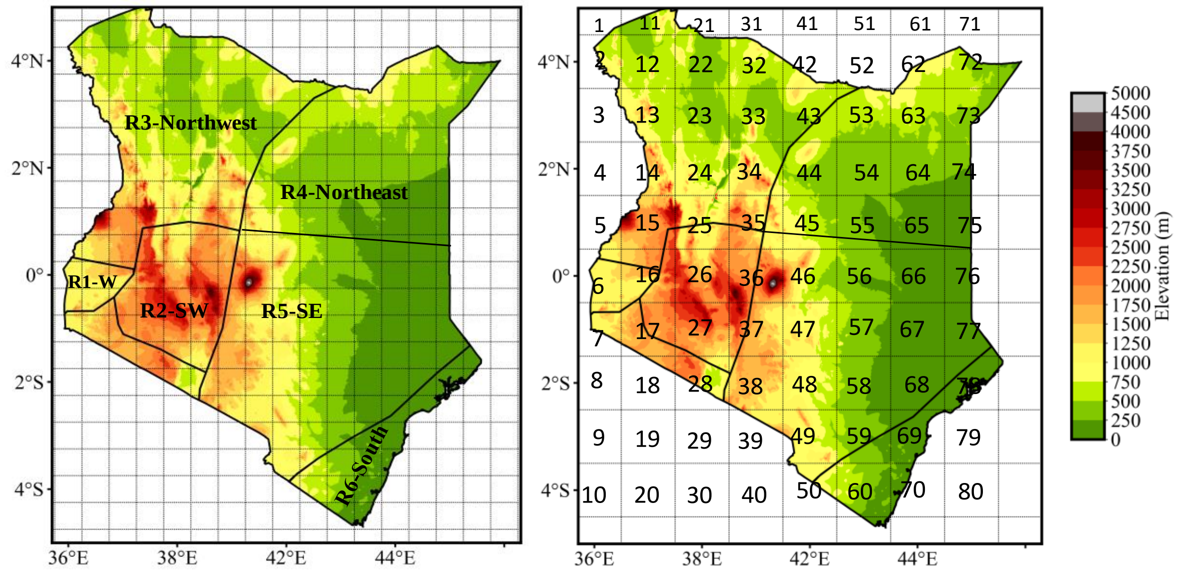

Figure 1. Study area with distinct homogeneous locations as delineated by [59] and the respective grid cells in each region.

2.2. Data Description

Comprehensive assessment of drought and pluvial events over a region involves use of a several climatic and socio-economic datasets. This study utilizes monthly maximum and minimum temperature datasets from Climatic Research Unit (CRU; [60]), monthly precipitation datasets obtained from Climate Hazard Group Infrared Precipitation with Station (CHIRPS; [61]), and Multi-model mean ensemble (MME) of five selected regional climate models (RCMs), including the CM5A-MR, CSIRO, EC-EARTH, MIROC5, and MPI-ESM-LR.

Both satellite derived precipitation datasets and RCMs were recently evaluated by inferring their performance over the study domain [62, 63]. The CHIRPS data covers the period 1981 to 2016. The CRU data with similar temporal resolution was used in deriving the potential evapotranspiration (PET). The MME of five RCMs are employed to delineate the recent past and future trends and variability of climatic features over the study domain. Historical analysis was performed during 1951-2005 while projections under different Representative Concentration Pathways (RCPs 4.5, 8.5), was for the period 2010 to 2100.

A summary of all datasets used is shown in **Table 1** indicating the type, sources and duration. In the present study, all datasets were extracted from 80 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.

Table 1. Data types, sources and the duration, retrieved over Kenya [34° E- 42° E and 5° S - 5°N]

Type of Data	Source	Duration
Topography	NOAA-NGDC	-
Monthly Temperature	Climatic Research Unit	1981-2016
Monthly Rainfall	Climate Hazard Group Infrared Precipitation with Station (CHIRPS)	1981-2016
Regional Climate Model monthly temperature & rainfall	Rossby Atmospheric modelling Centre (RCA4) for	1951-2005 2006-2100

2.3 Methods and Metrics

2.3.1. *Theil-Sen Slope*

The current study employed the Theil-Sen Slope (TSS) technique to appraise the long duration tendency of temperature and precipitation anomaly over the study region. This technique is utilized to evaluate the magnitude of the slope of the linear trend of given data [64]. This method is considered effective due to its robust features of outliers in the datasets. It is not affected by any extreme distributions and does not entail any normal distribution of the residuals. It has been generally employed in various studies to examine the linear tendencies of hydro climatic variables across various domains (e.g [7, 39, 65].

2.3.2. *Mann-Kendall test*

The study employed Mann-Kendall (MK) test [66, 67] to detect the significance of the linear trends based TSS analysis. The non-parametric feature of MK test allows it to confirm the existence of trend in any data against the null hypothesis of no trend. In addition, it does not require the sample to conform to any specific probability distribution since it works well even with insufficient or abnormal values.

The sequential MK trend applied in the present study explicitly elucidates the trends and significance of climate parameters and the influence of changes on water resources management and drought severity over the study area. The changes are demonstrated using forward u (t) and backward u′ (t) trends for temperature and rainfall season. The significance level (i.e., α = 0.05 significant level) for this study is depicted when intersection of u (t) and u′ (t) occurs above (below) the upper (lower) limit point. Numerous hydro-climate studies across various domains have employed MK tools for trend analysis [68-70].

2.3.3 *Standardized Precipitation Evapotranspiration*

The SPEI is computed using rainfall 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. [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 [76]. The values for SPEI, which defines the characteristics of drought or pluvial condition in terms of severity, intensity, and duration of occurrence, are indicated in **Table 2**. 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. In the present study, the threshold SPEI ≥ -1.0 corresponds to dry event whereas SPEI ≥ +1.0 represent wet events over the study domain.

The SPEI values were calculated in two-time scales namely, the average annual SPEI-3 and SPEI -12. Shorter time scale of 3 months is employed to detect soil moisture anomalies while longer time scales determine hydrologic drought [77]. The month of March to May represent the growing season, supporting 80 % of agricultural activities. In addition, soil moisture is fully utilized during this season, hence the deficit is associated with drought condition [78, 79]. Significant percentage of total annual rainfall is experienced during MAM season covering entire study location, and as such, water availability for land cover vegetation is primarily influenced by MAM rains.

However, the study disregarded in-depth assessment of other timescales beyond the scale 3 which are not regarded as growing season since they are usually characterized by dry anomaly weather patterns. In the event that rainfall is experienced during the months outside growing season, it is usually not useful for agricultural activities in the study domain. Thus, the current study examines how drought/wetness affect the region during this 3-month and 12-month time-scales.

The intensity 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. Consequently, the current study adopted frequency of occurrence as the total of months that the SPEI value attains the set point value as stated in **Table 2**, divided by the number of months in the whole duration. A summary of methodology and flow analysis herein utilized in this study is demonstrated in **Figure 2.**

Table 2. SPI classification systems [71]

SPI Values	Category	Time in Category
-0.99 to 0.99	Near normal	~24%
-1.0 to -1.49	Moderately dry	~9.2%
-1.5 to -1.99	Severely dry	~4.4%
≤2.00	Extremely dry	~2.3%
1.0 to 1.49	Moderately wet	~9.2%
1.5 to 1.99	Severely wet	~4.4%
≥2.0	Extremely wet	~2.3%

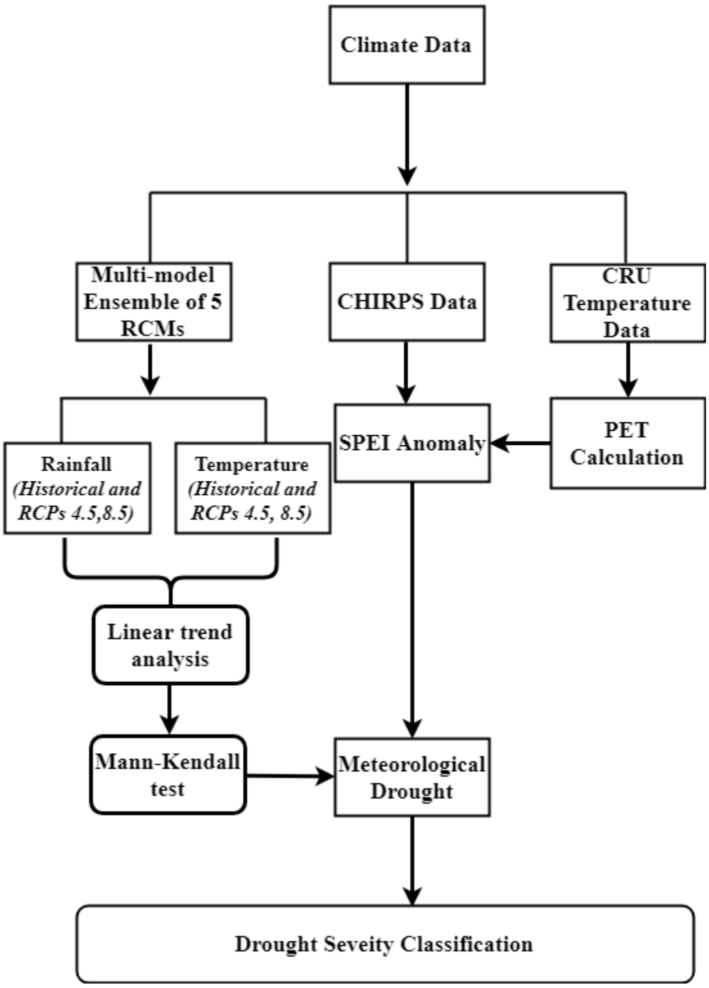

Figure 2. Flowchart illustrating the different steps followed in the drought computation.

3. Results and Discussion

3.1. Trends of rainfall and temperature

Drought occurrence is stochastic natural event that is mainly influenced from the changes in climatic variables, namely precipitation and temperature. The temperature and precipitation anomalies over study domain in yearly time step is presented in **Figure 3** while statistical analysis of the rate of change per year in every decade are shown in **Tables 3 and 4,** respectively. The results demonstrate variability in both temperature and precipitation on historical perspective although sharp increase is witnessed towards the end of twentieth century and beginning of twenty first century era.

In particular, the linear trends exhibit decreases in observed precipitation from 1960 to 1980s and slight intensification proceeding the end of the centenary. On the other hand, a steady increase is noted in temperature as indicated in **Tables 3 and 4**. This is agreement with recent IPCC report that stated unequivocal warming from 1950s across the globe, as a result of anthropogenic induced global warming [4].

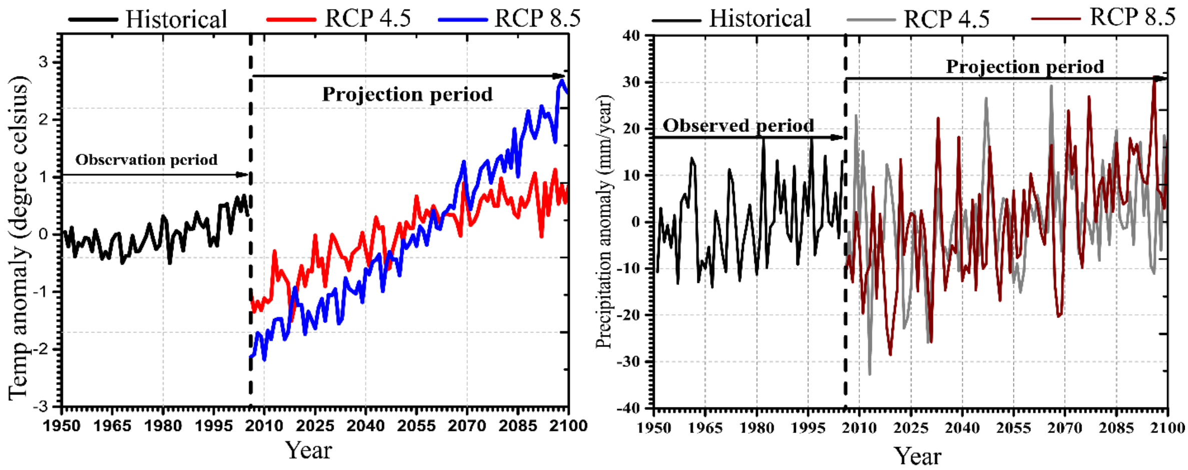

Figure 3. Temperature and precipitation anomaly over Kenya for the period 2006 to 2100 compared with 1951 to 2005 under representative concentration pathways (RCP4.5; 8.5) based on multi-model ensemble during March to May season.

The observed variability in climatic variables has profound impact in drought/flood mechanism which is influenced by ratio of precipitation and potential evapotranspiration [80, 81]. For instance, increase in surface air temperature towards the end of the 21st century over the study domain will significantly influence the PET level which epitomizes the evaporative demand of the atmosphere. Other factors encompass the low humidity and abundant solar radiation which remains a signature feature over the study domain [82].

Table 3. Decadal change in temperature (°C/year) and precipitation (mm/year) over Kenya based on RCA4 model data, during March to May season 1951-2005.

Historical	1950s	1960s	1970s	1980s	1990s	2000
Mean(°C)	24.7	24.6	24.7	24.8	25.0	25.3
Change (°C/Year)	0.02	0.06	0.3	0.2	0.36	-0.17
Mean (mm)	822.3	808.5	816.6	860.6	871.5	881.0
Rate (mm/Year)	13.15	-16.08	-10.83	-1.21	4.08	5.13

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Table 4. Decadal change in temperature (°C/year) and precipitation (mm/year) over Kenya based on RCA4 model data, 2011-2100 for RCP 4.5 and 8.5 respectively during March to May season.

RCP 4.5	2010s	2020s	2030s	2040s	2050s	2060s	2070s	2080s	2090s
Mean(°C)	25.6	26.0	26.2	26.4	26.8	26.9	27.1	27.1	27.2
Change (°C/Year)	-0.17	0.49	0.16	0.15	0.49	0.005	0.69	0.38	0.42
RCP 8.5									
Mean (°C/Year)	25.8	26.0	26.3	26.8	27.3	27.9	28.4	28.9	29.5
Change (°C/Year)	0.61	0.41	0.47	0.62	0.49	1.22	0.77	0.74	0.64
RCP 4.5									
Mean (mm)	887.3	806.8	859.9	932.9	870.3	946.1	922.9	946.2	942.9
Rate (mm/Year)	9.93	-8.75	4.74	10.02	-3.95	1.57	-22.38	-10.91	-12.95
RCP 8.5									
Mean (mm)	810.8	905.8	909.2	910.6	922.0	915.5	1028.6	1032.1	1067.9
Rate (mm/Year)	-16.45	-1.45	-6.81	3.79	15.77	-28.75	-12.1	5.58	-8.33

Further analysis of Sequential MK test of the resulting linear trends is demonstrated in **Figure 4** for temperature and rainfall with summary statistics presented in **Table 5**. As shown in **Figure 4,** the seasonal temperature and rainfall over Kenya exhibit increasing tendency for both observed and projections patterns. Significant intensification in temperature is observed both in historical and projected trends while precipitation demonstrate 99% confidence level during high emission scenario and 95% under RCP45 scenario. It is worth noting that the observed trends towards the end of 21st century are limited to GHG-induced changes and not changes induced by internal variability, e.g by ENSO and the Inter-decadal Pacific Oscillation (IPO) [83-85].

As a consequence of global warming, there is apprehension that increased temperature which is linked to evapotranspiration may lead to increased drought incidences and severity across many regions [12, 13]. Although wetting trend is observed in historical patterns, a decreasing trend in noted in 1970s which agrees with past studies [40, 57, 86]. This is mostly associated with heightened heating Sea Surface Temperatures (SST) of Indian Ocean which alters the Walker circulation anomalies contributing to drying trends.

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Table 5. Summary of Mann-Kendall (MK) test statistic for seasonal (MAM) temperature and rainfall over Kenya for period 1951-2005, and 2011-2100 for RCPs during March to May season.

	Temperature			**Rainfall**		
	Historical	**RCP45**	**RCP85**	**Historical**	**RCP45**	**RCP85**
S	644	2853	3523	312	771.0	1613
Z	4.7	9.9416	12.276	2.0	2.684	5.618
P(no trend)	<0.05	<0.05	<0.05	0.047308	0.00723	<0.05
Significance	Significant	Significant	Significant	Significant	Significant	Significant

*(**S**; represent the variance while **Z** depicts significance score of the trend, with negative (positive) denoting downward (upward) trends, respectively).*

The recent drying trend over the study domain may lead to substantial increase in regional aridity and drought areas [12, 13]. Consequently, the recent trend is a setback to the area's economy that entirely relies on season-based farming for livelihoods and sustainability [57]. Past studies have reported contrasting findings on the future projections of MAM rainfall, with [86], reporting reduction in future trends, relative to annual and short rains which are projected to increase significantly.

However, [36] on the other hand projected an increase in MAM rainfall, agreeing with the present study that continues the debate on the future MAM climate and possible drought scenario. Nevertheless, the projected changes could lead to more flash floods and concurrent droughts in the near future [87]. Hence, the need for evaluation of drought and flood characterization over the study domain that the present study explores.

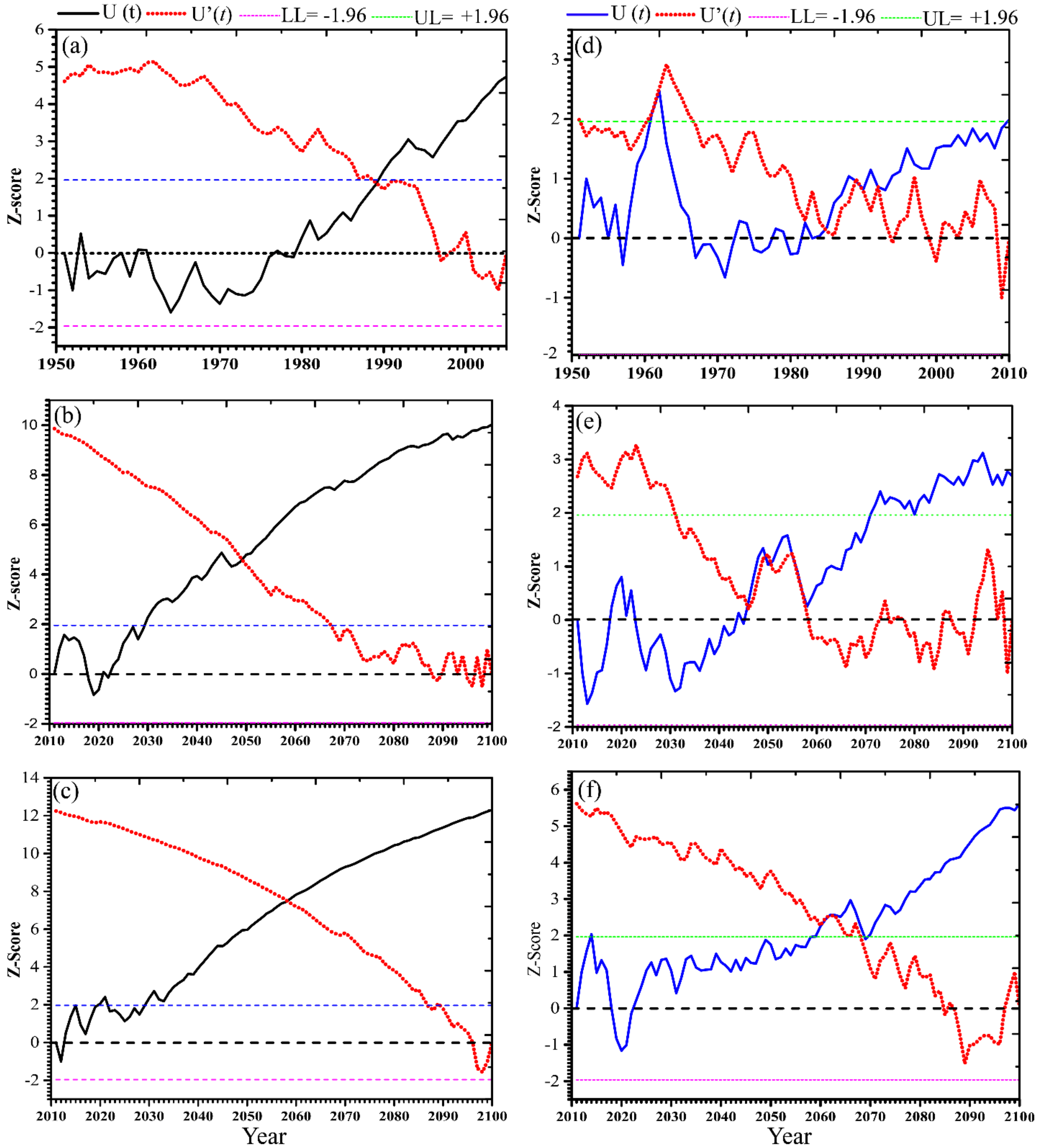

Figure 4. Abrupt change in surface air temperature range for (a) historical, (b) RCP4.5, (c) RCP8.5 and precipitation for (d) historical, (e) RCP4.5, and (f) RCP 8.5 as derived from Sequential Mann-Kendall test statistics, u(t) is forward sequential whilst u'(t) is backward sequential statistics over Kenya during March to May season.

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

Figure 5 provides an overview of historical analysis for SPEI 3- and 12 months for the period 1981 to 2016 over Kenya. It is apparent from results presented that SPEI-3 exhibit greater temporal occurrence of wet and dry cases whereas temporal frequency shows stability for annual period. This demonstrates that SPEI at elongated timescales respond more gradually and consistently to deviations in climatic variables indicating strong durations of annual and 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 interannual variations [41]. The evaluation of drought and wet events was conducted for moderate, severe and extreme frequencies as classified by [75].

From the SPEI-3 results (**Figure 5a**), it can be seen that the study domain experiences reduction in moderate drought events while severe and extreme cases are on upsurge nearing the end of the twentieth century. Despite the observed reduction in drought characteristic for SPEI-3 event, the intensity indicates moderate phenomenon at -1.43 although the severity recorded is more intense with noted value of -111.5 over the duration of 78 months (**Table 6**).

On the other hand, the SPEI-12 (**Figure 5c**) indices show an overall severe drought over the study location with observed intensity of -1.54 and cumulative frequency of 64 months during the study period (**Table 6**). This indicates that long term drought (SPEI-12) is severe while short term (SPEI-3) is much moderate and occurs over long duration. The frequency of drought events experienced is as result of changes in the tropical SSTs variations over Indo-Pacific [40, 50].

Table 6 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

In addition, the large-scale atmospheric circulation changes associated with a weaker west African monsoon also have some contribution [26, 27]. The extreme 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. 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 the better 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.

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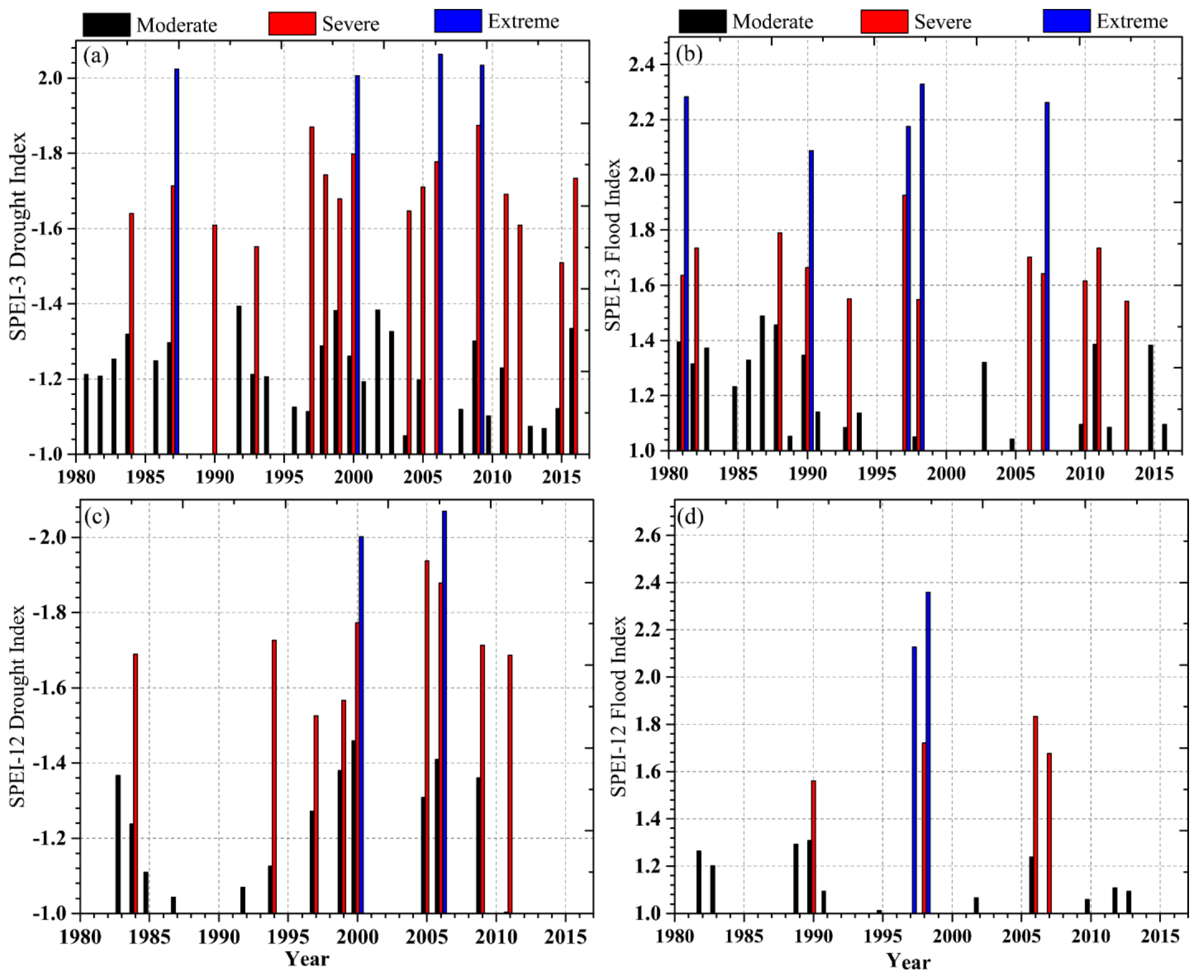

Figure 5 Evolution of the mean SPEI for 3- and 12-month timescale for moderate, severe and extreme drought and flood over Kenya showing the variation in the duration, severity and intensity of dry and wet events, 1981-2016.

Further evaluation for SPEI was conducted over six homogeneous climatic zones as delineated by [59]. **Figures 6 and 7** present 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. The rising patterns of dry events in R3, R4, R5 and R6 can be attributed to complex topography located in R1 and R2 that strongly impact the dryness in these regions. This is because, high terrains produce lee rain shadows and block the passing of rain bearing disturbances [88].

For instance, the below-normal rainfall witnessed over the eastern regions (R4 and R5) is due to presence of Great Rift Valley that separate the highlands domain characterized by raised table land on the western side (R1 and R2) as compared to lowland on the opposite side. Moreover, significant warming over the ASAL areas have also been reported in previous studies across other regions [6].

An in-depth analysis at each grid cells was conducted based on frequency, length, severity and magnitude of occurrences of some significant incidences. **Table 7** highlights the evolution of

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dry/wet events for some significant cases over the study region. The dry/wet years of all the grid cells based on the frequency, duration, severity and intensity concurred with similar years as noted over the whole area average.

This agrees with previous studies conducted over various parts of the study domain or based on different indices [43, 89, 90]. The driest month for both for SPEI-3 was experienced in pixel 26 and 63 in high altitude region and low-lying arid land, respectively. On the contrary, the SPEI-12 recorded driest month in grid cell 72 and 75, respectively, situated over northeastern sides of the study that lie in ASALs.

Meanwhile, the wettest month in May 1981 for SPEI-3 was recorded over grid cell 58 whereas in March 1998 for SPEI-12 experienced over grid cell 34. It is noted that variations of wet/dry events occur across different grid cells from one-time scale to another. This agrees with previous studies that noted similar variations of anomalous climate events of moderate to extreme dryness/wetness across different parts of the study domain [42-44, 91]. The cause of this variation from low lying region to humid vegetative areas could be attributed to surface and atmospheric interactions and dynamics.

Over ASAL areas, anomalous soil moisture content restraints dehydration as well as little vegetation cover results to depressed transpiration rates, ensuing in low mean latent heat flux as compared to over humid lands [6]. In summary, these results from analyses of frequency of wet and events for SPEI-3 and -12 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.

Table 7 presents the extent, severity, and magnitude of occurrence of some significant anomalous events over different grid cells in the study domain during the study period. The prolonged duration of dry event for SPEI-3 was observed in pixel 36 and 49 lasting for 83 months whilst for SPEI-12 was noted in grid cell 7 for 82 months. Likewise, the longest duration for wet events for SPEI-3 was 87 months recorded in grid cell 36 whereas for SPEI-12 observed in grid cell 55, persisting for 97 months.

Regarding the severity of below and above normal events over the study domain, **Table 7** gives locations which had experienced these abnormal climatic cases. The most severe dry event for SPEI-3 was noted in grid cell 36 while for SPEI-12 it ensued in pixel 62. On the contrary, the severe wet event for SPEI- 3 was experienced over grid cell 36 with a magnitude of 125.95 whilst for SPEI-12 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. The manifestation of extreme dry or wet events depicts evidence of changing climate primarily driven by anthropogenic effects and natural climate variability [30, 34]. The impact of these events is likely to impact on environment, communities, water resources, and agriculture [30].

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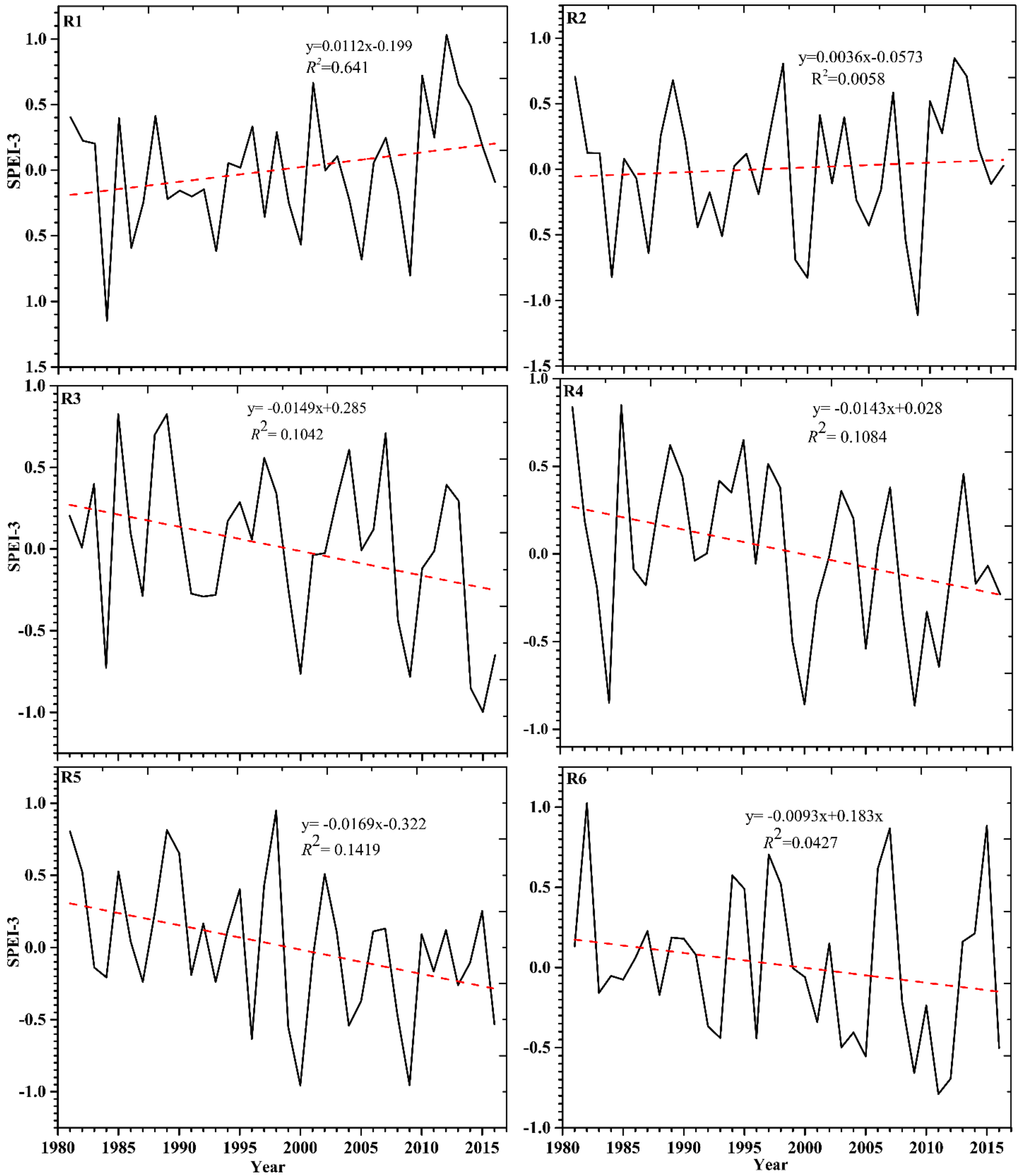

Figure 6 Linear trends of dry and wet events for SPEI-3 over six distinct climatic zones as presented in **Figure 1**

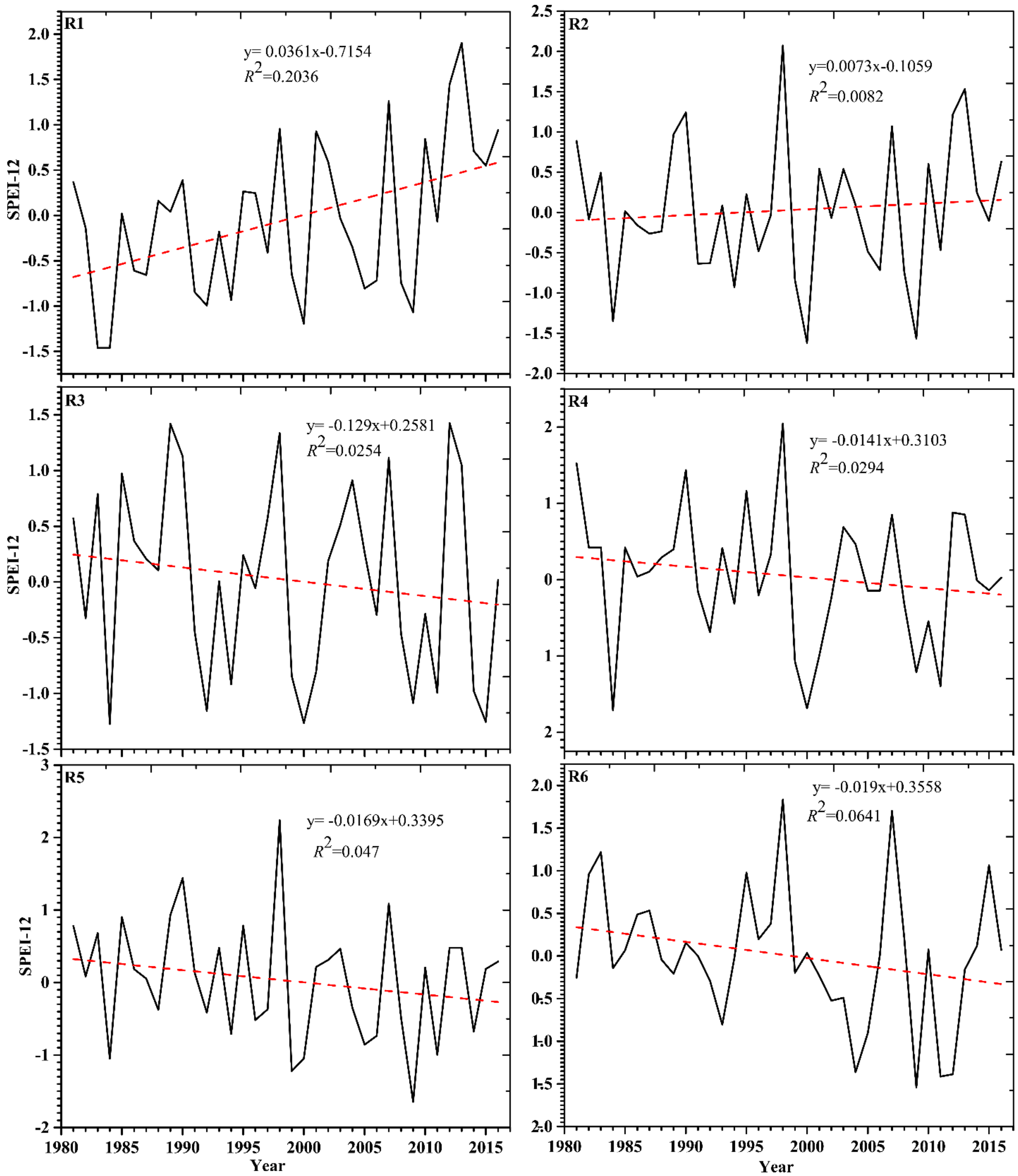

Figure 7 Linear trends of dry and wet events for SPEI-12 over six distinct climatic zones as presented in **Figure 1**

Table 7: The duration, severity and intensity of occurrence of some of the major dry and wet events (SPEI ≤ -1 SPEI ≥ +1) over 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 8 and 9,** respectively**.** From the analysis presented in **Figure 8**, it is apparent that the study area experiences mild extreme dry events in both categories whilst moderately severe dry events predominate the most parts of the domain. 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.

The maximum severe dry event for SPEI-12 was observed in grid cell 42 (8.6) characterized by ASAL ecosystems while least severe dry scenario recorded over in grid 72 (2.09), similar to the first category. Meanwhile, extreme dry events depict uniform distribution over the study locale with low incidences during SPEI-3 as compared to SPEI-12. The percentage occurrence ranged from 0.23 over grid cell 27 and 36 to 3.72 in grid cell 53.

Likewise, the SPEI-3 had maximum frequency recorded in pixel 63 with percentage value of 1.86. Overall, the no clear spatial pattern is observed from the two categories analyzed, which is in harmony with the previous studies [43, 47]. However, high intensity and frequency of drought are noted during SPEI-3 while least occurrences of extreme events are recorded during SPEI-12.

The severe and extreme wet events are presented in **Figure 9.** 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 and 12-month while extreme pluvial covers most parts of the study domain during SPEI-3 and strong wetness over northeastern during the SPEI-12 timescales.

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, the maximum severe wet events for SPEI-12 was observed in grid cell 19 (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. Similarly, the SPEI-3 had maximum frequency recorded in pixel 59 with percentage value of 3.25 whereas minimum wet event observed over grid 4 with recorded value of 0.46.

The study domain has been experiencing rapid increase in extreme events characterized by drought and pluvial events. The predominant occurrence of drought or flood events frequencies can observe to increase towards end of 20th century and beginning of 21st century. While drought event has prevailed, there are extreme flood conditions with devastating consequences equally witnessed [31]. Evidently, the severity and intensity of drought, along with abrupt deviations between the extremes continues to pause a threat to the livelihoods of people and infrastructure over the study domain.

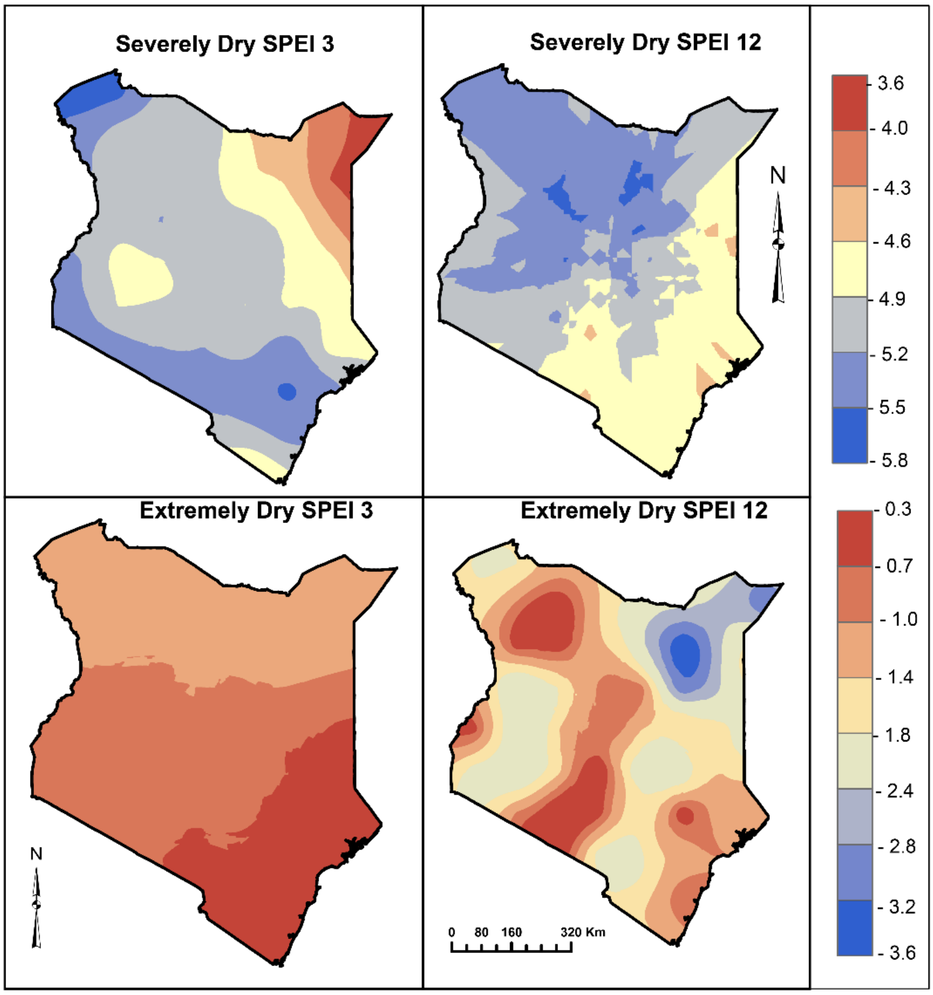

Figure 8 Frequency of severe (top) and extreme (bottom) dry events computed for the SPEI-3 and SPEI-12 month respectively over Kenya, 1981-2016.

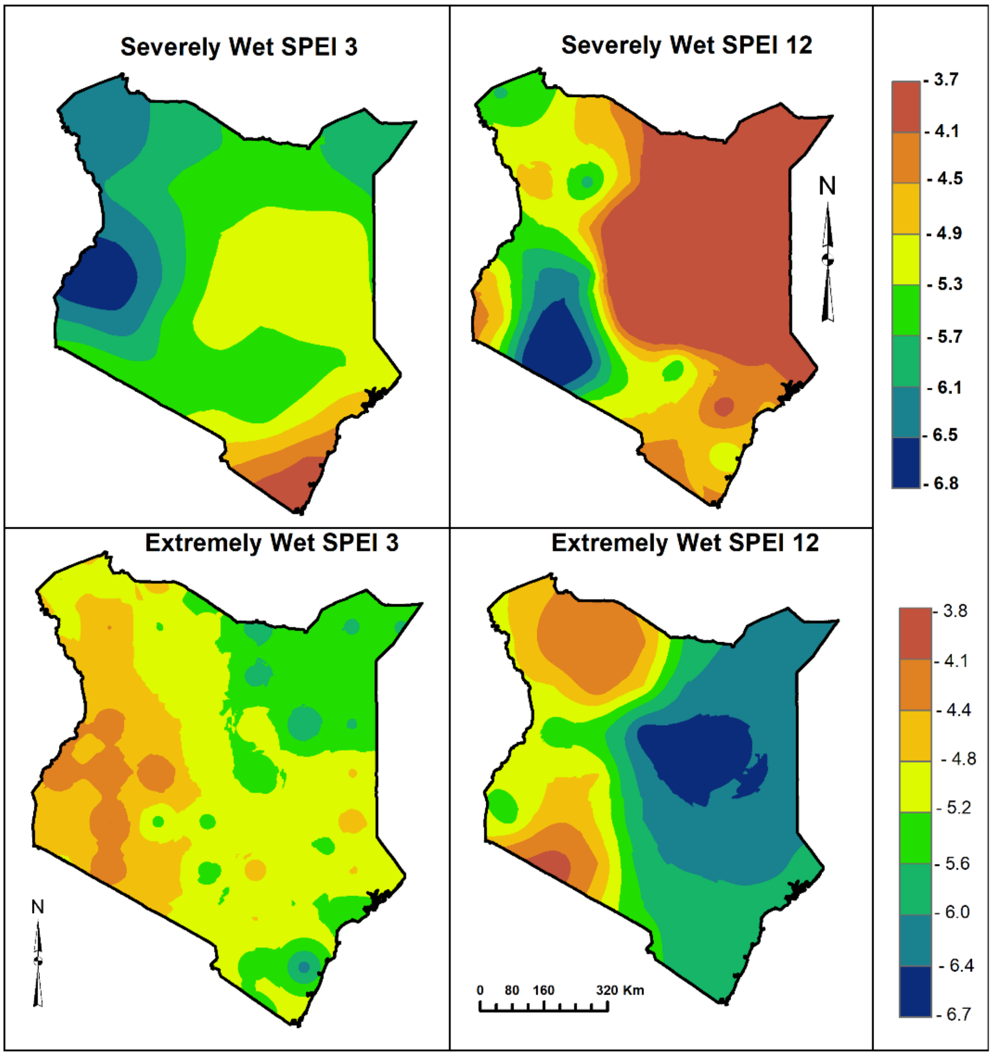

Figure 9 Frequency of severe (top) and extreme (bottom) wet events computed for the SPEI-3 and SPEI-12 month respectively over Kenya, 1981-2016

4 Conclusions

Drought remains the most complex natural phenomenon affecting the economy, environment and society at global, regional and local level. The present study examines drought and pluvial events by characterizing the trends, intensity, severity and frequencies based on widely accepted indices of SPEI over Kenya, East Africa from 1981 to 2016. Linear trends and significance test were computed using Theil-Sen Slope Estimator and Mann-Kendall test respectively.

The results for linear trends analysis demonstrate variability in both temperature and precipitation on historical perspective while sharp increase is witnessed towards the end of twentieth century and beginning of twenty first century level. Further analysis of Mann-Kendall sequential statistics for the significance test of the resulting linear trends depicts significant intensification in temperature is observed both in historical and projected trends while precipitation demonstrate 99% confidence level during high emission scenario and 95% through the RCP45.

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 reduction in moderate drought events while severe and extreme cases are on increase towards the end of the twentieth century whilst SPEI-12 depicts 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. 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 study area 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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