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Statistical Patterns of Rainfall Variability in the Great Rift Valley of Kenya

Francis M. Wakachala[1], Zablon W. Shilenje[1,*], John Nguyo[1], Saumu Shaka[1], and William Apondo[1, 2]

[1]Kenya Meteorological Department, P. O. Box 30259 – 00100, Nairobi, Kenya.
[2]Moi University, P. O. Box 3900-30100 Eldoret, Kenya.

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Abstract: Most economic activities like crop farming, livestock keeping, hydro-energy generation, transport, tourism, and other climate dependent sectors rely heavily on rainfall patterns in Kenya and the Great Rift Valley. In this study we examine rainfall patterns, long-term trends and variability in the Great Rift Valley of Kenya (06° 00'N to 03° 00'S and 38°.00-34.00'E) for the period ranging from 1950 to 2011. The study utilizes monthly rainfall data obtained from Kenya Meteorological Department for six synoptic stations in the region. The study examines the changing trends and variation of rainfall using statistical methods. Results indicate depressed rainfall in some stations while others showed increased rainfall activities. Difference between two means and comparison between two variances of equal sample data is carried out and shows changing trends in rainfall at seasonal and annual scales in all six stations of Great Rift Valley. Test for significance showed significant changes, thus showing climate change signals in rainfall patterns. Stations in arid and semi-arid areas had high percentage of variability with stations in the central rift having least percentage in variability. In conclusion, study observes a decreasing trend in annual rainfall during March-April-May season and high variability within seasons.

*Corresponding authors: Zablon W. Shilenje: zablonweku@yahoo.com

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1. Introduction

Kenya's mainstay in her socio-economic activities to a greater extend dependent on rainfall performance and distribution (DMC, 2002; Huho et al., 2012) with sixty per cent of these activities being weather and climate dependent (GoK, 2013; Nicholson, 2014). Climate variability, often through frequent occurrence of extreme weather events leads to devastation of societal and economic assets and contributing to fatalities and destruction of essential infrastructure (Hillier and Dempsey, 2012; Hirabayashi et al., 2013; Singh et al., 2014; Hirsch and Archfield, 2015). Over the past decades there have been incidences of heatwaves, droughts and floods affecting people (Mahoney et al., 2012; Hoedjes et al., 2014; Mallakpour and Villarini, 2015), especially those living in arid and semi-arid areas (Funk et al., 2010). Understanding the long-term rainfall trends and variability will therefore provide information that can be used to enhance resilience and socio-economic development.

This study focuses on variability of rainfall as a major climatic factor affecting the lives of people in the Great Rift Valley of Kenya. It seeks to better understand the changing trends in seasonal rainfall, investigating signals of climate change on the rainfall patterns. Climate change is presently a global topical issue (IPCC, 2013) that has put policy makers, scientists, and governments in an overdrive to mitigate or adapt (IPCC, 2013; GoK 2010; DMC, 2002).

Rainfall seasonality is complex in the Great Rift Valley (Indeje et al., 2001), changing within tens of kilometers with ground altitude playing an important contributing factor (Ogwang et al., 2015a; Endris et al., 2013; Anyah and Semazzi, 2006). However, effect of climate change, whose evidence is now unmistakable in Kenya (GoK, 2013), shows the rainfall regime undergoing significant changes.

Both minimum and maximum temperatures show a rising trend (Ongoma et al., 2013; Funk et al., 2010), rainfall and drought have become irregular and less predictable (Mwangi et al., 2013) although when it rains, downpour is more intense while extreme and harsh weather events are now frequent (Indeje et al., 2001) in Kenya especially in the arid and semi-arid regions.

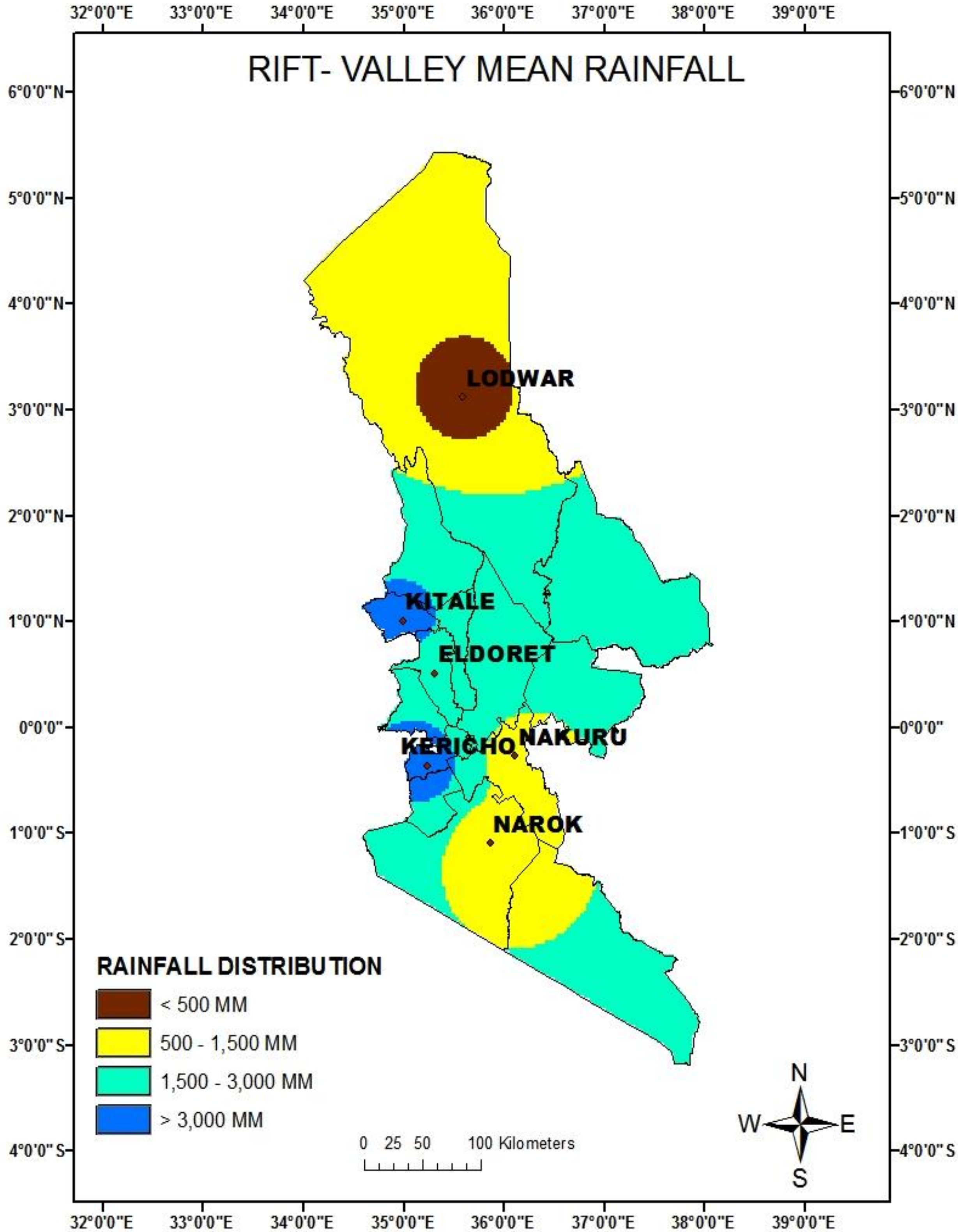

Fig. 1. Spatial map of the Greater Rift Valley, Kenya showing rainfall distribution. Figure is plotted with data shown in Table 1. (Map in the figure created by F.W. and Z.W.S using 'Archview').

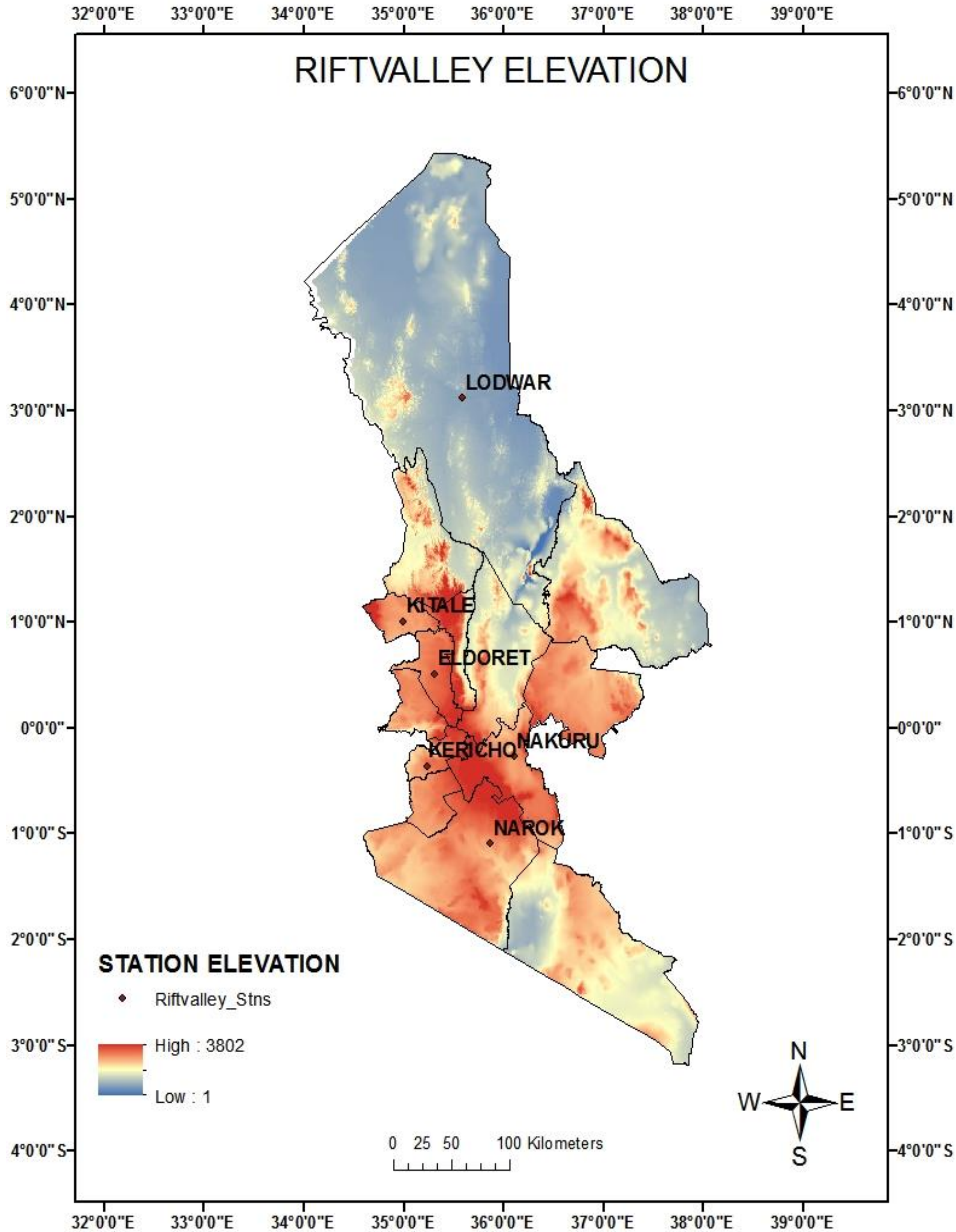

Fig. 2. Map showing topography of the Great Rift Valley. (Map in the figure created by F.W. and Z.W.S. using 'Archview').

Table1. Stations used in the study

No	Station	Latitude	Longitude	Altitude (m)	Length of data
1	Eldoret	00° 32' N	35° 17' E	2120	1973-2011
2	Kitale	01° 08' N	35° 00' E	1840	1957-2011
3	Narok	01° 08' S	35° 50' E	1585	1950-2011
4	Lodwar	03° 07' N	35° 22' E	506	1950-2011
5	Kericho	00° 22' S	35° 16' E	1976	1973-2011
6	Nakuru	00° 31' N	35° 17' E	1836	1964-2011

In this region rainfall and temperature are some of the key indicators of climate variability. The region experiences largely bimodal rainfall distribution (Ogwang et al., 2015a; Nicholson, 2014; Camberlin and Philippon, 2002) that comes in the months of March-May (MAM, long rains) and September-December for short rains although some areas have a third minor peak during June- July- August. Studies have associated the bimodal rain regime over equatorial Africa to the passage the Inter Tropical Convergence Zone (ITCZ), that sweeps the greater East Africa region twice annually (Ogwang et al., 2015b; Gitau et al., 2015; Omondi et al., 2012; Funk et al., 2010; Indeje et al., 2001). The climate and rainfall regime of the region is also influenced by the effect and presence of large maritime surfaces (Ogwang et al., 2015a; Endris et al., 2013) such as Lakes, Victoria, Naivasha, Bogoria and Nakuru especially regions in the highland west , and Central Rift Valley. The undulating valleys, ridges and hills modulate air flow in terms of speed and direction, often determining where moisture is deposited. This leads to certain areas around central rift to continue having rainfall throughout the year as there is no distinct cessation like, for instance, Kericho.

Spatial rainfall distribution in the region varies greatly with the lowest rains being experienced in the northwest Rift Valley and the highest being recorded in the highlands and central Rift Valley ranging from 200mm annually in semi-arid region of Turkana County to high values of 2700mm annually in Kericho County (Shisanya et al., 2011; Camberlin and Philippon, 2002). Precipitation is maximum in March in western (e.g. Kisumu and Kakamega) extreme north (e.g. Lodwar) of the region and during July-August for the mid regions (e.g. Eldoret, Kapsabet and Nyahuru).This provides adequate rainfall for farming and agriculture (Hillier and Dempsey, 2012), which is the economic base of the residents.

2. Materials and Methods

The Great Rift Valley, previously a regional province, now comprises of 14 counties since August 2010. It lies in the latitude and longitude of (060 00'N to 030 00’S, 380.00-34.00’E) (Fig. 1 and Fig. 2) covering an area of about 182,505km2 and with a population of about 10 million inhabitants (KNBS, 2010). Table 1 shows the stations used in the study. Rainfall distribution (Fig. 1) shows more rain in the mid and lower sections of the region as compared to the upper regions. Undulating topography (Fig. 2) of the region shows high grounds in the middle and lower areas reaching up to 3500m amsl. A large section of the mid and lower regions of the area serve as agricultural bread basket of some of the stable foods for a huge chunk of the Kenyan population. For instance Kitale produces 80% of maize crops (Lewis et al., 1998) and Kericho leads in production of tea, a leading export commodity from Kenya. Narok is rich in wheat production and livestock farming. Although tea from the highlands of Kericho County enjoys worldwide reputation, horticulture and cattle rearing are also important activities for the region’s economy.

The Great Rift Valley is characterised by diverse climate regimes ranging from desert or semi-arid in the north to forested areas in the mid to southern parts. Climate change impacts have the potential to undermine and even, reverse progress made in improving the socio-economic well-being of resident in the Great Rift Valley with rainfall variability contributing the most (DMC, 2002). Agriculture supports up to 75% of the Kenyan population and generates almost all the country’s food requirements (GoK, 2013). By analyzing the behavior of rainfall in the Great Rift Valley this study seeks to understand the changing patterns.

Data used in the study was acquired from Kenya Meteorological Department headquarters. These were daily rainfall figures for stations shown in Table 1 for the period 1950 to 2011. The stations were selected to represent the different homogenous zone within the region. There were a few missing data points, less than five percent, that were estimated based on equation 1.

$$\overline{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \quad [1]$$

Where $\overline{X}$ is the estimated value, N is the total observations and X_i are the available observational data points. Equation 1 replaces the missing value with a long term average. Although it has its weaknesses, particularly where there are huge outliers, it serves to estimate working values where no big disparities are expected (Huho et al., 2012). Single mass curve technique was used to test the data consistence where cumulative rainfall data is plotted against time to depict the homogeneity. A diagonal straight line graph depicts homogeneous data. Time series analysis investigated the seasonal variation and showed the trend of the rainfall.

In the end, the seasonal rainfall record was divided into two equal samples which were then tested for the significance of the difference using the Z-test or t-test depending on the sample size. Equation 2 shows the expression used for t–test.

$$t = \frac{(\overline{X_1} - \overline{X_2})}{S\sqrt{\left(\frac{1}{n_1} - \frac{1}{n_2}\right)}} \quad [2]$$

Where t the t – test, $\overline{X_1}$ Mean of first set of values, $\overline{X_2}$ Mean of second set of values, S is standard deviation n_1 and n_2 is number of items in set 1 and set 2 respectively. The computed value of t is compared to the tabulated value. The computed value of t is compared to the tabulated value. If the computed value is greater than tabulated value, then the null hypothesis is rejected and we accept the alternative hypothesis; that the means are different. The null (H_0) and alternative (H_A) hypotheses are given by equation 3, where μ_1, μ_2 are first and second mean respectively.

$$H_0 : \mu_1 = \mu_2, \Rightarrow \mu_1 - \mu_2 = 0 \text{ and}$$
$$H_A : \mu_1 \neq \mu_2, \Rightarrow \mu_1 - \mu_2 \neq 0 \quad [3]$$

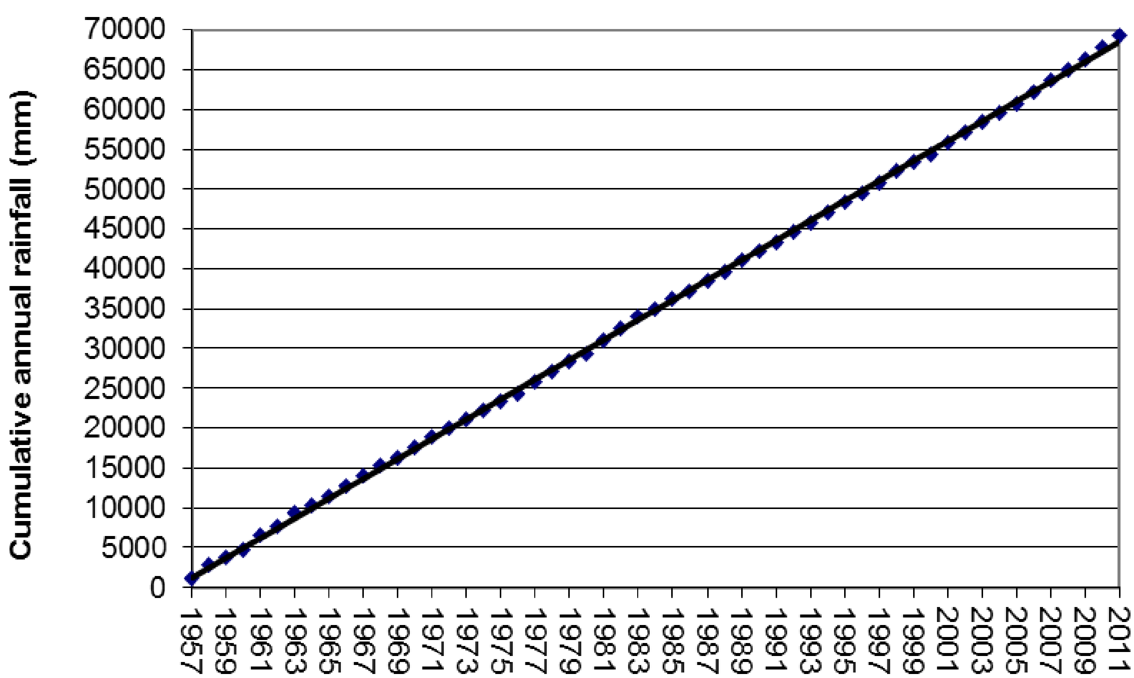

Fig. 3. Single mass curve, cumulative annual rainfall for Kitale. (Figure generated by FW using 'Excel').

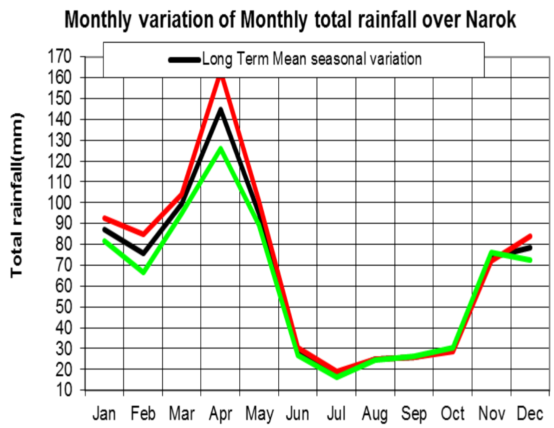

Fig. 4. Bimodal rainfall distribution, represented by Narok Station (Figure generated by F.W. using 'Excel').

Comparison between two variances approach was used to detect the variability of annual and seasonal rainfall. The variance statistical tests to compare the first and second population variances σ_1^2 and σ_2^2, basically looks at the ratio of two variances σ_1^2/σ_2^2. Again, the null and alternative hypotheses are given by equation 4.

$$H_0 : \frac{\sigma_1^2}{\sigma_2^2} = 1, \Rightarrow \sigma_1^2 = \sigma_2^2$$

and

$$H_A : \frac{\sigma_1^2}{\sigma_2^2} \neq 1, \Rightarrow \sigma_1^2 \neq \sigma_2^2 \qquad [4]$$

Fisher distribution test (F) with v1= (n1-1) and v2= (n2-1) degree of freedom (v1, v2) in the numerator and denominator respectively, was used and if the computed F is greater than tabulated F, then the null hypothesis is rejected and we accept the alternative hypothesis. Equation 5 shows the computation of the fisher test.

$$F_{computed}(X) = \frac{S_1^2}{S_2^2}$$

and

$$F_{tabulated}(X) = F_{(n_2-1)}^{(n_1-1)}(\alpha) \qquad [5]$$

Where F is fisher distribution test, S21 is variance of first sample and S22 is variance for the second sample. Coefficient of variability (equation 6) was used to calculate variability of seasonal rainfall and annual rainfall.

$$CV = \frac{\sigma}{\mu} \qquad [6]$$

Where: CV is the coefficient of variability, μ is mean, and σ is standard deviation.

3. Results and discussion

Homogeneity test checked for consistency in the data with derived single mass curves plots generally straight single lines. Fig. 3 shows sample mass curve for Kitale station indicative of good quality of rainfall records. Seasonal variation of the rainfall indicate largely bimodal and over some few regions tri-modal rainfall regimes (Fig. 4 and 5). This is in line with many studies (Ogwang et al., 2015b; Endris et al., 2013; Anyah and Semazzi, 2006) that have shown bimodal rain in most areas of Kenya.

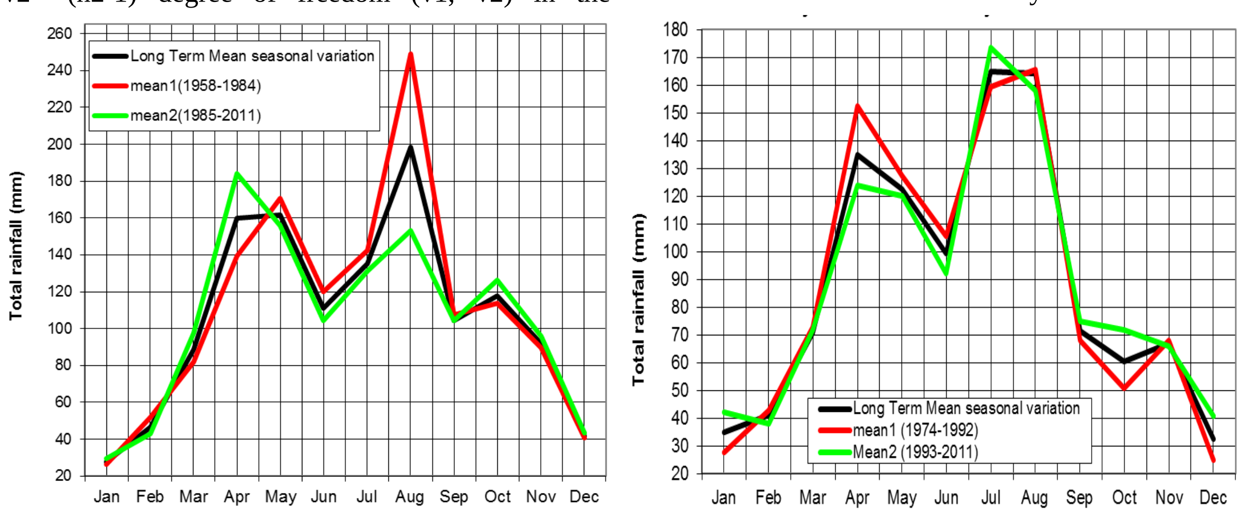

Fig. 5. Trimodal rainfall distribution, represented by Kitale (a) and Eldoret (b) weather stations. (Figure generated by FW. using 'Excel').

Table 2. Significance test between differences in two means

SEASONS	ANNUAL		MAM		JJA		OND		YEARS		CONFIDENCE LEVEL AT 95%
Station/Test	$^*T_{comp}$	$^*T_{tab}$	T_{comp}	T_{tab}	T_{comp}	T_{tab}	T_{comp}	T_{tab}	*SA1	*SA2	
Kitale	-0.27	1.71	-1.43	1.71	1.61	1.71	-0.65	1.71	27	27	
Nakuru	-0.52	1.71	0.23	1.71	1.04	1.71	**-2.57**	1.71	24	24	
Narok	**1.86**	1.64	**1.87**	1.64	0.71	1.64	0.17	1.64	31	31	
Lodwar	0.45	1.64	1.38	1.64	-0.55	1.64	-0.07	1.64	31	31	
Eldoret	-0.13	1.73	1.06	1.73	0.17	1.73	-0.99	1.73	19	19	
Kericho	1.3	1.73	1.42	1.73	1.59	1.73	**-3.23**	1.73	19	19	

$^*T_{tab}$ T tabulated, $^*T_{comp}$ T Computed *SA1, *SA2 Sample 1 and Sample 2. Highlight indicates significant difference

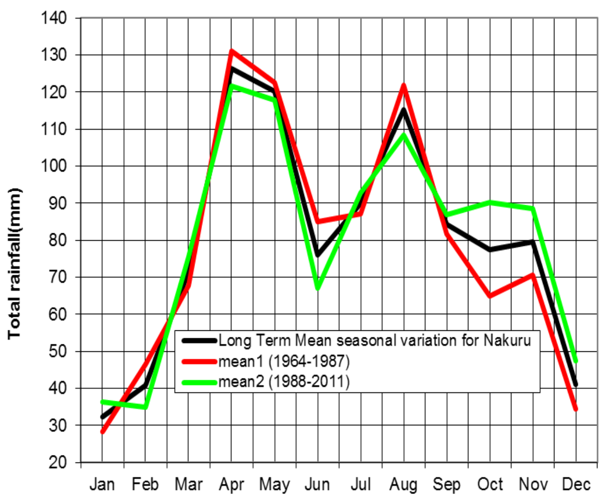

Fig. 6. Mean variation of rainfall for the two periods compared to LTM for Nakuru (Figure generated by FW. using 'Excel').

However a third peak in the highlands areas of the Great Rift Valley such as Kitale, Eldoret, and Kapsabet is significant and contributes the highest rainfall for a large area of the region under study (Fig. 5).This third peak is due to raised topography that results in orographic lifting of moist air masses from the Indian Ocean due the dominant south easterlies typical of the time (Anyah and Semazzi, 2006) or lifting of the Congo forests air mass for the west due to a quasi-permanent dynamic low pressure cell that oscillates around the Congo area.

Monthly variation is done by comparing two means of data, now subdivided into two sets, and drawing on the same graph. As an example Fig. 5 and 6 show such variations. It can be generally observed that for the main rain season (MAM) and intermediate rain season (JJA), the rainfall observed for mean 1 (1964-1987) has always been above the long-term, meanwhile in the recent decades the rains observed have tended to below the long-term mean values. This is an indication of the declining amounts during the two major seasons.

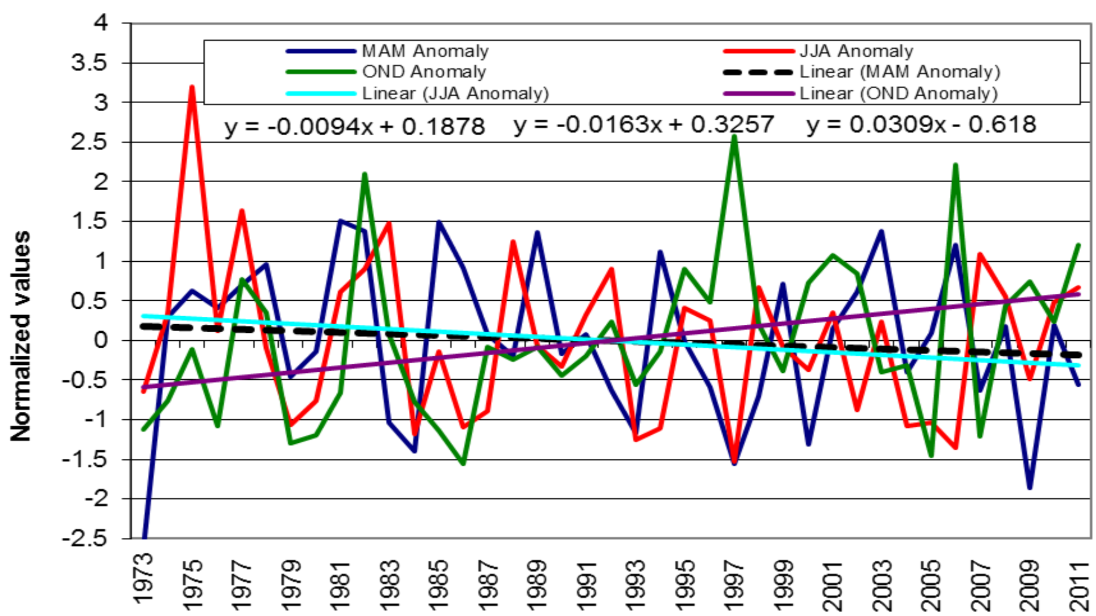

Fig. 7. Seasonal variation of normalized rainfall for Kericho (Figure generated by F.W. using 'Excel').

Table 1. Coefficient of variability in percentage (%)

STN /SEASONS	Annual 1	Annual 2	MAM 1	MAM 2	JJA 1	JJA 2	OND 1	OND 2
Kitale	19	20	36	24	18	27	54	40
Kericho	15	23	19	26	21	20	35	35
Eldoret	21	25	32	30	30	29	75	65
Nakuru	18	25	40	35	27	37	47	41
Narok	25	28	37	33	49	67	68	63
Lodwar	61	58	58	66	211	99	178	121

On the other hand, the short rain season (OND) shows more rain in the recent decades (1988-2011) with values above the long-term mean as compared to the period 1964 to 1987. This is an indication that, although, the annual rainfall performance is declining, it is still good over the OND period. This observation agrees with Omeny et al., (2008) who observed an increase in the OND rainfall performance. The results in the Fig. 6 are replicated in various stations under study.

The rainfall data was further divided into 3 seasons as MAM, OND and JJA. Sample results are presented in the Fig. 7. The results presented in the Fig. 7 support what is observed in the Fig. 6. Inter-annual variability of average rainfall anomalies for the period 1951–2010 is presented in the Fig. 7 for Kericho station over the various seasons. The amplitude of variability of the rainfall is generally high over the study period. The wet and dry years of various seasons are shown. This is based on the standardized rainfall anomalies with +1 and –1 for wet and dry years respectively. The categorization of above and below normal years employed herein is similar to the approach used by Ogwang et al., (2015b).

The anomaly in OND has an upward trend while MAM, JJA, and long-term mean seem to be reducing over the years. The other notable thing is that higher rainfall during MAM is mostly followed by suppressed rainfall for the other seasons and similarity when we have enhanced rainfall during OND then MAM of same year is slightly suppressed.

Table 2 presents test result for significance between two means for the whole region of study. It gives the computed and tabulated values for the annual rainfall and seasons so as to show if it is change significant or insignificant. The results indicate that there was significant changes of annual rainfall and MAM rainfall over Narok station in South Rift, but only other significant is shown over Nakuru and Kericho during the OND season with values of -2.57 and -3.23 computed as compared to tabulated of 1.71 and 1.73 respectively. This shows that station in central to south Rift shows significant changes in rainfall patterns as compared to the North Rift. Other station shows changes but they are not significant but with continued trend, it result into changing of rainfall patterns in future.

Coefficient of variability was calculated (Table 3) for the annual rainfall and seasonal rainfall to see how variable it is. The data set was also divided into two equal samples so that variability was calculated to see if we have any changing trends in the seasons. The annual rainfall is fairly predictable because of the small percentage of variability that ranges from 13% to 19% for the five stations of the six (Table 3). It is only Lodwar that has high variability which goes up to 60%. In general Lodwar has high variability throughout the years thus showing unreliability of rainfall. On decomposing the categories into two equal data sets, it shows that annual rainfall with time they are becoming more variable but with OND season having higher percentage of variability thus implying that this season has less predictability.

4. Conclusion

Rainfall variability is a crucial aspect of climate regime of any place that affects crop and animal production, particularly in areas dependent on rain-fed cultivation systems. Rainfall data analysis can help provide information to assess climate risks, potential impacts, and better target attendant interventions. In this study, over the Greater Rift Valley, rainfall analysis was done using difference between two means, comparison of variances, coefficient of variability and long term trends. Climate change signals and changing pattern in rainfall was observed. Generally there is observed decreasing trend in annual rainfall but high variability within seasons. This agrees with some studies undertaken on the general trend of Kenya spatiotemporal rainfall distribution (Camberlin and Philippon, 2002; Funk et al., 2010). Although the changing land use and the effect of varying climate could affect this cycle. The study recommends further research using other meteorological parameters and elements to detect climate change signals and their impact on the socio-economic activities.

List of Abbreviations: ITCZ: Inter Tropical Convergence Zone; JJA: June, July, August; MAM: March, April, May; OND: October, November, December.

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Competing Interests: The authors declare that there is no potential conflict of interest.

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