

# Variability of temperature properties over Kenya based on observed and reanalyzed datasets

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**Abstract** Updated information on trends of climate extremes is central in the assessment of climate change impacts. This work examines the trends in mean, diurnal temperature range (DTR), maximum and minimum temperatures, 1951–2012 and the recent (1981–2010) extreme temperature events over Kenya. The study utilized daily observed and reanalyzed monthly mean, minimum, and maximum temperature datasets. The analysis was carried out based on a set of nine indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI). The trend of the mean and the extreme temperature was determined using Mann-Kendall rank test, linear regression analysis, and Sen's slope estimator. December–February (DJF) season records high temperature while June–August (JJA) experiences the least temperature. The observed rate of warming is + 0.15 °C/decade. However, DTR does not show notable annual trend. Both seasons show an overall warming trend since the early 1970s with abrupt and significant changes happening around the early 1990s. The warming is more significant in the highland regions as compared to their lowland counterparts. There is increase variance in temperature. The percentage of warm days and warm

nights is observed to increase, a further affirmation of warming. This work is a synoptic scale study that exemplifies how seasonal and decadal analyses, together with the annual assessments, are important in the understanding of the temperature variability which is vital in vulnerability and adaptation studies at a local/regional scale. However, following the quality of observed data used herein, there remains need for further studies on the subject using longer and more data to avoid generalizations made in this study.

## 1 Introduction

The potential adverse impacts of climate change on human life, ecosystem, and infrastructure have led to increased research on the subject globally (Meehl et al. 2000; Alexander et al. 2006; Myoung et al. 2013). Temperature is one of the most important climate factors that affect agriculture, hydrological cycle, and to a significant extent, thermal comfort (Walther et al. 2002; Diaz et al. 2005). According to the Intergovernmental Panel on Climate Change (IPCC), the mean global surface temperature computed using a linear trend indicated a general warming of 0.85 (0.65 to 1.06) °C between 1880 and 2012 (IPCC 2014). Further, it was observed that the warmest 30-year period in the last 1400 years might have been between 1983 and 2012. The Fifth Assessment Report (AR5) of the IPCC approximated an average increase of global temperature in the period 1951–2012 to be 0.72 °C (IPCC 2013). The rapid warming is mainly attributed to increase in Greenhouse Gases (GHGs) linked to anthropogenic activities (IPCC 2007). The ongoing global warming is unequivocal (IPCC 2007, 2014); however, its extent varies from one region to another. For instance, over Africa, Collins (2011) observed increasing temperature trends in many parts including tropical region, with significantly warmer

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temperatures in the most recent time, 1995–2010, as compared to the period 1979–1994, indicated warming in the recent time. On a global scale, according to Brown et al. (2008), the temperature has been observed to increase, characterized by warming in extreme daily minimum and maximum temperature.

The vulnerability of a given society to surface air temperature changes equally varies greatly depending on a number of factors among them technology and social, economy, among others. For instance, globally, Africa is the most vulnerable continent to the effects of climate variability and change (Boko et al. 2007). East Africa (EA), made of three countries: Kenya, Uganda, and Tanzania (Fig. 1), is positioned in the tropics and is thus not affected by “harsh” temperatures experienced in extra-tropics during winter and summer seasons. The region’s temperature favors production of quality tea and coffee highly ranked globally. This and other forms of agriculture are the backbone of the region’s economy. The same temperature, coupled with rich biodiversity, is a major boost to tourism in the region. However, in the background of climate change, as a result of global warming among other factors, threatens the future of agriculture and tourism sectors in the region (Adhikari et al. 2015). Although it is not clear on the extent of the current warming in EA owing to data limitations, applied studies (Omumbo et al. 2011; Stern et al. 2011) show the high likelihood of the influence of temperature on the increase of malaria cases in many areas of the East African Highlands in the recent past. This calls for an understanding of the ongoing trends of the frequency and intensity of temperature variability, to aid in future projections of the same and appropriate planning based on the outcome of the studies.

Although the region does not witness harsh temperature conditions, it is worth knowing the ongoing temperature variability in the background of global warming. Although it is evident globally that temperature is on increase, according to IPCC (2001), extreme temperature events show complicated spatiotemporal variability in intensity and frequency. As per today, the knowledge on temperature variability and trend over the larger Great Horn of Africa (GHA) is still imperfect (Camberlin 2017). This study looks at temperature variation in Kenya, narrowing down to extreme climate events in the context of events commonly occurring to the tails of the probability density function (PDF). However, owing to the available climate data and analytical approach, this study is limited to moderate extreme events known to have a re-occurrence time of 1 year or less (Zhang et al. 2011). The knowledge on the occurrence of climate extreme in a given region is of great value in carrying out vulnerability assessment and devising mitigation options against climate variability and climate change. The knowledge equally plays an important role in the climate change detection and attribution studies, as well as in the evaluation of the ability of global/regional climate models in simulating the observed climate extremes.

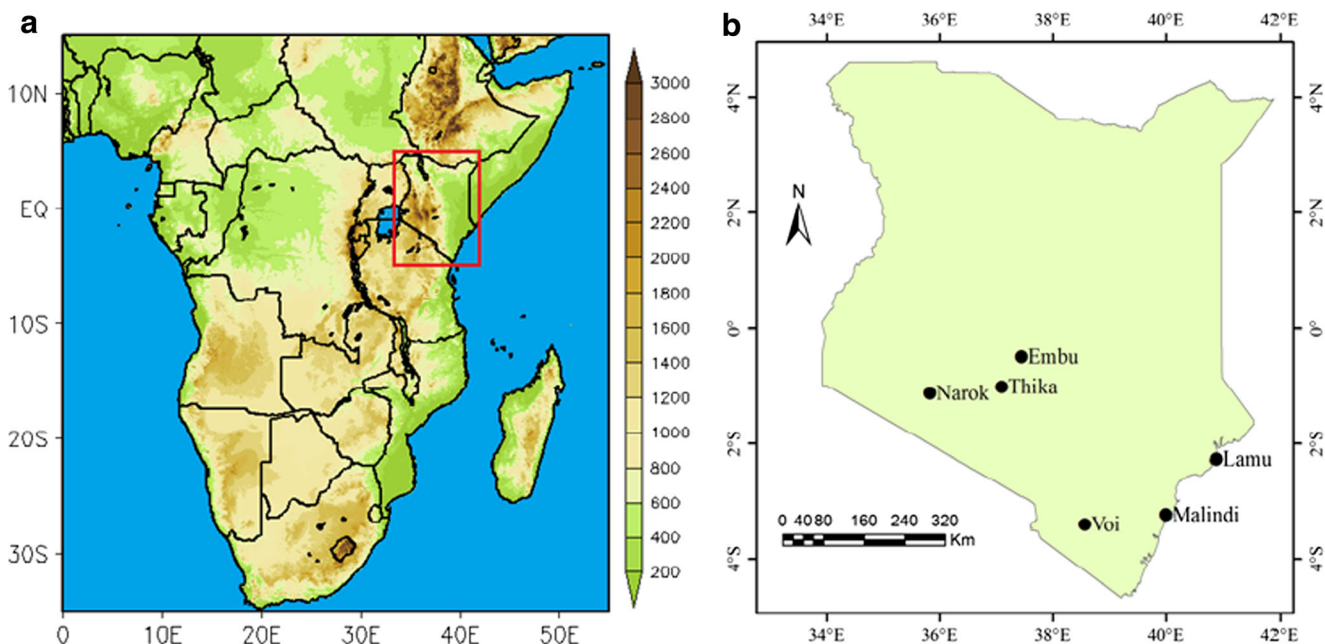
Extreme climate events are associated with losses of lives and devastating economic impacts (Meehl et al. 2000). Extreme climate has become one of the top ranking themes of current climate variability and climate change research on a global scale (Meehl et al. 2000; Easterling et al. 2003; Alexander et al. 2006; Trenberth et al. 2007; Fischer et al. 2012; Tao et al. 2014). Temperature extremes are useful in the assessment of climate change impacts since the extremes have a reasonable impact on many socioeconomic sectors ranging from energy, health, agriculture, tourism, and ecosystems, among others (Easterling et al. 2000; Meehl et al. 2000; Myoung et al. 2013). Many studies around the globe (e.g., Klein Tank and Können 2003; Easterling et al. 2003; Alexander et al. 2006; Fischer et al. 2012; IPCC 2012, 2014; Hartmann et al. 2013; Labajo et al. 2014; Dashkhuu et al. 2015), have looked into the spatiotemporal variability of daily temperature extremes. Most of the studies reported the high likelihood of a reduction in the number of cold days and nights over the globe and an increase in warm days and nights.

Many climatological studies in EA and Africa as a whole have focused on rainfall in comparison to temperature as noted by Collins (2011). Other than rainfall being the most important weather parameter in the region (Muthama et al. 2012), more studies centered on rainfall as compared to temperature can be explained by two reasons, one being the sparse station network and incomplete temperature records. Another reason is that the rainfall in the region is characterized by high spatiotemporal variability as well as the recent observed increase in frequency and intensity of droughts and floods (Lyon and Dewitt 2012; Nicholson 2014). Besides, many studies have observed a reduction in March–May (MAM “long rains”) seasonal rainfall (Lyon and Dewitt 2012; Tierney et al. 2015; Ongoma and Chen 2017).

King’uyu et al. (2000) focused on trends of maximum and minimum temperature trends over eastern Africa, covering 19 countries, between 1939 and 1992. According to the study, the nighttime temperatures were observed to be on the increase, with high variability in space. The observation was attributed to many reasons among them land use patterns, pointing out urbanization that was not considered in their study. However, the study falls short of looking into extreme temperature events. Daron (2014) found that the temperature over GHA has increased by 1.5 to 2 °C on average in the past 50 years.

A recent study by Opiyo et al. (2014) focused on rainfall and temperature variability in Turkana County. The county is located in the northwestern part of Kenya which is mainly arid and semi arid land (ASAL). The study utilized monthly temperature data from one meteorological station running from 1979 to 2012. According to results, both MAM and October–December (OND) minimum and maximum temperature trends were significantly increasing.

Studies in extreme temperature events are gaining attention very fast across the globe. However, the studies are still



**Fig. 1** Area of study. **a** Topographical elevation map (m) of Kenya [red rectangle; 34° E–42° E, 5° S–5° N]. The areas shaded blue are the major water bodies (Data source: Hastings and Paula 1999). **b** The distribution of weather stations considered in this study

challenging and require a keen monitoring since changes in extreme changes may occur without significant changes in the mean climate (Trenberth et al. 2007). In the neighboring country, Uganda, a study by Nsubuga et al. (2014) looked into the variability of the surface temperature over the entire country, from 1960 to 2008. The study observed that the frequency of hot days and nights, warm nights, and warm spells were on the increase. The overall warming was depicted by the reduction in the gap between maximum and minimum temperature.

Ngaina and Mutai (2013) looked into extreme temperature and rainfall events over EA observing a significant increase in temperature of the region. Although the study employed climate change indices, their study did not investigate the abrupt changes in the climate parameters. Moreover, the study also gives generalized results despite there being varying seasonality in temperature. Therefore, looking into the seasonal variability of temperature over Kenya could give finer details that could help to easily single out temperature variation patterns in the background of climate change.

Omondi et al. (2014) utilized climate change indices to study changes in rainfall and temperature over the GHA, from 1960 to 2010. The study noted that the temperature change varies from one station to another. According to their study, despite the high variability, the warm days were observed to increase, while the cool days exhibited a decreasing trend. The study, however, did not consider seasonal variability which is importance for most socioeconomic activities in the region.

Despite the efforts made to understand the temperature variability over EA, there is no recent study on the same over Kenya, utilizing the existing climate change indices. Karl and Easterling (1999) advocate for continuous examination and documentation of climate variability, focusing on the extreme since the information is valuable in decision making relating to environmental change. The current study therefore seeks to answer one main question, “What is the variability in near surface temperature and extreme temperatures events in Kenya?” Assessment of extreme temperature on regional and local scales in relation to the ongoing climate change provides further insight into local climate conditions forming the basis upon which adaptation to climate change effects should be drawn.

The remaining part of this work is structured as follows: Section 2 describes the data and methodology employed in the study. Section 3 illustrates the results and gives the discussion, while Section 4 puts forward the conclusions and recommendation of the study.

## 2 Data and methodology

### 2.1 Area of study

Kenya is located in the tropics, within longitude 34° E–42° E and latitude 5° S–5° N (Fig. 1). The equator passes through Kenya, dividing it into nearly two halves.

The country’s climatology is characterized by bimodal rainfall pattern (Camberlin et al. 2009; Yang et al. 2015;

Ongoma and Chen 2017). The rainfall and temperature are mainly influenced by the north–south march of the Inter-Tropical Convergence Zone (ITCZ). The country is relatively warm throughout the year and is characterized by limited seasonality slightly different from that observed in rainfall. The warmest months are December–February (DJF), followed by March–May (MAM) season, while June–August (JJA) reports the lowest temperatures (Daron 2014; Ongoma and Chen 2017). Kenya’s elevation increases from the coast lowlands, towards the central parts of the country, with its peak being Mt. Kenya (at over 5000 m). Mt. Elgon is equally located in the west side of Kenya, putting the western side of the country at a higher elevation as compared to the eastern region.

## 2.2 Data

The database utilized in this study consists of reanalyzed monthly temperature: mean, diurnal temperature range (DTR), and maximum and minimum data, from the Climate Research Centre (CRU) were used to investigate temperature variability. The CRU TS3.22 dataset spans from 1901 to 2012, gridded at  $0.5^\circ \times 0.5^\circ$  horizontal resolution. A comprehensive description of the CRU data is given by Harris et al. (2014) and University of East Anglia Climatic Research Unit et al. (2014). Although the data covers the entire twentieth century, this study is limited to the period between 1951 and 2012. This timeframe is based on the observation by IPCC (2012, 2013), being the period that witnessed the highest warming in the observation history on a global scale. The CRU is used to study temperature climatology owing to its long length. CRU mean monthly temperature data was successfully utilized by Ogwang et al. (2016) to validate RegCM4 performance over East Africa. Camberlin (2017) reported that there is a very high positive correlation between observed station temperature and CRU datasets. The study used the two datasets to investigate temperature variability over GHA and its interactions with precipitation. Other studies that have made use of the CRU temperature datasets in EA are Stern et al. (2011), Yang et al. (2014), and Ongoma and Chen (2017).

Observed daily data from Kenya Meteorological Department (KMD) was used to study changes in temperature extremes. The station data used in this study was chosen based on the continuity and quality of their records. The data spans from 1981 to 2010. Table 1 gives a summary of the observed data used in the study while Fig. 1b displays their locations in Kenya. Although the stations were considered based on data quality, it is also notable that they are mainly positioned in the southern section of the country. This is mainly because the northern part of the country has a sparse network of weather stations, being ASAL.

Data inhomogeneity can affect the identification of extreme events in a given dataset (Trewin 2010). The observed

**Table 1** Source stations of the observed temperature data utilized in this study

Number	Name	WMO Code	Lon ( $^\circ$ E)	Lat ( $^\circ$ S)	Data length
1	Thika	63,740	37.100	1.020	1982–2010
2	Embu	63,720	37.450	0.500	1981–2010
3	Narok	63,737	35.830	1.130	1986–2010
4	Voi	63,793	38.570	3.400	1981–2009
5	Lamu	63,772	40.900	2.270	1981–2010
6	Malindi	63,799	40.000	3.230	1986–2010

temperature data was tested for homogeneity test using standard normal homogeneity test (SNHT) at 5% significance level. Details on the procedure, weakness, and strengths of this approach are documented in Alexandersson (1986). The analysis is carried out using XLSTAT statistical analysis software (<https://www.xlstat.com/en/>).

All the stations were found to have less than 4% of missing observations. The missing data was estimated using the arithmetic mean method. The data was found to be homogeneous in all the stations and thus was considered for examination of extreme temperature events.

## 2.3 Methodology

The basic temperature characteristics such as the spatial distribution and decadal anomalies based on reanalyzed data are computed using Climate Data Operator (CDO) and displayed using Grid Analysis and Display System (GrADS).

Extreme climate indices were defined by the Expert Team on Climate Change Detection Indices (ETCCDI), an initiative supported by World Meteorological Organization Commission for Climatology (CCI)/World Climate Research Programme (WCRP) project on Climate Variability and Predictability (CLIVAR) (Easterling et al. 2003; Zhang et al. 2011). Table 2 gives definitions of extreme temperature indices applied herein. The indices have been used globally, e.g., over GHA (Omondi et al. 2014), Djibouti (Ozer and Mahamoud 2013), Italy (Fioravanti et al. 2016), Qatar (Cheng et al. 2015), Iran (Soltani et al. 2016), over West Africa (Mouhamed et al. 2013), and China (Tao et al. 2014), among others.

Mann-Kendall (MK) analysis (Mann 1945; Kendall 1975) is applied in trend analysis to detect the type of trend in the extreme temperature indices, as well as test its significance. The analysis is carried out at 5% significance level. In the analysis, the null hypothesis ( $H_0$ ) assuming no trend in the data is rejected if standard normal test statistics  $Z > 1.96$ .

Sequential Mann-Kendall (SMK) test is employed to show a change in trend with time. Forward sequential statistic ( $u(t)$ ) and backward sequential statistic ( $u'(t)$ ) from the progressive

**Table 2** List of the ETCCDI temperature change indices used in this study

ID	Indicator name	Description	Units
TXMean	Maximum temperature	Mean of Tmax (daily maximum temperature)	°C
TNMean	Minimum temperature	Mean of Tmin (daily minimum temperature)	°C
TX <sub>x</sub>	Max Tmax	Monthly maximum value of daily maximum temperature	°C
TN <sub>x</sub>	Max Tmin	Monthly maximum value of daily minimum temperature	°C
TX <sub>n</sub>	Min Tmax	Monthly minimum value of daily maximum temperature	°C
TN <sub>n</sub>	Min Tmin	Monthly minimum value of daily minimum temperature	°C
DTR	Daily temperature range	Monthly mean difference between TX and TN	°C
TN90p	Warm nights	Percentage of days when TN > 90th percentile	%
TX90p	Warm days	Percentage of days when TX > 90th percentile	%

analysis of the MK test help in the investigation of change in trend with time (Sneyers 1990). In the computation, the test compares the relative magnitudes of data instead of the data values directly. In this case,  $u(t)$  is a standardized variable that has a unit standard deviation and zero mean. The progressive MK values  $u(t)$  and  $u'(t)$  were calculated using the appropriate MK test for each dataset, from the start to the end of the study period. In the plot of SMK, the confidence limits of the standard normal Zvalues at  $\alpha = 5\%$ . The upper and lower confidence limits, therefore, correspond to + 1.96 and - 1.96, respectively. The method has been successfully employed in related research in EA (Nsubuga et al. 2014; Ongoma and Chen 2017; Ongoma et al. 2016). The temporal trends of temperature were analyzed using linear regression, and the magnitude of the trend slope was estimated using Sen’s slope estimator (Sen 1968).

Probability density function (PDF) is used to show the change in mean and variance of temperature characteristics during two equal timelines: 1951–1981 and 1982–2012. The computations for probability employed kernel density estimation (KDE), with a bi-weight kernel to design PDFs. The KDE is a non-parametric approach of estimating PDF. The methodology is discussed in detail by Bernacchia and Pigolotti (2011). Application of PDF to investigate temperature variability in different timeframes has been successfully applied in previous studies (Galdies 2012; Kumar et al. 2016).

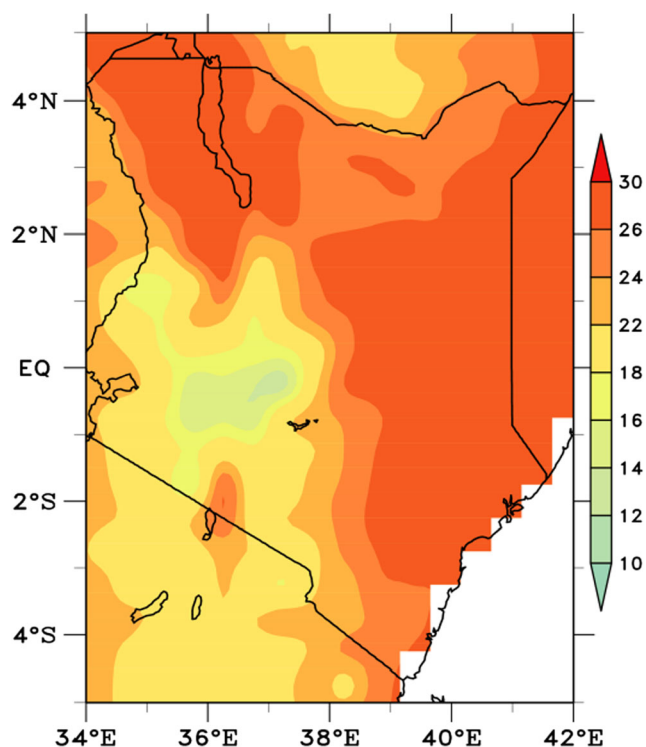
### 3 Results and discussion

#### 3.1 Temperature climatology

Kenya experiences moderate temperatures ranging within the range of 19 to 30 °C (Fig. 2). The lowest temperatures are recorded in the central and western parts of the country. The cold zone is generally in the areas at the high elevation, in the mountainous areas, and on either side of the Rift Valley. In support of the elevation’s effect on temperature, low

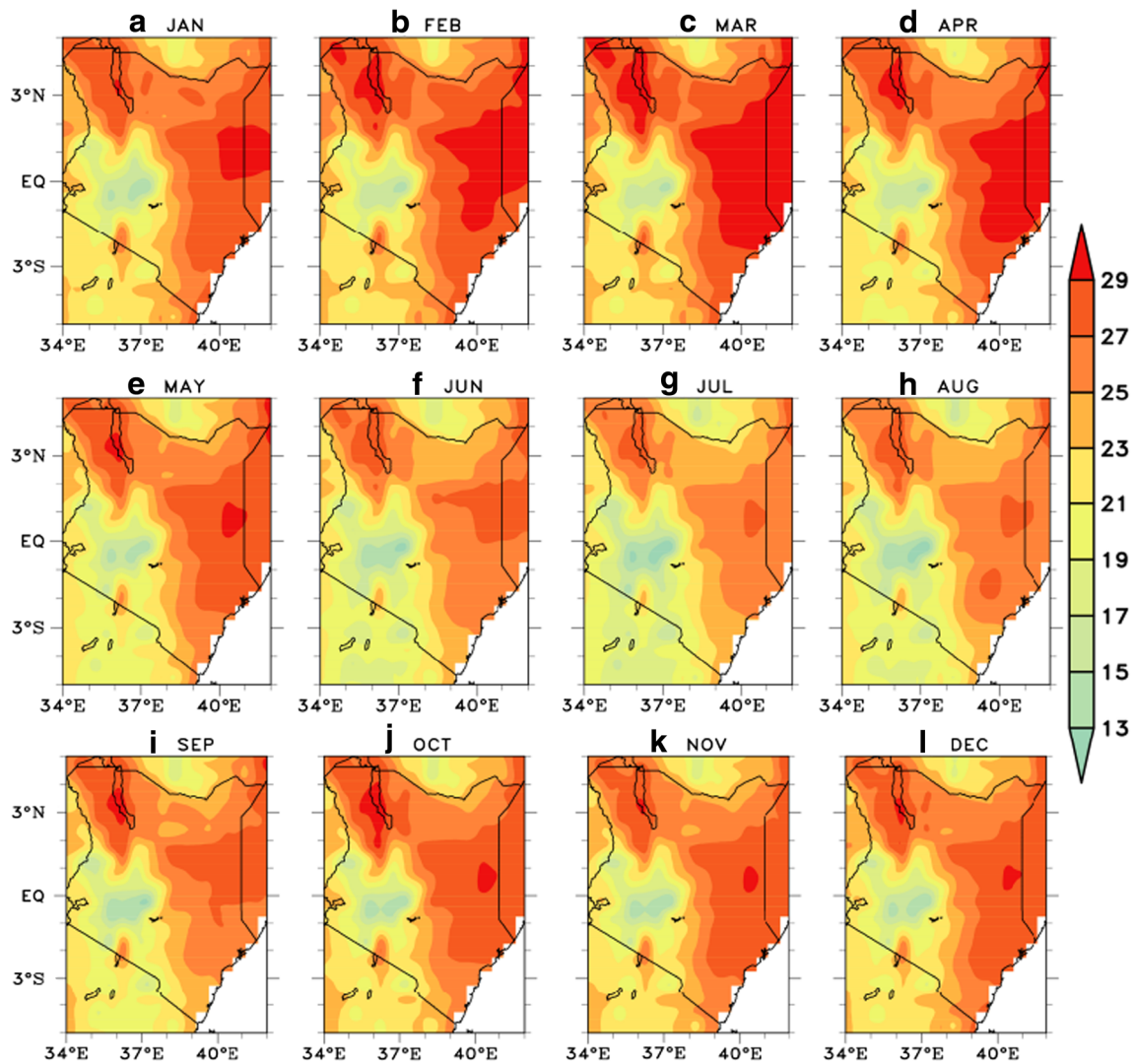
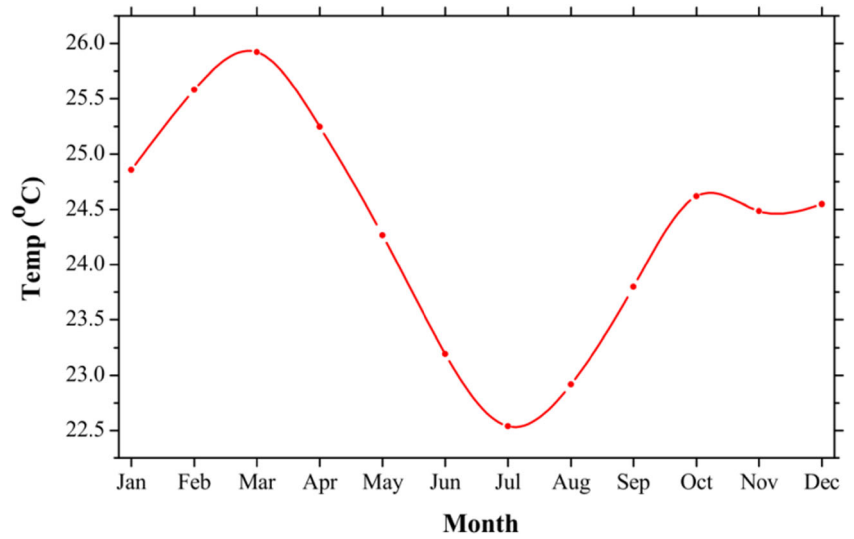
temperatures are observed in the vicinity of the Rift Valley. The eastern and northwestern parts of the country record the highest temperature. The areas are mainly ASAL; characterized by low rainfall of less than 500 mm annually.

The intra-annual distribution of temperature over Kenya is presented in Figs. 3 and 4. Figure 3 gives the annual cycle of temperature over Kenya. The month of July records the lowest mean temperature (22.5 °C). The month of February experiences the highest maximum temperature (32.5 °C), while July experiences the lowest minimum temperature (17.2 °C) (Table 3). The months of July–August, and January–February are the two consecutive months that observe the least and the highest DTR values, respectively, in the year.



**Fig. 2** Annual mean temperature (°C) climatology over Kenya, based on CRU dataset for the period 1951–2012

**Fig. 3** Long-term mean of mean temperature annual cycle over Kenya based on CRU data for the period 1951–2012



**Fig. 4** Mean monthly temperature distribution for a January, b February, c March, d April, e May, f June, g July, h August, i September, j October, k November, and l December. The analysis is based on the Climate Research Unit (CRU) datasets over the period 1951–2010

**Table 3** The monthly climatology of mean, maximum, and minimum temperatures, and DTR over Kenya based on CRU data for the period 1951–2012

Month	Mean temp.(°C)	Maximum temp. (°C)	Minimum temp. (°C)	DTR (°C)
January	24.9	31.6	18.2	13.4
February	25.6	32.5	18.6	13.7
March	25.9	32.4	19.5	12.8
April	25.3	30.8	19.7	11.1
May	24.3	29.5	19.0	10.5
June	23.2	28.7	17.7	11.9
July	22.5	28.0	17.2	10.8
August	22.9	28.5	17.4	11.0
September	23.8	29.9	17.7	12.2
October	24.6	30.6	18.6	12.0
November	24.5	30.3	18.7	11.5
December	24.5	30.7	18.4	12.3

The country is positioned in the tropics, experiencing relatively warm conditions throughout the year. The months of December to February (DJF) record high mean temperature while June to August (JJA) record relatively low temperature (Okoola 2000). The two seasons have formed the basis of temperature studies in previous works over Kenya (Okoola 2000; Daron 2014), East Africa (Ongoma and Chen 2017), GHA (Omondi et al. 2014), and Africa (Collins 2011). According to Fig. 3, the CRU dataset tends to overestimate the temperature in the months of March and April. Although the sun is always overhead equator in March and September, these months, and to a large extent, the rain two seasons: March–May (MAM) and October–December (OND), are characterized by cloudy and rainy conditions, resulting in relatively cold conditions over Kenya. According to Kuhnel (1991), the observed cloud cycle over East Africa is a function of both the movement of the ITCZ and the effect of the monsoonal circulation.

The DJF season is characterized by an influx of dry air driven by northeastern monsoons, leading to dry conditions over Kenya. As a result, the country experience cloudless and dry conditions during the time (Okoola 2000). On the contrary, low temperatures are observed in JJA (Southern Hemisphere winter season), attributed to the inflow of cold air from the Southern hemisphere (SH) pumped in by the Mascarene High (Ogwang et al. 2015). According to the observation by Okoola (2000), the influx of moisture into East Africa from SH is enhanced whenever there is a notable surface pressure ridge from the SH subtropics stretching to the equator or beyond. The dominant cloud cover during the JJA season blocks the shortwave solar radiation from getting to the earth surface resulting into the cold conditions.

The two seasons, DJF and JJA being the warmest and coldest, respectively, form the basis of the further investigation of temperature variability in this study. A summary of basic seasonal temperature characteristics is given in Table 4. The difference in the mean temperature between the

warmest and the coldest seasons is approximately 2 °C. The standard deviations in temperature in the two seasons differ slightly by 0.1 °C. The observation hints on the possibility of similar variability in temperature in the two seasons.

### 3.2 Inter-annual temperature variation

The seasonal temperature standardized anomalies over Kenya are presented in Fig. 5. The two seasons display almost the same pattern of variability. The 10-year moving average herein is employed to minimize random variability by smoothing the curve, giving the general trend of 10 years; decadal, temperature variability. Increasing positive anomalies in the two seasons are substantially enhanced since the mid-1990s. It worth noting that the minimum anomaly,  $< + 2$ , was recorded in 1968 for both seasons, while the highest,  $> + 2$  was recorded in 2009 for JJA and 2010 for DJF.

The moving average for both seasons depicts warming, evidenced by positive trends. This is clearly visible in the last two decades, before which, relative cooling was observed in the 1960s. The warming is depicted by the positive standard anomaly recorded from the early 1990s to date. It is worth nothing that although the temperatures in the 1970s–1980s recorded negative anomalies relative to the temperature in the entire period, there was a positive trend in temperature during the time. The observation is in agreement with global warming pattern where the warmest 30-year period in more than the past 1000 years may have been observed between 1983 and 2012 (IPCC 2014).

A comparison of the rate of warming in the two seasons shows that JJA season has recorded higher warming rate as compared to DJF. The results are supported by observations made in by Hulme et al. (2001) who observed that the rate of warming was slightly larger in JJA season as compared to the months of DJF over Africa between 1901 and 1995.

**Table 4** Seasonal characteristics of mean temperature over Kenya based on CRU data, 1951–2012

Season	Length (years)	Min. (°C)	Max. (°)	Mean (°C)	Std. deviation
DJF	62	23.8	26.3	25.0	0.5
JJA	62	21.8	23.9	22.9	0.4

### 3.3 Trends analysis

Area averaged trend analysis for temperature is presented in Table 5. The  $Z$  scores in surface temperature and maximum and minimum temperatures are positive, an indication of an upward trend. The scores exceed the significant value at  $\alpha = 5\%$ , the evidence against the null hypothesis ( $H_0$ ). The alternative hypothesis ( $H_a$ ); there is a trend in the series, was thus accepted. The magnitude of the change in temperature with time is measured using Sen's slope estimator. The Sen's slope value for the mean temperature is  $0.015\text{ }^\circ\text{C}/\text{year}$ . The value for the maximum (minimum) temperature exceeds (less than) the observation made in mean temperature by  $0.001\text{ }^\circ\text{C}/\text{year}$ . On the other hand, absence of slope and insignificant trend are noted in DTR (Table 5). This is explained by the temperature trends in maximum and minimum temperatures which are almost similar in magnitude.

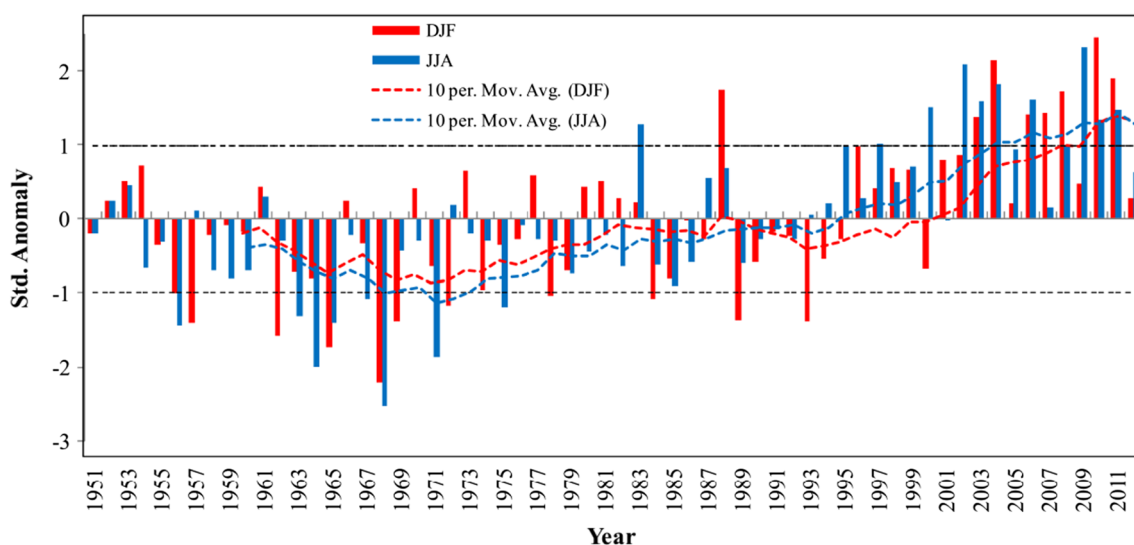
Decadal temperature anomalies for DJF and JJA are displayed in Figs. 6 and 7, respectively. In agreement with the observed standardized anomaly (Fig. 5), the highest warming was observed in the last decade, covering almost the whole country. The 1960s witnessed negative anomaly over most parts of the country.

The highest warming is experienced in the western and central parts of the country, which are climatologically cooler than other parts of the country. In a comparison of seasonal anomalies over the period, more warming is witnessed in JJA as compared to DJF. This affirms that initially cool (high

elevation) areas are warming faster than the warm (low elevation) zones, an indicator of global warming. The noted trend is in agreement with recent findings by Fan et al. (2015), a study that was carried out across the globe. Fan et al. (2015) focused on maximum and minimum temperature over the globe, observing that high-elevation areas are warming faster in comparison to their low-elevation similitude. A similar conclusion was made in the Swiss Alps by Jungo and Beniston (2001).

A summary of the linear decadal area averaged temperature tendency is presented in Table 6. The rate of change of mean surface temperature per decade is  $+0.15\text{ }^\circ\text{C}/\text{decade}$ . This is less (higher) than the rate observed in maximum (minimum) temperature by  $0.01\text{ }^\circ\text{C}$ , over the same period. The results are in agreement with upward linear trend noted by Collins (2011) while investigating temperature variability over Africa. Using satellite data for 1979–2010, Collins (2011) observed a linear trend in mean surface temperature, at a rate of  $+0.15\text{ }^\circ\text{C}/\text{decade}$  over tropical Africa. However, the findings of this study are slightly lower as compared to the recent results presented by Camberlin (2017) over GHA. Using a combined dataset; observed and CRU data, for 1973 to 2013, Camberlin (2017) reported that minimum (maximum) temperature increased at rate of  $+0.20$  to  $+0.25$  ( $+0.17$  to  $+0.22$ )  $^\circ\text{C}/\text{decade}$ .

The variation in the variance and mean of averaged temperatures over Kenya are investigated using a density function for two 32-year periods: 1951–1981 and 1982–2012 (Fig. 8). There is an increase in average maximum, minimum, and



**Fig. 5** Standardized seasonal temperature anomaly over Kenya based on CRU data for the period 1951–2012. The dotted lines represent the 10-year running mean, DJF (red), and JJA (blue)



**Table 5** A summary of Mann-Kendall test analysis for temperature at 95% confidence level, based on CRU data, 1951–2012

	Z score	Sen’s slope	Significance
Max. temp.	4.847	0.016	Significant
Min. temp.	4.677	0.014	Significant
Mean temp.	4.883	0.015	Significant
DTR	0.316	0.000	Insignificant

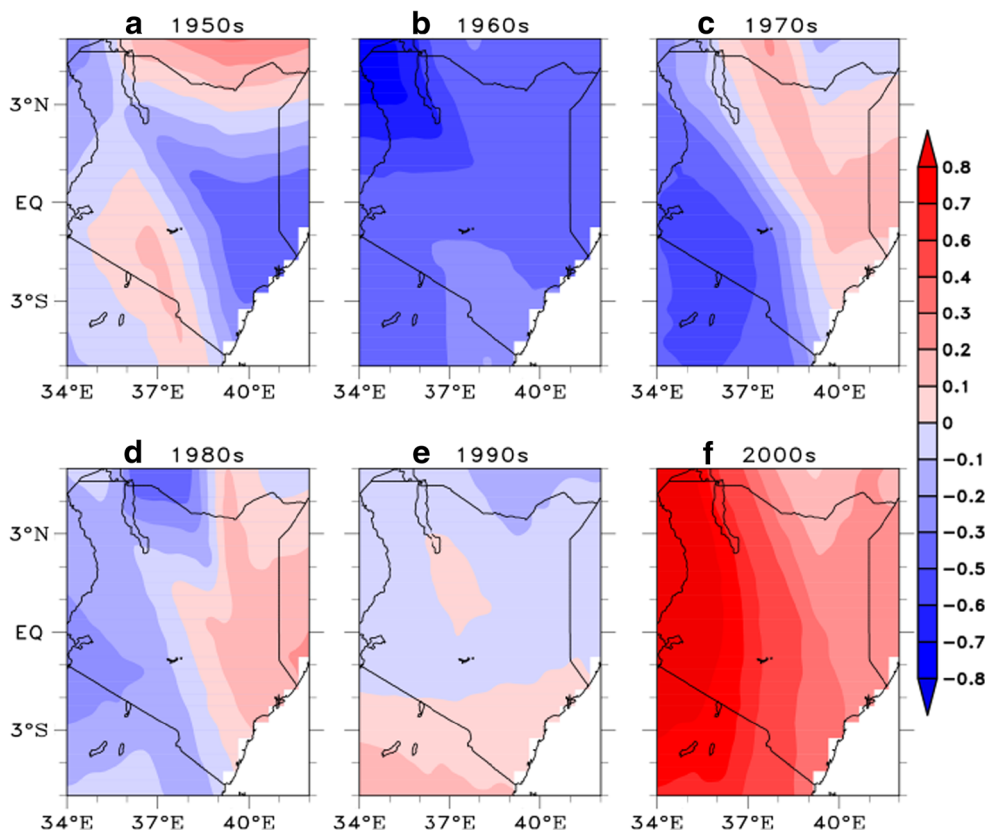
mean temperature in 1982–2012 as compared to 1951–1981. Equally, there is an observed increase in variance in the three aspects of temperature during 1982–2012 as compared to 1951–1981. The positive shift temperature was observed in maximum temperature (+ 0.5 °C), minimum temperature (+ 0.4 °C), and mean temperature (+ 0.5 °C). The change in mean and variance of DTR during 1982–2012 is negative relative to the observations made in 1951–1981.

The observed increase in variance of mean, maximum, and minimum temperature is an indicator of increased probability in occurrence of extreme events. Although the change in mean temperature is small, it can have a noticeably large effect on the number of cold and warm days. For, the observed shift of the frequency distribution of the average maximum and minimum temperature to the right, the probability distribution of

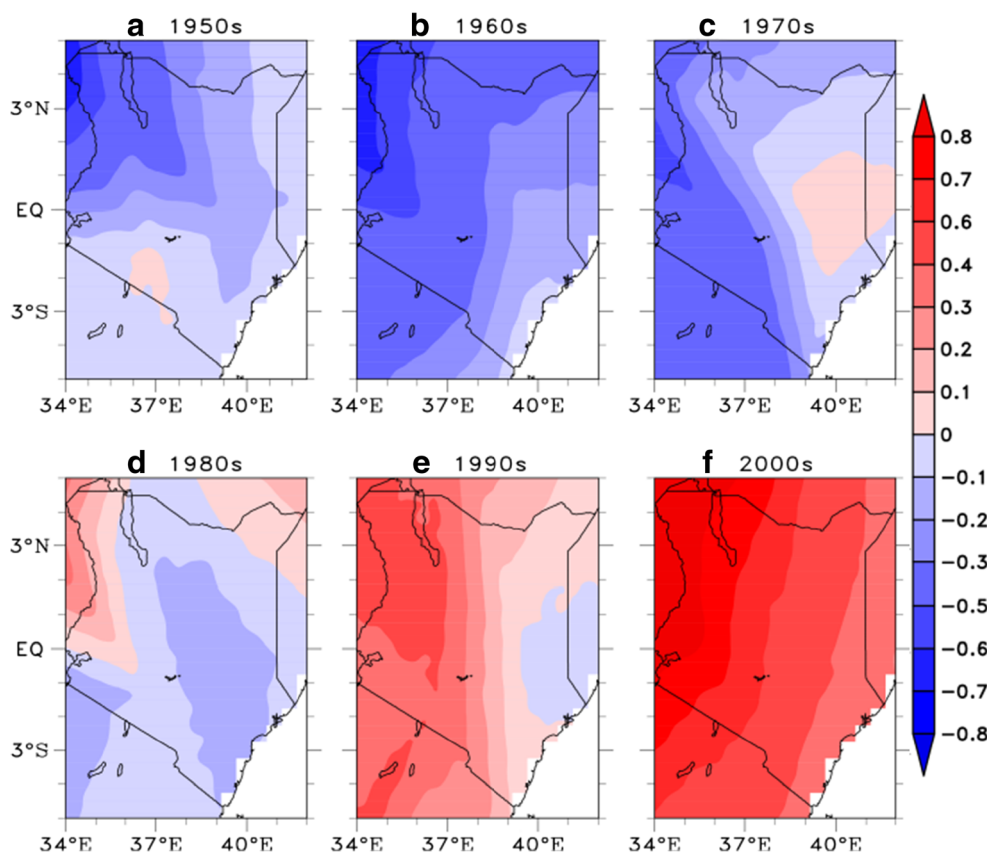
relatively cold and hot ends shift, an indicator of higher chances of hot days and low possibility of cold days. On the other, there is a slight decrease in DTR. A reduction in DTR is a characteristic of a warming atmosphere whereby minimum daily temperature is increasing at a higher rate than the maximum temperature. This has been attributed to global warming that makes the temperature changes between daytime and nighttime asymmetric (Karl et al. 1991). The results here are not different from results observed on various spatial scales, over Uganda (Nsubuga et al. 2014), South Africa (Kruger and Shongwe 2004), Africa (Hulme et al. 2001), and over the entire globe (Karl et al. 1991). The observed increase in mean and variance of maximum, minimum, and mean temperature (Fig. 8a–d) display increased certainty in the warming over Kenya. The certainty in warming has been reported globally, with IPCC reports reporting that global warming is unequivocal (IPCC 2007, 2014). The interest in global warming studies remains in the understanding of how the warming varies from one region to another, and how it’s likely to influence the occurrence of extreme temperature events which have adverse health effects.

The seasonal temperature trend over Kenya is presented in Figs. 9 and 10. It is evident that temperature started increasing in the late 1960s in both seasons. An abrupt change in temperature occurred in early the 2000s in DJF while in JJA, it

**Fig. 6** Spatial distribution of December–February decadal temperature (°C) anomalies. **a** 1951–1960, **b** 1961–1970, **c** 1971–1980, **d** 1981–1990, **e** 1991–2000, and **f** 2001–2010, relative to mean temperature for the period 1951–2010. The analysis is based on the Climate Research Unit (CRU) data, 1951–2010



**Fig. 7** Spatial distribution of June–August decadal temperature (°C) anomalies. **a** 1951–1960, **b** 1961–1970, **c** 1961–1970, **d** 1971–1980, **e** 1991–2000, and **f** 2001–2010, relative to mean temperature for the period 1951–2010. The analysis is based on the Climate Research Unit (CRU) data, 1951–2010



occurred the mid-1990s. The temperature increase in both seasons got to significant levels almost at the times when they experienced their respective abrupt changes.

The rate of change of temperature during the cold season is evidently higher than the change in dry season. This is an indication of overall warming over the country. This is backed by earlier studies such as Vose et al. (2005), and Easterling et al. (1997). The study by Vose et al. (2005) investigated temperature variability over the globe and explained the relative decrease in diurnal temperature range by higher increase in minimum temperature as compared to the maximum temperature. Generally, higher warming is observed in cold season as compared to the hot season. The warming of the initial cold areas that are known to be the country’s food basket is likely to lead to reduction in food productivity in the country. The temperature pattern explains the observed melting of snow on Mt. Kenya, which is located in the central part of the country. The mountain has enormous value in the region

and to the country as a whole ranging from tourism, being a water tower, and a rich ecosystem.

Activities that take place within a relatively short time require the understanding of how temperature changes within the specific time periods. According to Karl and Easterling (1999), it is very important to carry out continuous monitoring of climate trends, especially with regard to climate extremes is beneficial in decision making on environmental changes and socioeconomic activities. Table 7 presents a detailed analysis of the observed trend in temperature for the period 1951–2012.

Based on an assumption that the linear model in Table 7 gives the best description of monthly trends, the month of August exhibits the strongest positive trend. The months of March, May, and November show the weakest trends. Despite variation in the strength of the trends from month to month, in overall, the results depict a consistent significant positive trend at 95% confidence level in all months.

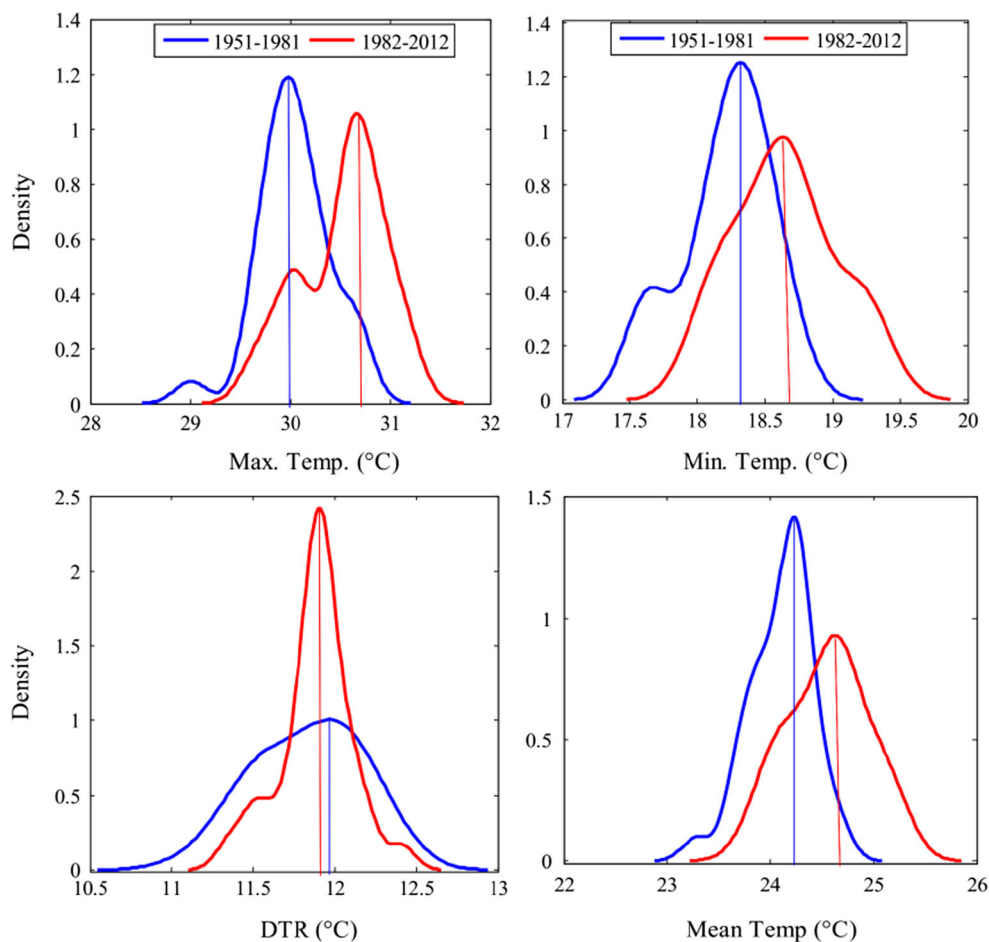
**Table 6** Linear decadal area averaged temperature trend over Kenya based on CRU data, 1951–2010

Temp.	Trend (°C/decade)
Max.	0.15
Min.	0.13
Mean	0.14

### 3.4 Changes in temperature extremes

The summary of the observed long-term mean of temperature characteristics/indices: TXmean, TNmean, DTR, TXx, TXn, TNx, and TNn based on observed daily observations are presented in Table 8. In agreement with the climatology (Fig. 2), the stations in the coastal Kenya record high temperatures as

**Fig. 8** Variations in the probability density function of mean annual maximum and minimum temperature, DTR and mean temperature for the two equal periods, 1951–1981 (red) and 1982–2012 (blue), based on CRU data

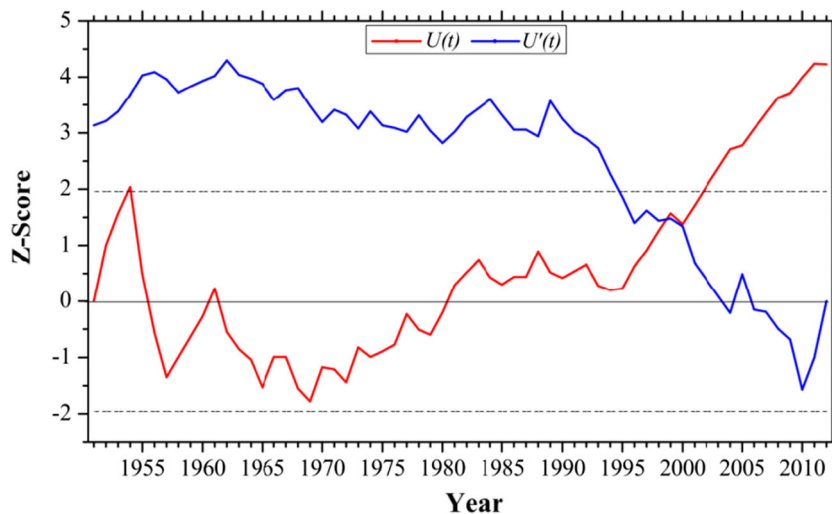


opposed to those in the central and western parts of the country. The lowest monthly minimum value of daily minimum temperature is recorded in the highland areas, evidenced by the low TNn observed in the region (Table 8).

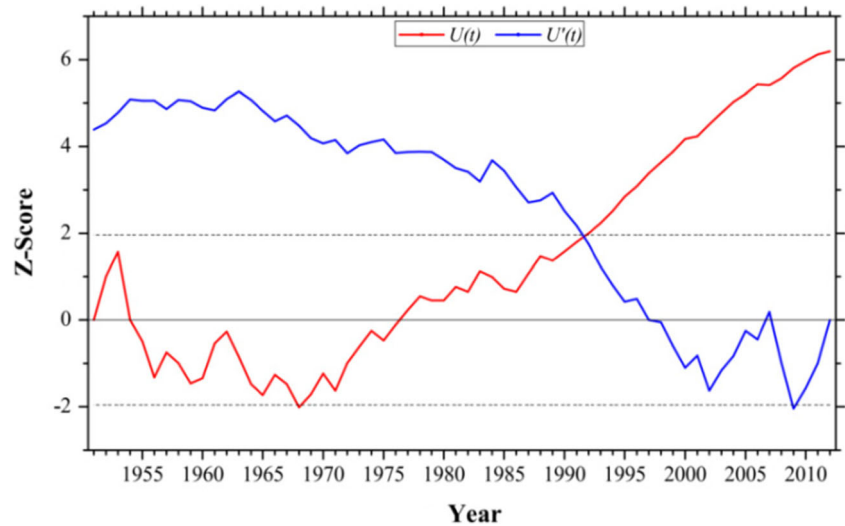
The trends in DTR are presented in Fig. 11. The reduction in DTR in most stations and increase in warm days and nights (Table 8) in all of the stations is an evidence of warming in

Kenya. In Voi and Malindi, abrupt changes in DTR were reported in the mid-1980 and the 1990s, while significant changes at  $\alpha = 5\%$  were observed in the early 1990s and the mid-2000s, respectively. In an interesting case, contrary to the expectations that warming is occurring at higher rate in the highland areas as compared to lowland areas, as observed using reanalyzed data (Figs. 6 and 7), DTR is found to

**Fig. 9** Abrupt change in DJF seasonal temperature as derived from Sequential Mann-Kendal test statistic based on CRU data;  $u(t)$  is forward sequential statistic [red],  $u'(t)$  is backward sequential statistic [blue]. The upper and lower dashed lines represent the confidence limits ( $\alpha = 5\%$ )



**Fig. 10** Abrupt change in JJA seasonal temperature as derived from Sequential Mann-Kendal test statistic based on CRU data;  $u(t)$  is forward sequential statistic [red],  $u'(t)$  is backward sequential statistic [blue]. The upper and lower dashed lines represent the confidence limits ( $\alpha = 5\%$ )



decrease more in lowland areas as compared to their highland counterparts (Fig. 11). A reduction in DTR is a good indicator of atmospheric warming. The results obtained using reanalyzed data are in agreement with the findings of other studies conducted globally including Fan et al. (2015), and Jungo and Beniston (2001), among others.

A summary of the percentage of warm days (TX90p) and warm nights (TN90p) is presented in Table 9. Although the data length differs in most stations, the available data is divided into two equal parts at each station and the percentages of 90th percentile exceedance compared in the two timelines. In all stations, the percentage for both TX90p and TN90p for the current years surpassed what was recorded in previous years. The only exception was observed in Lamu where the observations in TN90p for the earlier years slightly exceeded what was recorded in previous years. The general pattern, especially in warm nights, is a good indicator of warming in a given locality.

**Table 7** Regression equations of monthly mean air temperature anomaly for the period 1951–2012, based on CRU data

Month	Linear regression
January	$Y = 0.014x + 24.43^*$
February	$Y = 0.017x + 25.06^*$
March	$Y = 0.011x + 25.58^*$
April	$Y = 0.015x + 24.76^*$
May	$Y = 0.011x + 23.93^*$
June	$Y = 0.015x + 22.71^*$
July	$Y = 0.01x + 22.06^*$
August	$Y = 0.018x + 22.37^*$
September	$Y = 0.015x + 23.33^*$
October	$Y = 0.015x + 24.16^*$
November	$Y = 0.011x + 24.14^*$
December	$Y = 0.016x + 24.04^*$

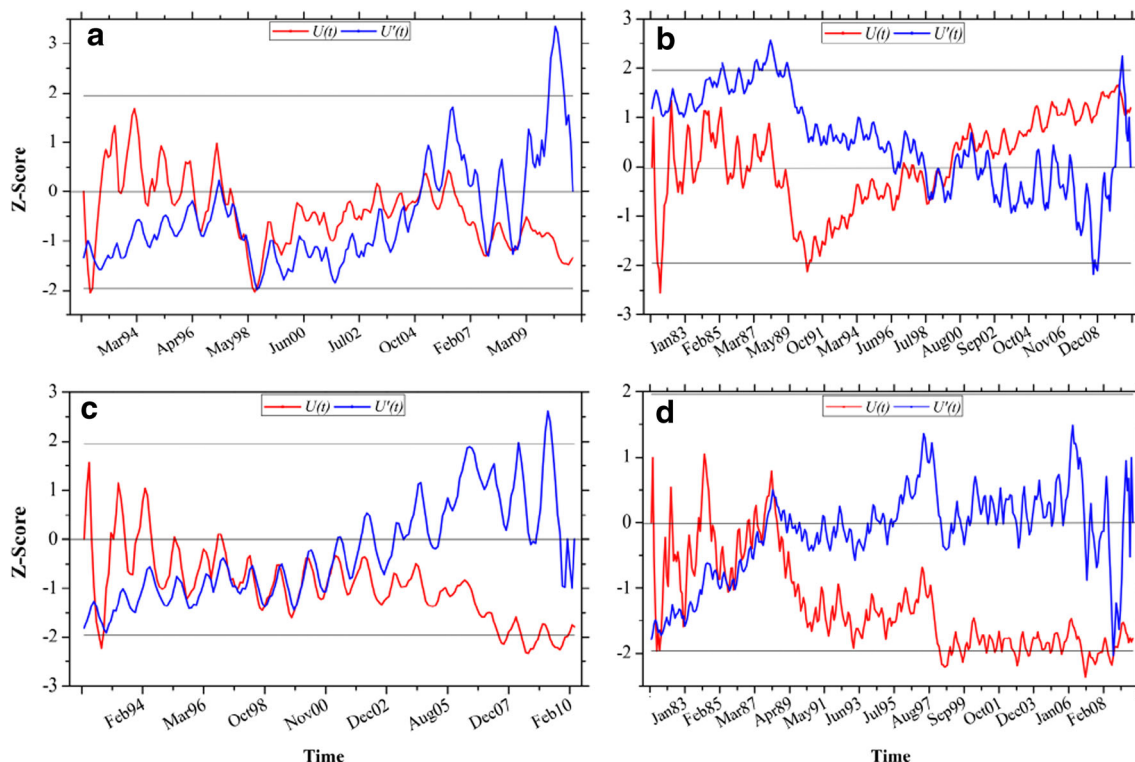
\*Statistically significant trends at the 95% confidence level

Though this affirms that the temperature in the country and the equatorial region is increasing just like many other places globally, it equally rules out the possibility of regional cooling throughout the study period. The results are in agreement with the main conclusions of the IPCC (2012) which reported that it is very likely that the number of cold days and nights has decreased, while the number of warm days and nights has increased on the global scale since 1950.

The overall warming, though being insignificant in some parts of the country, is likely to negatively affect agriculture and tourism especially in central Kenya, where warming rate is expected to be higher than in lowlands. The crops that thrive best in the region owing to low temperature are likely to be affected in the wake of globe warming. The impact extends to the tourism sector, which is affected by events related to warming, such as the ongoing melting of the snow on the top of Mt. Kenya as observed by Thompson et al. (2009). The snow at the top of the mountain forms a beautiful scene that attracts tourists into the region. The melting of the snow will equally affect other sectors such as water and rain-fed agriculture since the hydrological cycle will have been destabilized.

**Table 8** A summary of mean temperature; TXMean, TNMean, and DTR, and selected long term mean extreme temperature indices over selected stations in Kenya based on observed data

Station	TXMean (°C)	TNMean (°C)	DTR (°C)	TX <sub>x</sub> (°C)	TX <sub>n</sub> (°C)	TN <sub>x</sub> (°C)	TN <sub>n</sub> (°C)
Embu	24.5	14.2	10.3	32.6	11.1	25	7.1
Thika	25.7	14.2	11.6	33.2	15.5	23.6	5.8
Narok	24.9	10.2	14.6	36.6	11.9	25.4	0.3
Voi	31.0	19.8	11.2	39.2	21.4	31.3	13.0
Lamu	31.0	23.8	7.1	39.6	20.1	33.5	13.5
Malindi	30.0	23.7	6.3	35.0	20.9	29.1	17.6



**Fig. 11** Abrupt change in diurnal temperature range for **a** Narok, **b** Embu, **c** Malindi, and **d** Voi as derived from Sequential Mann-Kendal test statistic,  $u(t)$  is forward sequential statistic [red],  $u'(t)$  is backward

sequential statistic [blue]. The upper and lower dashed lines represent the confidence limits ( $\alpha = 5\%$ )

The other concern about the increasing temperature in Kenya and EA at large is how it is likely to influence of the occurrence of malaria. Omumbo et al. (2011) observed that warming is likely to have increased malaria cases in Kericho, Kenya. Although there are no clear thresholds of the temperature that can influence the survival of mosquitoes of the *Anopheles* genus which transmit malaria in EA, there remains

a concern of the possible increase in the cases, given the projected warming as pointed out by Omondi et al. (2014).

The challenges posed by the warming extend to the health, thermal comfort, and economic sectors. The increase in warm nights is likely to force people to spend their resources on cooling systems in their houses. Thermal discomfort is known to reduce human productivity (Dunne et al. 2013), affecting the economy of a given area/country in the long run.

**Table 9** The percentage of warm days and nights in two different timelines based on observed data

Station		TX90p (%)	TN90p (%)
Embu	Years	(%)	(%)
	1981–1995	81.7	77.4
Thika	1996–2010	85.9	81.2
	1982–1996	84.6	73.2
Narok	1997–2010	87.4	78.4
	1986–1998	81.8	58.1
Voi	1999–2010	84.3	64.4
	1981–1995	88.8	83.6
Lamu	1996–2010	90.3	87.7
	1981–1995	93.4	94.9
Malindi	1996–2010	97.0	94.6
	1986–1995	94.5	93.7
	1996–2009	97.1	96.9

### 4 Conclusions and recommendations

This study has examined the temperature variability over 1951–2012, and the recent extreme temperature events over Kenya for a 30-year period (1981–2010). The relatively short period and a few stations considered in the study of extreme events are dictated by data quality, as observed in previous studies (Christy et al. 2009; Omondi et al. 2014; Hawinkel et al. 2016). The number of stations observing temperature is generally lower and has been done over a shorter period as compared to rainfall records. The stations utilized in this study do not cover the northern part of the country given that the distribution of synoptic stations in the area is very poor and the available stations have made temperature observations over a relatively short period. The reanalyzed CRU data (1951–2010) is used to study spatiotemporal variability

temperature over Kenya. The special report on managing extreme events (SREX, IPCC 2012) pointed out that the occurrence of extreme events over EA with low to medium confidence owing to the sparse and unreliable observations across much of EA.

Understanding of the variability and occurrence of extreme events in temperature and other climate variables provide useful information in monitoring climate change at a local/regional scale. In the temporal evolution of temperature over Kenya, the DJF season is the hottest while JJA is the coldest, exhibiting almost similar standard deviation. The SMK test analysis shows that temperature in both seasons is increasing since the late 1960s, with abrupt change occurring in end of the 1990s. The noted rate of warming per decade is + 0.15 °C/decade. The causes for the observed warming are beyond the context of the research; however, an attribution can be made to anthropogenic forces (Daron 2014).

Overall, the results show a consistent increase in mean surface temperature in all stations under study. The rate of increase is higher in cold season as compared to the warm season, an indicator of increased warming. The noted increase in temperature is higher in high-elevation regions as compared to low-elevation zones. However, the warming extent between high and low-elevation regions has not been looked into in this study, opening room for further studies on the same. The warming is further supported by an increase in the percentage of TX90p and TN90p with time in all stations. Further, the diurnal temperature range is observed to decrease in most stations, especially those in lowland areas, reaching significant levels at 95% confidence level in the early 1990s and mid-2000s.

The observed warming and the projections made in other studies suggest that future climatological and hydrological alterations within the country (Omondi et al. 2014). This will eventually affect several sectors that are sensitive to climate variability such as health, water, transport, and agriculture. Thus, future climatic variability requires more attention through comprehensive studies to provide more detailed information for decision-making.

The results of this work form a good reference source for extreme temperature events studies over Kenya, and to the larger extent, EA region. The findings are useful in validation and application of regional climate models in the effort to simulate the current and future climate, focusing on extreme climate events. This information is important in regional climate change impact assessment, aimed at providing accurate and reliable information for planning purposes that promotes socioeconomic development by minimizing loss of lives and destruction of property. However, owing to the length and distribution of the observed data considered herein, the results in the extreme temperature events should be regarded as a preliminary estimate of the observed variability of mean and extreme temperature events over EA. It is our hope that these

results will drive curiosity in researchers who will look into the topic or related subjects using long and more observed datasets in their reach. Future related studies should consider looking into possible mechanisms for the observed trend changes. Today, the adoption of automatic weather stations to supplement the poor network of manned stations presents an opportunity for quality research in EA in the near future based on data availability. Meanwhile, it is advisable to adopt inter-country research collaborations, an approach used in Omondi et al. (2014) to maximize accessibility of the available observed data in EA.

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