Research article

# Suitability of different data sources in rainfall pattern characterization in the tropical central highlands of Kenya

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### ARTICLE INFO

### ABSTRACT

Uncertainty in rainfall pattern has put rain-fed agriculture in jeopardy, even for the regions considered high rainfall potential like the Central Highlands of Kenya (CHK). The rainfall pattern in the CHK is spatially and temporally variable in terms of onset and cessation dates, frequency and occurrence of dry spells, and seasonal distribution. Appraisal of the variability is further confounded by the lack of sufficient observational data that can enable accurate characterisation of the rainfall pattern in the region. We, therefore, explored the utilisation of satellite daily rainfall estimates from the National Aeronautics and Space Administration (NASA) for rainfall pattern characterisation in the CHK. Observed daily rainfall data sourced from Kenya meteorological department were used as a reference point. The observation period was from 1997 to 2015. Rainfall in the CHK was highly variable, fairly distributed and with low intensity in all the seasons. Onset dates ranged between mid-February to mid-March and mid-August to mid-October for long rains (LR) and short rains (SR) seasons, respectively. Cessation dates ranged from late May to mid-June and mid-December to late December for the LR and SR, respectively. There was a high probability (93%) of dry spell occurrence. More research needs to be done on efficient use of the available soil moisture and on drought tolerant crop varieties to reduce the impact of drought on crop productivity. Comparison between satellite and observed rain gauge data showed close agreement at monthly scale than at daily scale, with general agreement between the two datasets. Hence, we concluded that, given the availability, accessibility, frequency of estimation and spatial resolution, satellite estimates can complement observed rain gauge data. Stakeholders in the fields of agriculture, natural resource management, environment among others, can utilise the findings of this study in planning to reduce rainfall-related risks and enhance food security.

## 1. Introduction

Globally, around 80% of the agricultural land is rain-fed that contribute at least two-thirds of the world's food production (Alam and Ekhwan 2011). About 90% of staple food production in sub-Saharan Africa (SSA) is under rain-fed agriculture (Savenije 2001; Rockström 2003). For example, approximately 90% of the population in Malawi and Botswana, 70–80% in Zimbabwe and at least 76% in Kenya with the comparable patterns throughout Eastern and Southern Africa rely on rain-fed subsistence agriculture for their livelihoods (Rockström 2000). In the Central Highlands of Kenya (CHK), smallholder agriculture is

entirely rain-fed (Ngetich et al., 2014). The dependence on rainfall by most smallholder farmers is still expected to intensify in future due to the rapid population growth (Mélanie et al., 2010). Thus, rainfall characterisation is paramount in the quest to not only understand agricultural production systems for SSA but also in the pursuit of agricultural production intensification for enhanced food security.

Central Highlands of Kenya is among the high potential areas in Kenya and East Africa, receiving a substantial amount of rainfall that can support the growth of a wide range of crops (Jaetzold et al., 2007a, b). However, uncertainty, high variability and poor distribution have put the advantages in jeopardy. False start, late-onset, early cessation, high

rainfall intensity and variability and dry spells, are among the hindrances to rain-fed agriculture in the region. Although many soil management practices can be used to enhance water use efficiency in alleviating plant moisture stress (Evett and Tolk 2009), they can be more reliable when they are tailored to the pattern of rainfall (Wang et al., 2016).

Late-onset and early cessation may reduce crop productivity as the length of the crop growth period are reduced (Jury 2002). A significant relationship between the start of rains and the length of the rainy season has been established in semi-arid parts of West Africa (Sivakumar 1988). Sowing close to the optimal planting date has been reported to increase crop yield significantly (Nyagumbo et al., 2017). Knowledge of the onset, cessation, and length of the growing season can substantially support the timely planning of most agronomic activities, and most likely reduce the risk of planting too early or too late (Omotosho 2002).

Increased volatile and erratic rainfall patterns have been observed over time (National Research Council, 2001). For example, Lobell and Field (2007) observed that 30% or more of yearly deviation in global average yields of top-six widely grown crops (Corn, wheat, rice, sweet potatoes, cassava and beans) is attributed to precipitation and temperature variations. High rainfall variation has also been observed in Ethiopia (Seleshi and Zanke 2004) and Sudano Sahelian region (Sivakumar 1991). A similar observation has been made in Kenya upon characterising rainfall in the western part of the country (Mugalavai et al., 2008). The high variability has become a climatic maze that has left rain-fed agriculture captive. Farmers are uncertain about what to plant and when to plant, making agriculture a gambling venture with abundant risks. This has resulted in reduced agricultural investment while the population has continued to bloom; consequently, food insecurity is chronic. The impact of rainfall variability ranges from extremely high rainfall events, both regarding quantities and intensities, which have adverse effects on crop production. Continuous evaluation of rainfall variability is thus crucial, especially in SSA where human activity and agricultural production, in particular, is firmly hinged to inter-annual rainfall variability (Jury 2002).

Poor rainfall distribution has been a significant challenge on rainfed agriculture even in the regions considered to be receiving enough rainfall like the CHK (Ngetich et al., 2014). The sparse distribution of rainfall constitutes the causes of crop failure than absolute water scarcity (Rockström 2000). Meehl et al. (2007) noted that up to 25% of the rainfall received falls within a few rainfall events causing soil erosion besides subjecting crops to moisture stress during a cropping season. The sparse rainfall distribution in Kenya has been attributed to natural causes such as atmospheric, oceanic and local conditions (winds, waterbody, vegetation cover and topography) (Mugalavai et al., 2008; Kalantari et al., 2018). The causes being natural, manipulating rainfall distribution into a pattern desirable for agricultural production is not possible, but there are techniques to moderate/mitigate the impact of variation. However, the use of some mitigation strategies is less effective if the pattern of distribution is not well established.

Prolonged dry spell occurrences are the main contributor for crop failure in SSA (Shin et al., 2015). The dry spell disrupts crop growth and lowers yield (Mzezewa et al., 2010). Even during high seasonal rainfall, up to total crop failure may be realised if the interval between consecutive rain events is too long (Tilahun 2006; Araya and Stroosnijder 2011; Araya et al., 2012). The impact of the dry spell depends on the timing, magnitude, crop growth stages and resilience to water stress (Ngigi et al., 2005). Intra-seasonal dry spells and their severe effects on crop productivity has become a standard feature in agricultural production (Rockstrom 2003). For instance, in the CHK there have been recent crop failures for both the short and long rains between 2016 and 2017, resulting in food insecurity in the region and other places as it is one of the food baskets in Kenya. Dry spells are associated with poor seasonal rainfall distribution that is common in most parts of the world (Mzezewa et al., 2010) and has threatened agricultural production. Characterising the pattern of occurrence of the dry spell can contribute to reducing their severity by allowing for proper planning.

Unreliability and insufficient observational rainfall data have limited characterisation of rainfall in the CHK due to low rain gauge density (Franz et al., 2012). In a region where rainfall is highly variable like the CHK, extrapolating of rainfall data from sparse and unevenly distributed rain gauge network leads to inaccuracies (Li and Heap 2008; Scheel et al., 2011). Other shortcomings of rain gauges include errors and omissions by human operators, power outages from the devices used and data transmission faults that could cause valuable data lost, damaged, or altered, compromising data quality (Kneis et al., 2014). The mistakes contribute to discrepancies detected between the different rainfall datasets (Barros 2014). The errors and inaccuracies provoke need to relook into the studies that have been based on observed rain gauge data such as Mugalavai et al. (2008); Recha et al. (2011) and Ngetich et al. (2014). Use of satellite-based rainfall data can be an alternative data source to bridge the gap (Ward and Trimble 2003). However, the quality of data from satellite estimations needs prior evaluation and validation before use.

Hence, we sought to characterise rainfall in the central highlands of Kenya using satellite rainfall estimates by determining rainfall onset, cessation date and the length of growing period. We also established the spatial and temporal pattern of rainfall and characterised seasonal dry spells. Lastly, we assessed satellite-derived rainfall estimates and the meteorological stations observed rain gauge data.

## 2. Materials and methods

### 2.1. Study area

The study was carried out in seven counties in the Central Highlands of Kenya (CHK): Meru, Tharaka-Nithi, Nyeri, Embu, Kirinyaga, Murang'a and Kiambu (Figure 1). The CHK is one of the high agricultural potential regions in Kenya with average annual rainfall ranging from 450 mm to 1400 mm per annum (Jaetzold et al., 2007a, 2007b). The counties have a bimodal rainfall pattern with long rains (LR) starting in March to May and short rains (SR) in October to December, hence two cropping seasons per year. The "long rains" are normally the main rainfall period lasting between Mar-Apr-May in east Africa while the "short rains" last from October, November and December in East Africa. Coastal and topographic influence moderates the bimodal rainfall regime (Mutai et al., 1998).

The central highlands of Kenya generally have a daily mean temperature of about 19 °C. The predominant soil type is *Humic Nitisols*, typically deep and weathered soil with moderate to high inherent fertility (Jaetzold et al., 2007a, 2007b). The main land-use activities in these counties are cash crop farming, subsistence farming, livestock rearing, agro-forestry and forestry. The main cash crops are coffee and tea while maize (*Zea mays L*) and beans (*Phaseolus vulgaris*) are the essential and dominant annual crops. The primary farming system in the area is mixed farming.

Meru and Tharaka Nithi Counties cover the northern to the eastern slopes of Mt. Kenya. The counties lie at an average altitude of about 1,500 m above sea level (a.s.l) and receive an annual average rainfall of about 1500 mm. Long rains come from around March to June and SR from October to February (Jaetzold et al., 2007a; Smucker and Wisner 2008). The rainfall received is influenced by Mount Kenya (rographic rainfall) in combination with latitude, inter-tropical convergence zone, ENSO and sea surface temperatures, among others (Odingo et al., 2002). The counties cover the AEZs Tropical-Alpine 0, 1 and 2 (TA 0, TA 1 and TA 2), Lower Highlands 0, 1, 2, 3, 4 and 5 (LH 0, LH 1, LH 2, LH 3, LH 4 and LH 5), Upper Highland 0, 1, 2 and 3 (UH 0, UH 1, UH 2, UH 3), Upper Midland 3, 4, 5 and 6 (UM 3, UM 4, UM 5 and UM 6), Lower Midland 3, 4 and 5 (LM 3, LM 4, LM 5) (Jaetzold et al., 2007a).

Embu County is located on the eastern slope of Mount Kenya. It lies at an altitude of about 1,700 m above sea level (asl) and average annual rainfall ranging from 450 to 1400 mm (Jaetzold et al., 2007a). The LR come from around March to June and SR from around October to
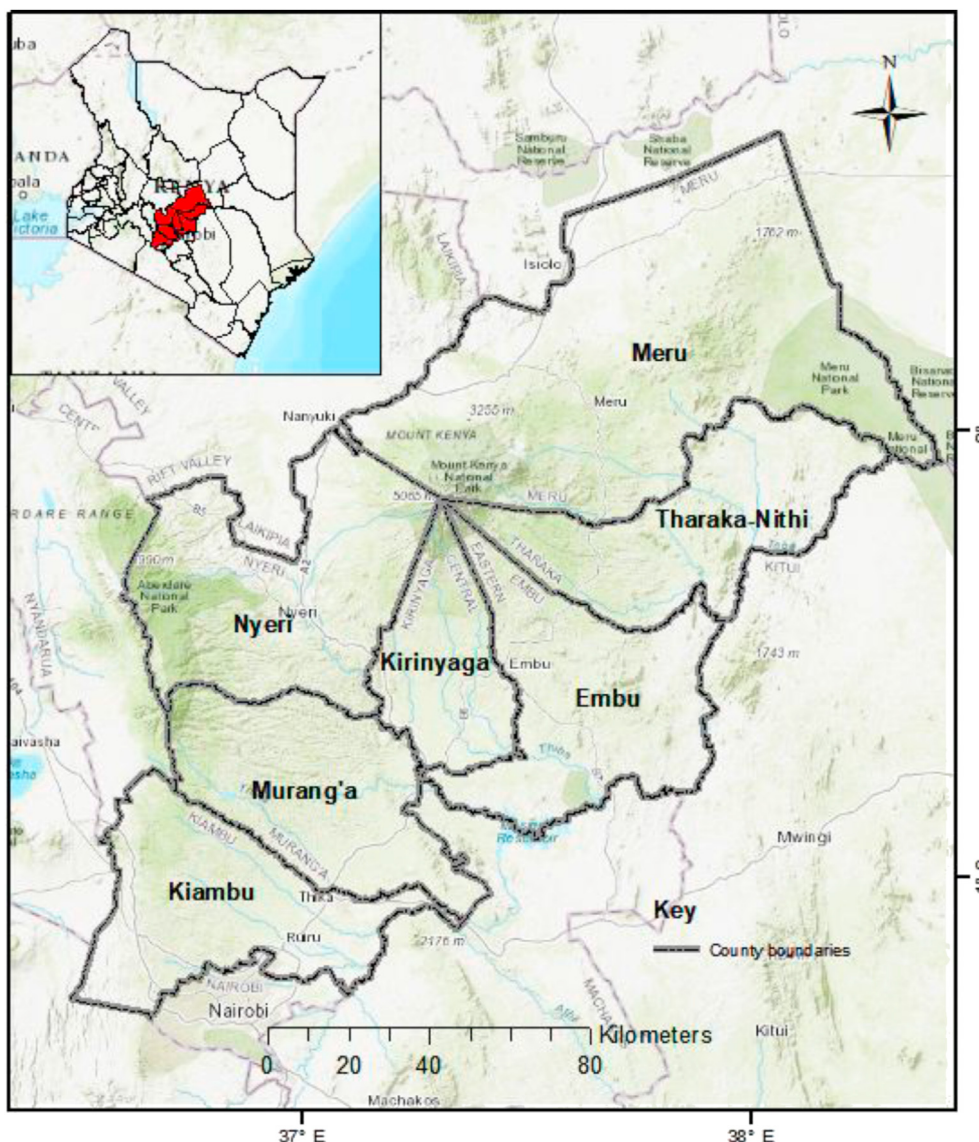
**Figure 1.** Map showing the counties under study (Source of the base map: Esri, HERE, Garmin FAO OpenStreet contributors).

February (Jaetzold et al., 2007a). Mount Kenya majorly influences rainfall in combination with other factors. The region lies in the LM3, LM 4, LM 5, UM 1, UM 2, UM 3, UM 4, and inner lowland 5 (IL 5).

Nyeri County is between the Aberdare ranges and Mt. Kenya. It is located on the eastern slope of the Aberdare ranges and the western slope of Mt. Kenya. Average annual rainfall ranges from 700 to 2200 mm. The county has high rainfall reliability in both seasons (Jaetzold et al., 2007b). The long dry season is from June to September and a short dry season from January to February. Lies at an altitude of about 1500 m asl. The south-easterly trade winds are forced up by the mountains in the wet areas causing frequent mists and drizzle above 1500 m asl. Dry North Eastern Trades winds that blow over the region from the Somalian deserts are responsible for the short dry season (Jaetzold et al., 2007b). Nevertheless, in the higher areas, there is still enough moisture in the soil to enable permanent cropping possible in the zones. The County covers the AEZs TA 0, TA 1, TA 2, UH 0, UH 1, UH 2, UH 3, LH1, LH 2, LH 3, LH 4, LH 5, UM 1, UM 2, UM 3, and UM 4 (Jaetzold et al., 2007b).

Kirinyaga County lies on the Southern slope of Mt. Kenya and southeastern slopes of the Aberdare Range. Annual rainfall ranges from 1600 mm in low altitude areas (1600 m asl) to 2200 mm in higher altitude areas (2500 m asl). Rainfall is influenced by Mount Kenya and Aberdare range which affects the southeast trade winds (Jaetzold et al., 2007b). The reliability of rainfall is high. Covers the AEZs UH 0, LH 1, UM 1, UM 2, UM 3, LM 3, LM 4.

Murang'a County is located on the eastern slope of the Aberdare Range in the central part of Kenya with an altitude from 900 to 3300 m and mean annual temperature of 26.3 °C (Jaetzold et al., 2007b). Long rain comes from March to the end of May and a short rain from October to December. The sub-county receives a total annual rainfall of 900–1400 mm which is highly variable both spatially and temporally and poorly distributed (Ovuka and Lindqvist 2000). During the rain periods, much of the precipitation falls as showers at late night or early in the morning. Between June and September, the rainfall mostly falls as drizzle. January and February are the two dry months (Ovuka and Lindqvist 2000). The county lies in the AEZ, UH 0, LH 1, UM1, UM 2, UM 3, UM 4, LM 3 and LM 4.

Kiambu County is on the eastern slope of Aberdare ranges. Has an altitude of between 1300 to 2200 m asl and receives rainfall of between 900 to 1200 mm annually (Jaetzold et al., 2007b). The LR comes from around March to June and SR from October to February and is highly

variable. The region lies on the AEZ UH 0, UH 1, UH 2, LH 1, LH 2, LH 3, LH 4, LH 5, UM 1, UM 2, UM 3, UM 4, UM 5, UM 6, LM4, LM5 and LM6.

### 2.2. Data source

Daily satellite data used in this study was downloaded from Prediction Of Worldwide Energy Resource (POWER) website https://power.larc.nasa.gov/cgi-bin/agro.cgi?na (Stackhouse et al., 2015) while observed rain gauge data was obtained from Kenya Meteorological Department (KMD) stations in Embu, Meru and Tharaka-Nithi counties. The POWER 2017 gave rainfall estimates at any grid point intersection. Point rainfall data was used to correct the satellite data. It was notable that the satellite based data underestimated the observed rain gauge data by half. The satellite estimate was multiplied by a factor of 2 for correction before the data was used for rainfall characterization. However, the satellite estimates used for comparison with the observed were not corrected. Satellite data obtained covered the region between latitude -1 to 1 and longitude 36 to 38 that covers the whole study area (CHK) from 1997 to 2015 (19 years). In each county, grid point intersection near and within the county boundaries was used to represent the rainfall estimate for that entire county by computing the average. The points were picked at a 1-degree interval that resulted in rainfall data from nine points of grid intersection which were used in computing satellite averages. The points include (1° S, 36° E), (1° S, 37° E), (1° S, 38° E), (0°, 36° E), (0°, 37° E), (0°, 38° E), (1° N, 36° E), (1° N, 37° E) and (1° N, 38° E).

### 2.3. Estimation of missing values in the observed data

In this study, arithmetic mean method was used (Lu et al., 2016). The missing data were replaced with the mean for the given station as per Eq. (1).

$$X_m = \left(\frac{\overline{X}}{\overline{Y}}\right) Y_m \tag{1}$$

Where $X_m$ is the missing record at station X, $\overline{X}$ is the long-term mean for the station with the missing data in specific year and month, $\overline{Y}$ is the long-term mean of the station with complete data, and $Y_m$ is the corresponding records of the station Y having complete data.

### 2.4. Homogeneity test and data correction

Homogeneity test for the historical rainfall data from both observed rain gauge and satellite data was conducted using RAINBOW software package (Institute for Land and Water Management of the K.U. Leuven, Belgium) (Raes et al., 2007). The programme is designed to test the homogeneity of hydrologic records like rainfall and evaporation data and to perform their frequency analysis. The programme can also predict the probability of occurrence of the rainfall amounts. It is a menu-driven programme and runs on an IBM that is compatible on personal computer (Raes et al., 2007).

In testing the homogeneity, the software package works under the principle of cumulative deviation from the mean. (S_k, k = 1, 2, …n), defined as:

$$S_k = \sum_{i=1}^{k} (x_i - \overline{x}) \tag{2}$$

Where $x_i$ is the annual rainfall records and $\overline{x}$ the mean. The cumulative deviation, $S_k$ should fluctuate around zero for the homogenous rainfall series. The initial value of $S_k = 0$ and last value $S_k = n$ are all equal to zero.

The cumulative deviations are rescaled by dividing them by the sample standard deviation (s). Afterwards, the homogeneity of the rainfall time series is tested by calculating the maximum (Q) (Eq. (3)) or

the range (R) (Eq. (4)) of the rescaled cumulative deviations. A high value of Q or R indicated that the data of the time series is not from the same population and that the fluctuations are not purely random. The homogeneity hypothesis of the data set was at the 99% probability level. None-homogenous data was considered for transformation if the homogeneity hypothesis was rejected.

$$Q = max\frac{s_k}{s} \tag{3}$$

$$R = max\frac{s_k}{s} - min\frac{s_k}{s} \tag{4}$$

Satellite-based rainfall data underestimate total annual averages by a factor of 2. To correct the anomaly, all the satellite data was multiplied by two before being used in the rainfall analysis.

### 2.5. Determination of rainfall onset, cessation date and the length of the growing period

RAIN software was used in determining the onset, cessation and the length of growing period (Kipkorir 2005). RAIN is a computer model for determination of the onset, cessation, length and evaluation of the growing season, seasonal crop water shortage and forecasting the relative yield, using soil water balance model, for a particular crop grown on a particular soil type (Kipkorir 2005). It was used in the characterization of rainfall onset, cessation and the length of the crop growth period in the central highlands of Kenya (Ngetich et al., 2014).

Search dates were specified in the RAIN software that encompasses the normal rainy period. The specified date is the average early date at which the rainy season starts and the cessation date. An appropriate initial search date eliminated the false start, and the corresponding onset window was selected, with the help of the RAIN software (Kipkorir 2005). The date having a probability of at least 20% that the root zone has adequate soil moisture was regarded as the date after which the onset criteria apply for each station. Starting from the initial search data, the onset was taken to be the date on which the criterion was first satisfied (Kipkorir et al., 2004). The onset date was determined by soil water balance model based on accumulated rainfall for four days to be at least 25 mm (Raes et al., 2004). It was centred on the farmers' practices as an appropriate wet season sowing, that at least 25 mm is enough to support seed germination and initial development. A lag time of the season was set at seven days after onset. The threshold for a rainy day was set at 1 mm (Lazaro et al., 2001).

The soil water balance was used to determine the cessation date. It was the date on which the set threshold water stress coefficient ($K_s$) was exceeded. The $K_s$ below 40% was taken to be the end of the growing season as it was assumed to cause rapid water stress to crops (Mugalavai et al., 2008). The difference between the cessation date and the onset date was taken to be the length of the growing period.

### 2.6. Establishing the temporal and spatial pattern of rainfall variation over the years

Long term trends of annual and seasonal rainfall variation were analysed using cumulative departure index (CDI) and rainfall anomaly index (RAI) (Tilahun 2006) in Microsoft Excel spreadsheet. Tilahum (2006) and Kisaka et al. (2015) used CDI and RAI in the analysis of long term rainfall trend. Cumulative departure index was derived from the arithmetic mean of seasonal and annual rainfall during the period. Thus, the arithmetic means of seasonal and annual rainfall were as Eq. (5);

$$CDI = \frac{(r - \overline{r})}{S} \tag{5}$$

Where *CDI* is cumulative departure index, r the actual rainfall (seasonal or annual) of a given years, the mean rainfall of the total length of the period and S the standard deviation of the total length of the period.

Results of the values were added cumulatively added to each other for the entire period and plotted to achieve long-term trends for annual and seasonal rainfall. The RAI was plotted to illustrate inter-seasonal rainfall variations and calculated Eq. (6) for positive and Eq. (7) for negative anomalies;

$$RAI = +3 \left( \frac{RF - M_{RF}}{M_{H10} - M_{RF}} \right) \tag{6}$$

$$RAI = -3 \left( \frac{RF - M_{RF}}{M_{L10} - M_{RF}} \right) \tag{7}$$

Where RAI represents the seasonal rainfall anomaly index, RF the actual rainfall for a given year, $M_{RF}$ mean of the total length of the record, $M_{H10}$ mean of the ten highest values of rainfall on record and $M_{L10}$ the lowest values of rainfall on record.

Coefficient of variation (CV), defined as the ratio of the standard deviation to the mean was used to analyze both annual and seasonal rainfall variation and dry spell frequency. The CV was calculated for annual and seasonal rainfall amount and rainy days for each county. Use of CV has been applied analyze both annual (Mzezewa et al., 2010; Kisaka et al., 2015) and seasonal (Barron et al., 2003; Seleshi and Zanke, 2004) rainfall variation and variability of a dry spell (Kisaka et al., 2015).

Spatial presentation of rainfall onset, cessation and length of the growing period was determined by first getting the seasonal onset, cessation dates and the length of growing period for all the grid points within and near the study area over the years under consideration (Dunning et al., 2012). The dates were used as the input in generating a spatial representation (maps) of seasonal rainfall throughout the study area in ArcGIS® 10.5. Ordinary kriging method was used in the interpolation in a semi-variogram model to create the raster layers. The raster layers were then reclassified and extracted by masking to generate digital maps for the onset cessation and the length of the growing period.

### 2.7. Establish rainfall distribution pattern and intensity over the years

To establish temporal rainfall distribution pattern over the years, cumulative precipitation amount was calculated for both the long and short rains separately. The cumulative totals were then converted into percentages and graphs of the percentage cumulative precipitation plotted against time.

To evaluate rainfall intensity, precipitation variability index (PVI) (Eq. (8)) was used (Gu et al., 2016). Precipitation variability index has been used in the analysis of rainfall intensity in Namibia (Lu et al., 2016). The PVI is an index defined as the standard deviation of the ratio ($R_i$) between a time series of cumulative precipitation measurement ($C_i$) and a time series of cumulative mean precipitation rate ($E_i$) (Gu et al., 2016)

$$PVI = \sqrt{\frac{\sum_{i=1}^{n} (R - \overline{R})^2}{n}} \tag{8}$$

$$R_i = \frac{C_i}{E_i} \tag{9}$$

$$C_i = \sum_{j=1}^{i} p_j, \quad i = 1, ..., n. \tag{10}$$

$$\overline{P} = \frac{\sum_{i=1}^{n} pi}{n} \tag{11}$$

$$E_i = i\overline{P}, \quad i = 1, \&, ..., n \tag{12}$$

From the measured daily precipitation $p_j$, a time series of cumulative rainfall $C_i$ (Eq. (10)) and mean precipitation rate $\overline{P}$ (Eq. (11)) were computed. The time series of cumulative mean $E_i$ then were computed

based on mean precipitation rate $\overline{P}$ (Eq. (11)), and $R_i$ is the ratio of the cumulative precipitation to the cumulative mean (Eq. (9)). $\overline{R}$ is the average of $R_i$ over n.

### 2.8. Analysis of dry spells during the cropping seasons

Dry spell frequency was determined by counting the number of dry spells. In this study, a dry spell was defined as 'n' days without rainfall sandwiched between rainy days (Kumar and Rao 2005). The 'n' values were taken to be > 5, on the basis that consecutive dry days of more than 5 are enough to cause a significant reduction in crop productivity (Shin et al., 2015). A dry day was taken to be any day that receives less than 1 mm of rainfall (Lazaro et al., 2001). This was according to the argument by Angel (2004) that rainfall less than this amount is evaporated back directly to the atmosphere.

The variability of dry spells was determined by computing the coefficient of variation of the dry spells, and significance of variation evaluated using t-test at 95% confidence level. Dry spell frequency of 5 > 10, 10 > 15 and more than 15 days were computed. The probability of experiencing a dry spell was determined using the concept by Belachew (2000); that in the Y years of record, the frequency ($i$) that a dry-spell of duration ($t$) days occurs was counted on a seasonal basis (N = Y *i). Then the frequency ($I$) that a dry-spell of duration longer than or equal to $t$ occurs was computed cumulatively. The sequential dry days (1d, 2d, 3d ...) were computed from historical data. Chances of consecutive dry days occurrence were estimated by considering the number of days within a given season $d$. The total probable number of days, $D$, for that season over the period of record was computed as $D = d *Y$. In this study, $t$ was taken as 6. The probability P that a dry-spell starts on a specific day within a growing season was given by Eq. (13). The probability R, that a dry-spell less than $t$ does not occur at a certain day in a growing season was computed by Eq. (14); probability Q that a dry-spell of longer than $t$ days will occur in a growing season was calculated by Eq. (15), and probability L, that a dry-spell of more than $t$ days would occur at least once in a growing season was computed by Eq. (16) (Kisaka et al., 2015).

$$P = \left( \frac{1}{N} \right) \tag{13}$$

$$R = (1 - P) = \left( 1 - \frac{1}{N} \right) \tag{14}$$

$$Q = \left( 1 - \frac{1}{N} \right)^n \tag{15}$$

$$L = 1 - Q = 1 - \left( 1 - \frac{1}{N} \right)^n \tag{16}$$

### 2.9. Comparison of satellite and observed rainfall data

Cumulative departure index (CDI) was used to compare the trend of rainfall variation. The CDI was computed for both the satellite and the observed rainfall and their graphs plotted against the time of the record.

Onset-cessation dates and the length of growing period as per each data set were compared. The range with which the dates differed was noted and t-test at a 95% significance level was used to test the significance of the variation. The ranges with which the dates differ also form part of the evaluation of the two data sets.

Correlation analysis was used in evaluating the degree of association between satellite estimates and observed rain gauge data using Pearson correlation coefficient in SAS 9.3 software package (SAS Institute 2011). Student t-test was used to test the significance of the strength of the correlation at p = 0.05. The computation was as per Eqs. (17) and (18). Correlation was done at daily and monthly rainfall averages.

$$r_{xy} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \ \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{17}$$

$$t_{n-2} = {}^{r}\sqrt{\frac{n-2}{1-r^2}} \tag{18}$$

Where $r_{xy}$ is the correlation coefficient, $n$ is the sample size, $x_i$ and $y_i$ are the variables being correlated and $\overline{x}$ and $\overline{y}$ are the mean values of the variables of satellite and gauge based data, respectively and $t_{n-2}$ is the calculated $t$ value.

Scatter plot was also used to establish the relationship between the two data sets. Satellite estimates and observed rain gauge data were plotted against each other for both daily and monthly rainfall averages. A line of best fit was drawn and the coefficient of determination observed as the relationship indicator.

Root Mean Square Error (RMSE), a frequently used measure of the difference between model-predicted value and the actual observation was also used in the comparison. It measures how accurate a model simulates the actual reading value. The computation was as per Eq. (19);

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_i - g_i)^2} \tag{19}$$

Where $s_i$ and $g_i$ are the satellite and observed rainfall values, respectively and $n$ is the number of observations.

## 3. Results

### 3.1. Data quality

There were no missing values in the satellite rainfall estimates being one of its advantages. The observed rain gauge data had less than 10% of the missing data. The missing values were estimated using the arithmetic mean approach (Eq. (1)). Results of the homogeneity test from rainbow software for the two sets of data showed that the data sets were homogenous and were accepted at 99% probability since the deviation from the zero mark did not cross the 99% probability line. The data was then used for further analysis.

### 3.2. Seasonal rainfall onset, cessation date and the length of the growing period

The onset dates for the long rains (LR) ranged from 25th of February to 3rd of April across all the seven counties. Onset dates for the short rains (SR) ranged from 12th of September to 10th of October. A range of at least 38 days for long rains and 28 days for the short rains indicating high variation both spatially and temporally. Long rains, however, had high variability in the onset dates than the short rains portraying higher uncertainty compared to the short rains. The onset was generally early from the South-Western towards North-Eastern direction and the reverse during the short rains season (Figure 2).

Cessation dates varied from 21st May to 2nd June for LR and from 3rd to 26th of January for SR across the counties. The cessation dates ranged from 12 and 23 days for long and short rains, respectively. Unlike the onset dates, cessation dates were more heterogeneous during the SR than the LR. Cessation was earliest from the eastern to the western part of the study area during the LR. During the SR, cessation was earliest from the south towards the northern part of the study area (Figure 3).

The length of the growing season was highly variable, the averages ranging from 81 to 92 days during the long rains and from 97 to 133 days during the short rains. Generally, SR had a longer length of the growing period than the LR, thus could support a broader range of crops and give crops more time to grow. Table 1 summarises the average onset, cessation and the length of growing period across the counties.

The variability in onset, cessation and length of growing period observed in the CHK is in agreement with those observed by Recha et al. (2011) and Ngetich et al. (2014). Amekudzi et al. (2015) reported the same trend in Ghana with similar patterns across the various parts in Africa.

Rainfall onset range of about 38 days for long rains and 28 days for the short rains makes the onset windows long enough to cause uncertainties in onset dates and consequently planting dates. This corroborates findings by Ngetich et al. (2014) that rainfall onset in the central highlands of Kenya is highly variable. The uncertainty in the onset dates has often led to the poor timing of planting date among farmers which has had remarkable repercussion in agricultural production. Early planting before the onset date or dry planting could hamper seed germination, and plant development should rain delay. On the other hand, late planting was reported to cause up to 10 kg/ha yield loss after
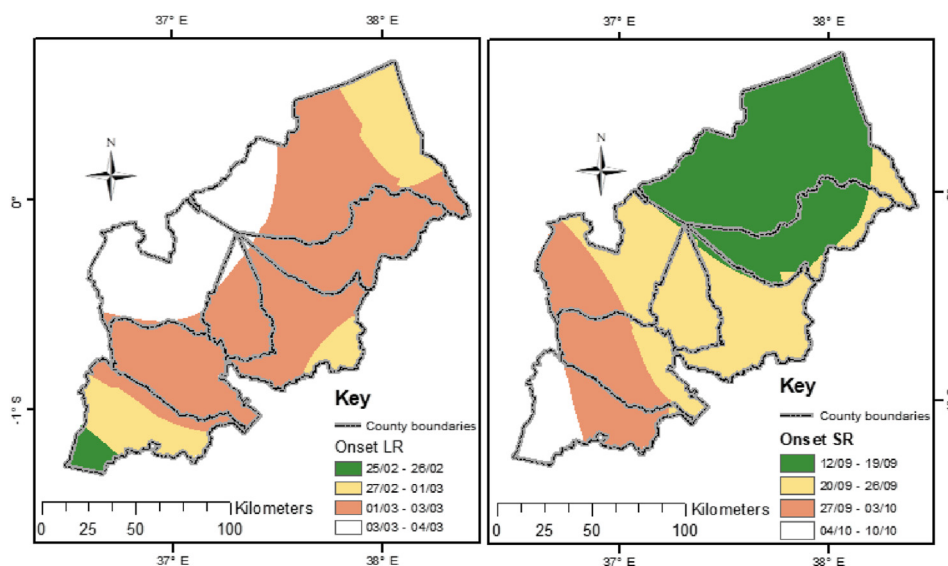


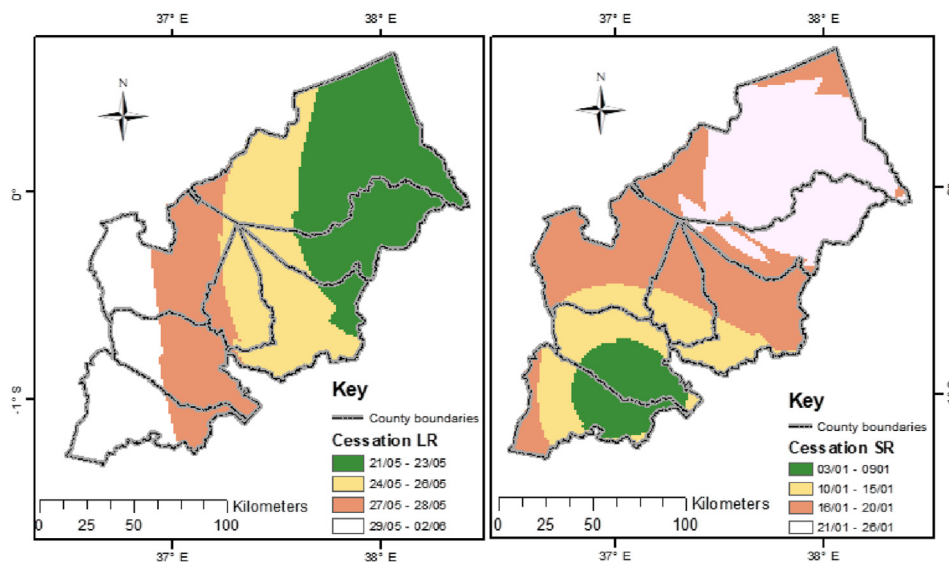**Figure 2.** Map showing onset dates for long rains and short rains.

**Figure 3.** Map showing cessation dates for long rains and short rains.

**Table 1.** Average onset, cessation dates and the length of growing period across the counties from 1997 to 2015.

| County | Onset date | | Cessation date | | Length | |
|---|---|---|---|---|---|---|
| | LR | SR | LR | SR | LR | SR |
| Embu | 29-February | 20- September | 24-May | 13-January | 84 | 115 |
| Kiambu | 28-February | 8- October | 30-May | 19- January | 92 | 103 |
| Kirinyaga | 2-March | 22- September | 26-May | 9- January | 85 | 109 |
| Murang'a | 1-March | 26- September | 27-May | 1- January | 87 | 97 |
| Meru | 1-March | 11- September | 24-May | 22- January | 84 | 133 |
| Nyeri | 2-March | 22- September | 26-May | 9- January | 85 | 109 |
| Tharaka-Nithi | 28- February | 14- September | 19-May | 24- January | 81 | 132 |

every single day of delayed planting date (Nielsen 2009). Timely planting, therefore, is vital for the farmers as it helps increase the yield (Nyagumbo et al., 2017).

Cessation dates varied though not as high as the onset dates with short rains showing higher seasonal variation than the long rains. The findings are in agreement with those of Camberlin and Okoola (2003) who observed high variability in rainfall onset than the cessation in Eastern Africa. However, in northern Ethiopia, Araya and Stroosnijder (2011) established that, over the study area, rainfall cessation date was more varying than the onset date. Like the onset, variation in cessation dates affects crop production as it can cause reduced crop yields or complete crop failure as the planning of the farming activities becomes challenging in rainfed farming systems.

Late-onset and early cessation shorten the length of growth period, which may decrease crop productivity (Jury 2002). Studies conducted in semi-arid parts of West Africa indicated that there is a significant relationship between the start of rains and the length of the rainy season (Sivakumar 1988[12]). Omotosho (2002) reported that the length of the rainy season is more dependent on the rainfall onset than its cessation. In the central highland of Kenya, the length of the growing period was long enough to support the growth of a wide range of crops to maturity; portraying the region as one of the high potential areas in Kenya, categorised by Jaetzold et al. (2007a and b) to be the humid areas. However, short rains had a longer length of the growing period than the long rains making it a more reliable season. Funk et al. (2008) explained the short growing period during the LR to be as a result of increasing sea surface temperature (SST) in tropical Atlantic or the Indian Ocean that favour local enhancement of precipitation with the resultant latent heating altering regional wind and moisture flux patterns, eventually reducing long rains. The reliability of the SR over LR had been echoed by various studies (Amissah-Arthur et al., 2002; Hansen and Indeje, 2004; Ngetich et al., 2014). The studies pointed out SR to constitute the primary growing season in Eastern Kenya on which annual crops such as maize, sorghum, green grams and finger millet are dependent on. Thus, farmers should focus more on the SR period as the main cropping season in the central highlands of Kenya to boost their net crop productivity.

The high variability in the rainfall onset and cessation was associated with local factors and position of sites in relation to the amplitude of the inter-tropical convergence zone (Recha et al., 2011). Variability in East African rains is claimed to be caused by changes in the sea surface temperatures in the tropical Pacific, Indian and Atlantic oceans (Lyon and Dewitt 2012). In the humid region of western Kenya, Mugalavai et al. (2008) pointed on the local effect (escarpments and Lake Victoria) plus atmospheric winds (NE and SE monsoon) to be the contributors of variability in onset and cessation for the long rains and short rains. The causes being natural, farmers can only hope for precision in the climatic forecast to enable them efficiently utilise the rainfall water for agricultural production (Recha et al., 2011). In the bimodal rainfall regions of Kenya, Stewart (1985) suggested growing of maize when there was early-onset while millet and sorghum during late onset to reduce the impact of untimely planting. While the suggestion could help cut losses, maize still stands to be the staple food, and farmers are willing to risk planting it even when the conditions are not favourable. Soil moisture conservation measures that can ensure efficient utilisation of the
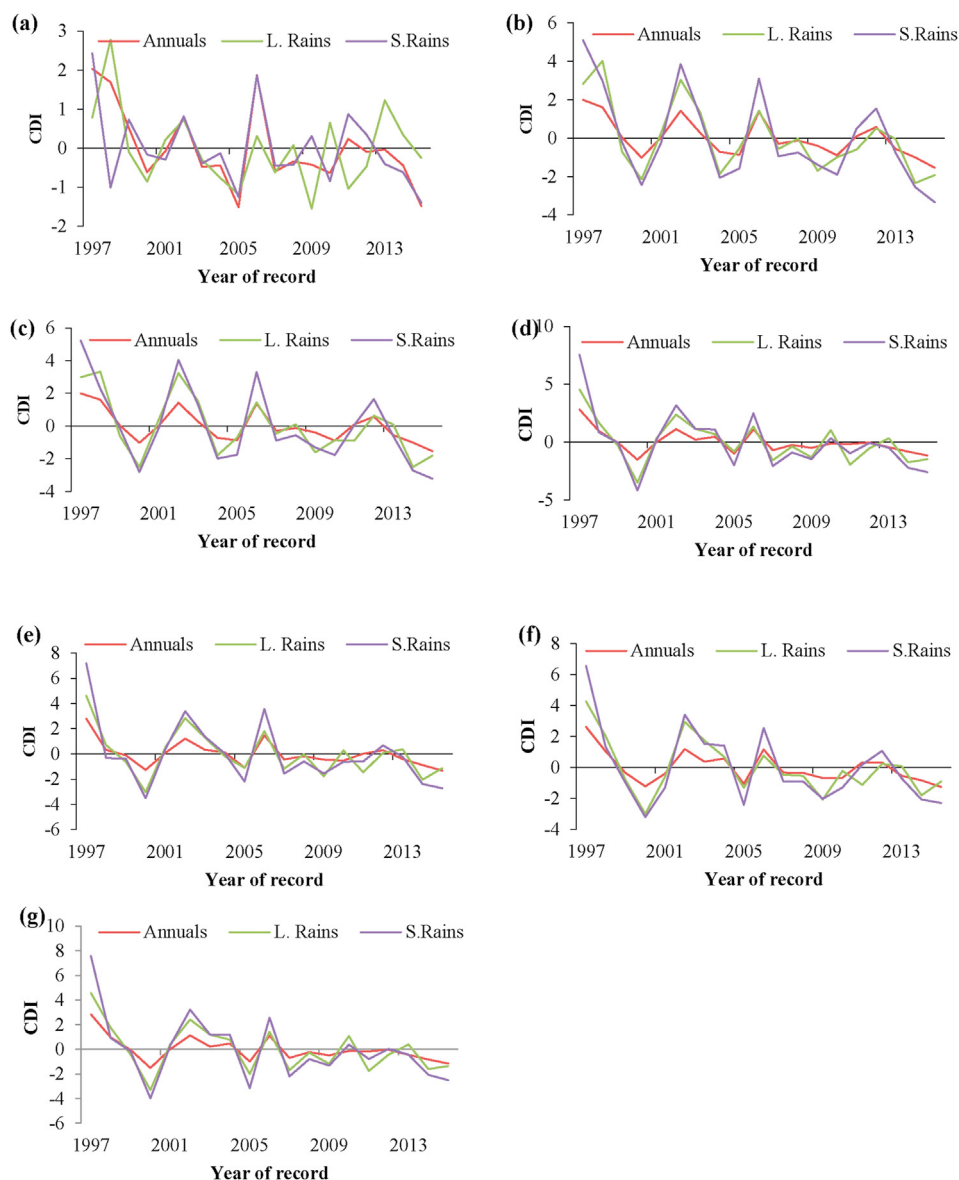
**Figure 4.** Times series of Cumulative departure index (CDI) for annuals, long rains and short rains in (a) Embu, (b) Kiambu, (c) Murang'a, (d) Meru, (e) Kirinyaga, (f) Nyeri and (g) Tharaka-Nithi counties.

available rainfall should be promoted to cushion farmers from losses ascribed to high rainfall variability in the region.

### 3.3. Spatial and temporal rainfall variation

The departure from the mean as exhibited by cumulative departure index generally reduced across the period from 1997 to 2015 (Figure 4) indicating that rainfall pattern became less variable in the past 19 years' period. From 2007 to 2013 the rainfall was oscillating around the average indicating minimal variation until 2014–2015 when the trends significantly drop to below average (CDI < -2). Between the periods 1999–2000 and 2005, the trend was consistently below average in all the seven counties. Both seasonal and annual rainfall was consistently above the average between 1997 and 1999 in all the counties except Embu where the short rains in 1998 were below average. Generally, the trend was similar in almost all the counties except Embu County. For instance, in all other counties, SR was the most variable followed by LR, with annuals having the least variation, while in Embu County the annual rainfall had the highest variability, then long rains with the short rains being the least variable.

A similar trend was detected by the rainfall anomaly index (RAI) (Figure 5). Short rain emerged to be the most variable rainfall period across the years and the counties in general with the highest positive anomaly (RAI = +13) in Kirinyaga County in 2006 being the wettest across the seasons and years of the record. The driest (RAI = -8) was in Murang'a County in 2000. For LR, the highest positive anomaly index was +12, and the highest negative anomaly index was -8 during. For SR highest positive anomaly index was +13, and the highest negative anomaly index was -7. Generally, short rains showed more variation than the long rains.

The coefficient of variation also showed high rainfall variability (Table 2). The CV value of more than 0.3 (30%) was considered to be indicating high variation (Araya and Stroosnijder, 2011). The CV for annual rainfall varied from CV = 0.29 to 0.42 across the counties indicating high rainfall variability (Table 2). For the LR and SR, the range was CV = 0.33 to 0.48 and CV = 0.56 to 0.69, respectively. Again, this portrayed SR to be the most variable followed by LR and then the annual rainfall. The number of rainy days within the season also indicated a similar pattern with the CVs ranging between CV = 0.23 to 0.40 and CV = 0.36 to 0.48 for the LR and SR, respectively (Table 3).
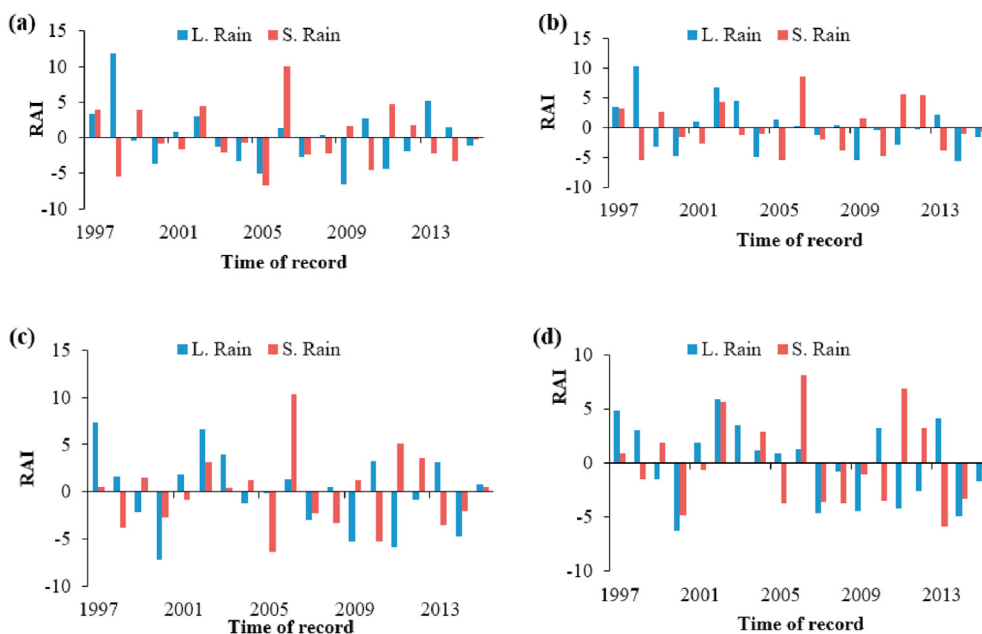
**Figure 5.** Time series of rainfall anomaly index (RAI) for long rains and short rains in (a) Embu, (b) Kiambu, (c) Murang'a, (d) Meru, (e) Kirinyaga, (f) Nyeri and (g) Tharaka-Nithi.

**Table 2.** Variability of annual and seasonal rainfall amounts across the counties from 1997 to 2015.

| County | The coefficient of variation (CV) | | |
|---|---|---|---|
| | Annual | LR | SR |
| Embu | 0.34 | 0.37 | 0.57 |
| Kiambu | 0.29 | 0.33 | 0.56 |
| Kirinyaga | 0.32 | 0.36 | 0.63 |
| Meru | 0.42 | 0.33 | 0.57 |
| Murang'a | 0.29 | 0.44 | 0.68 |
| Nyeri | 0.32 | 0.39 | 0.60 |
| Tharaka-Nithi | 0.42 | 0.48 | 0.69 |

**Table 3.** Rainy days analysis from 1997 to 2015.

| County | LR | | SR | |
|---|---|---|---|---|
| | No. of rainy days (RD) | CV-RD | No. of rainy days (RD) | CV-RD |
| Embu | 403 | 0.23 | 505 | 0.44 |
| Kiambu | 614 | 0.23 | 597 | 0.36 |
| Kirinyaga | 554 | 0.26 | 586 | 0.46 |
| Muranga | 572 | 0.27 | 595 | 0.36 |
| Meru | 318 | 0.35 | 419 | 0.45 |
| Nyeri | 505 | 0.32 | 556 | 0.40 |
| Tharaka-Nithi | 285 | 0.40 | 426 | 0.48 |

The high rainfall variation observed was also reported by Recha et al. (2011) in Tharaka-Nithi, where he observed year-to-year and season-to-season rainfall variation. The variation indicated short rains being highly variable than the long rains and the annuals. Hansen and Indeje (2004) reported that the long rains to be the most reliable in terms of variability and can be predicted with a reasonable degree of accuracy, unlike the short rains. The high variability of the seasonal rainfall has thus impacted on agriculture negatively considering agricultural production in sub-Saharan Africa is heavily hinged on the seasonal rainfall than the annual. This has made planning for agricultural production difficult. Farmers are not sure of what to expect of the rainfall pattern

every season or year. To overcome the high rainfall variability, the farmers could practice supplemental irrigation and use soil moisture conservation measures.

### 3.4. Rainfall distribution pattern

Rainfall distribution pattern showed a bimodal rainfall pattern in the central highlands of Kenya, there was the long and short rains making two seasons per year (Figure 6 a and b). Both the long and short rain distribution pattern were almost homogeneous across the different counties. For the Long rains, the month of April received about 60% of
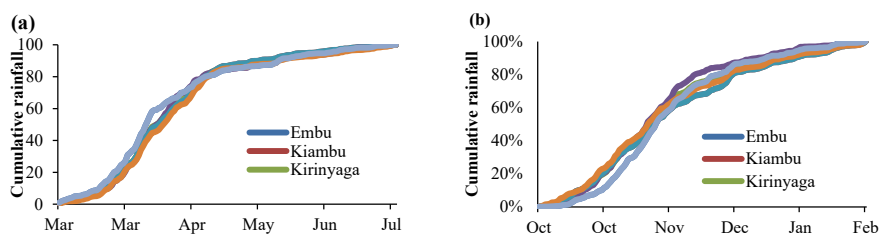
**Figure 6.** Temporal distribution of average daily rainfall as a percentage of the total rainfall received over the long rains (a) and short rains (b) seasons across the counties.

the season's rainfall, with March receiving around 20% and the remaining 20% spread from the month May to July (Figure 6a). For the SR, the month of November and December received about 70% of the seasonal rainfall. October received 20% while the remaining 10% is spread between January and February (Figure 6b). The months of April and November during the short and long rains, respectively, received bigger chunk of the seasonal rainfall that is ideal as these are the months within the season where active vegetative growth takes place. Thus, rainfall distribution is ideal for the growth of many crops such as maize, where the onset month receive just sufficient rainfall that allows for germination and initial crop growth.

Much of the rainfall is received during the heavy crop vegetative stage and the least amount received towards the harvesting of the crop. This showed a well-distributed rainfall pattern similar to the findings of Recha et al. (2011) in Tharaka district in the central highlands of Kenya over the short rain period and argued that the fair spread has the potential of reducing the impact of high rainfall variability. On the contrary, Ovuka and Lindqvist (2000) reported poor rainfall distribution in Murang'a County that had contributed to reduced crop productivity and recommended more research and advising of the farmers in the region on how to elude the poor rainfall pattern. Farmers in the regions, therefore, should take advantage of well rainfall distribution to balance out the impact of high rainfall variability. Also rain water harvest for supplemental irrigation could be practiced in case of poor distribution.

On rainfall intensity, precipitation variability index (PVI) of more than 0.3 was considered to be indicative of high rainfall intensity. The results showed low PVI values ranging from PVI = 0.09 to 0.27 in the study area indicating low intensity (Table 4). This indicate that the incidences of extreme rainfall events are not common.

The results are inconsistent with the global findings of increasing extreme precipitation events (Alexander et al., 2006). The last report from the Working Group 1 (WG1) of the International Panel on Climate Change (Summary for Policy Makers, SPM WG1-IPCC 2007) reported increased heavy precipitations on most of the land surface during the 20th century. Groisman et al. (2005) also showed a widespread increase in the frequency of very heavy precipitations during the past 50–100 years. In Namibia, Lu et al. (2016) reported extreme precipitation events such as heavy rainfall and drought on analysing rainfall intensity. The observed low rainfall intensity thus should continuously be monitored to establish any changes in the coming years. This will help in averting the

tragedies associated with rainfall extremities such as droughts and floods which affect crop production and the human livelihood significantly.

The low intensity and evenly distributed rainfall in the central highlands of Kenya is a characteristic of relief rainfall common in the mountainous region (Elvis et al., 2015). The regions experience this rainfall type due to the effect of Mount Kenya and Aberdare ranges. The counties are all in the windward side of the Mt. Kenya and Aberdare range thus receive high rainfall amounts. On the leeward side of Mt. Kenya, the regions receive low rainfall amount with cool temperature due to the dry cold winds that blow over the area. The low rainfall intensity is ideal for agricultural production since there is no crop destruction due to either droughts or floods associated with high rainfall intensity. While there are low frequencies of rainfall extremities in the CHK, farmers still need to be equipped with ameliorative measures in preparation for such.

### 3.5. Pattern of dry periods during the cropping seasons

Dry spell frequency during the long rains for the 19 years was highest in Embu with 83 occurrences and lowest in Murang'a with 57 occurrences (Table 5). During SR frequency of dry spell was highest in Nyeri with 88 occurrences and lowest in Embu with 69 occurrences during the 19 years of record (Table 6). The frequency of dry spell of more than five and less than ten days was consistently high in all the counties during both seasons while the dry spell frequency of more than 10 and less than 15 and the ones more than 15 days were almost the same. On average there is at least a dry spell within a season for long and short rains. Depending on the severity or magnitude of the dry spell and the stage of crop growth, the dry spell can cause significant damage to the crop. While dry spell of more than five days is enough to cause a reduction in crop yield, dry spell of more than 15 days can reduce yield up to 50% or cause complete crop failure especially when the crop is at its critical growth stage (Shin et al., 2015). In the study area, the dry spells of greater magnitude like more than 15 days were not common, hence there was low risk of complete crop failure.

The coefficient of variation analysis of the dry spell indicated high seasonal variability in Kirinyaga, Murang'a, and Nyeri counties during the LR. Kiambu, Kirinyaga and Murang'a had high variability during the short (Table 7). This leaves Embu and Tharaka-Nithi as the only counties with the low variability of dry spell in any season.

The probability analysis of the dry spell (Table 8) showed that the probability that a dry-spell starts on a particular day within a growing season ranged from 4 to 5% for LR and was 4 % for the SR. The probability of a dry spell less than five day does not occur at a certain day in a growing season ranged from 95 to 96% for LR and was 96% for the SR. The probability that a dry spell longer than five days will not occur in a growing season ranged from 1 to 5% for the LR and 1–2% for the SR. The probability that a dry spell exceeding five days would occur at least once in a growing season ranged from 97 to 99% for LR and was 98% for the SR.

Generally, the results indicate a high incidence of dry spell in the study region. This agrees with the findings of Rockstrom et al. (2003) that intra-seasonal dry spells have become a common feature. They disrupt

**Table 4.** Rainfall intensity across the counties from 1997-2015.

| County | Precipitation variability index |
|---|---|
| Embu | 0.15 |
| Kiambu | 0.09 |
| Kirinyaga | 0.13 |
| Meru | 0.27 |
| Murang'a | 0.09 |
| Nyeri | 0.12 |
| Tharaka-Nithi | 0.26 |

**Table 5.** Frequency of dry spell across the counties during the long rains from 1997-2015.

| Year | County Embu | | | Kiambu | | | Kirinyaga | | | Murang'a | | | Meru | | | Nyeri | | | Tharaka-Nithi | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 |
| 1997 | 0 | 3 | 1 | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 | 1 | 2 | 0 | 2 | 0 | 0 | 2 |
| 1998 | 1 | 1 | 2 | 0 | 2 | 1 | 0 | 2 | 1 | 0 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 0 | 1 | 1 |
| 1999 | 5 | 1 | 0 | 3 | 0 | 0 | 4 | 0 | 0 | 3 | 0 | 0 | 2 | 1 | 0 | 4 | 0 | 0 | 3 | 0 | 0 |
| 2000 | 2 | 1 | 2 | 3 | 2 | 1 | 2 | 0 | 2 | 2 | 1 | 1 | 0 | 0 | 3 | 4 | 0 | 0 | 0 | 1 | 2 |
| 2001 | 1 | 2 | 2 | 1 | 1 | 1 | 2 | 0 | 2 | 2 | 1 | 1 | 1 | 0 | 2 | 0 | 1 | 1 | 1 | 0 | 2 |
| 2002 | 1 | 2 | 1 | 1 | 1 | 0 | 2 | 1 | 0 | 1 | 1 | 0 | 2 | 2 | 0 | 1 | 1 | 0 | 3 | 1 | 0 |
| 2003 | 2 | 0 | 2 | 2 | 1 | 1 | 3 | 0 | 1 | 3 | 0 | 1 | 2 | 0 | 2 | 3 | 0 | 1 | 2 | 1 | 1 |
| 2004 | 0 | 1 | 1 | 1 | 1 | 1 | 2 | 3 | 1 | 1 | 2 | 1 | 3 | 1 | 2 | 2 | 1 | 1 | 2 | 2 | 0 |
| 2005 | 1 | 1 | 1 | 2 | 2 | 2 | 1 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 2 | 2 | 3 |
| 2006 | 1 | 2 | 0 | 2 | 0 | 0 | 1 | 2 | 0 | 2 | 0 | 0 | 3 | 1 | 1 | 2 | 0 | 0 | 3 | 0 | 1 |
| 2007 | 4 | 3 | 0 | 3 | 1 | 0 | 3 | 1 | 0 | 5 | 1 | 0 | 3 | 2 | 2 | 4 | 2 | 0 | 1 | 1 | 2 |
| 2008 | 2 | 0 | 2 | 2 | 0 | 1 | 2 | 0 | 2 | 2 | 0 | 1 | 1 | 1 | 2 | 1 | 1 | 2 | 1 | 1 | 1 |
| 2009 | 1 | 1 | 2 | 3 | 1 | 0 | 0 | 1 | 1 | 3 | 1 | 0 | 0 | 0 | 2 | 0 | 1 | 2 | 0 | 0 | 2 |
| 2010 | 2 | 1 | 1 | 1 | 2 | 0 | 2 | 1 | 0 | 1 | 1 | 0 | 2 | 1 | 0 | 1 | 2 | 0 | 1 | 2 | 0 |
| 2011 | 1 | 0 | 2 | 3 | 0 | 1 | 1 | 0 | 1 | 3 | 0 | 0 | 1 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 2 |
| 2012 | 2 | 1 | 1 | 1 | 0 | 1 | 2 | 1 | 1 | 0 | 1 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 |
| 2013 | 5 | 0 | 3 | 1 | 2 | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 1 | 2 | 1 | 1 | 0 | 0 | 2 | 1 |
| 2014 | 4 | 2 | 0 | 1 | 0 | 3 | 3 | 1 | 0 | 1 | 2 | 0 | 2 | 2 | 0 | 3 | 1 | 0 | 2 | 2 | 0 |
| 2015 | 0 | 1 | 2 | 0 | 0 | 3 | 2 | 0 | 1 | 2 | 0 | 1 | 4 | 1 | 0 | 1 | 1 | 0 | 4 | 1 | 0 |
| Totals | 35 | 23 | 25 | 30 | 16 | 18 | 32 | 17 | 17 | 32 | 15 | 10 | 31 | 18 | 25 | 34 | 16 | 13 | 28 | 18 | 21 |

**Table 6.** Frequency of dry spell across the counties during the short rains from 1997-2015.

| Year | County Embu | | | Kiambu | | | Kirinyaga | | | Murang'a | | | Meru | | | Nyeri | | | Tharaka-Nithi | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 | >5 | >10 | >15 |
| 1997 | 4 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 2 | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 |
| 1998 | 2 | 1 | 1 | 1 | 1 | 1 | 2 | 0 | 2 | 3 | 1 | 1 | 2 | 0 | 3 | 3 | 3 | 0 | 2 | 0 | 3 |
| 1999 | 0 | 0 | 1 | 4 | 1 | 1 | 2 | 0 | 1 | 3 | 0 | 1 | 2 | 0 | 2 | 3 | 0 | 0 | 2 | 0 | 2 |
| 2000 | 1 | 1 | 3 | 4 | 2 | 1 | 5 | 2 | 0 | 4 | 2 | 0 | 2 | 1 | 3 | 4 | 0 | 2 | 2 | 1 | 3 |
| 2001 | 3 | 0 | 1 | 3 | 1 | 1 | 4 | 0 | 1 | 2 | 1 | 1 | 0 | 2 | 2 | 2 | 1 | 1 | 1 | 2 | 1 |
| 2002 | 1 | 3 | 0 | 2 | 0 | 2 | 1 | 1 | 1 | 2 | 0 | 1 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 |
| 2003 | 2 | 1 | 1 | 0 | 1 | 1 | 1 | 2 | 1 | 0 | 2 | 0 | 1 | 1 | 1 | 1 | 3 | 1 | 2 | 0 | 3 |
| 2004 | 1 | 2 | 0 | 1 | 0 | 1 | 2 | 1 | 1 | 0 | 0 | 1 | 2 | 1 | 1 | 2 | 1 | 2 | 2 | 1 | 1 |
| 2005 | 1 | 1 | 2 | 2 | 0 | 3 | 4 | 3 | 0 | 3 | 1 | 1 | 1 | 2 | 3 | 3 | 3 | 0 | 1 | 0 | 3 |
| 2006 | 0 | 1 | 0 | 1 | 0 | 1 | 4 | 1 | 0 | 1 | 0 | 1 | 2 | 0 | 1 | 1 | 3 | 1 | 3 | 0 | 1 |
| 2007 | 2 | 1 | 1 | 5 | 0 | 0 | 2 | 0 | 0 | 4 | 0 | 0 | 2 | 1 | 0 | 2 | 3 | 0 | 2 | 1 | 0 |
| 2008 | 1 | 1 | 2 | 2 | 0 | 2 | 2 | 0 | 1 | 1 | 0 | 1 | 2 | 0 | 1 | 3 | 0 | 2 | 1 | 1 | 1 |
| 2009 | 1 | 1 | 1 | 5 | 0 | 0 | 1 | 1 | 1 | 5 | 0 | 0 | 3 | 1 | 2 | 1 | 0 | 2 | 3 | 1 | 1 |
| 2010 | 2 | 1 | 2 | 2 | 3 | 0 | 3 | 1 | 1 | 3 | 2 | 0 | 2 | 2 | 1 | 4 | 1 | 0 | 1 | 2 | 2 |
| 2011 | 2 | 3 | 0 | 3 | 4 | 1 | 2 | 1 | 1 | 5 | 0 | 1 | 0 | 1 | 2 | 1 | 1 | 3 | 1 | 1 | 2 |
| 2012 | 1 | 0 | 2 | 0 | 4 | 0 | 2 | 0 | 1 | 0 | 3 | 0 | 2 | 1 | 1 | 3 | 1 | 1 | 2 | 1 | 1 |
| 2013 | 2 | 2 | 0 | 2 | 1 | 2 | 2 | 2 | 1 | 3 | 0 | 2 | 1 | 1 | 1 | 1 | 3 | 1 | 0 | 1 | 2 |
| 2014 | 1 | 1 | 2 | 1 | 1 | 3 | 2 | 2 | 3 | 1 | 1 | 3 | 2 | 0 | 2 | 3 | 1 | 2 | 2 | 1 | 2 |
| 2015 | 2 | 1 | 0 | 2 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 2 | 0 | 3 | 1 | 0 | 1 | 1 |
| Totals | 29 | 21 | 19 | 41 | 20 | 21 | 41 | 17 | 16 | 42 | 14 | 16 | 28 | 16 | 30 | 39 | 28 | 21 | 29 | 15 | 31 |

crop growth and lower crop yield (Barron et al., 2003; Mzezewa et al., 2010). Within-season dry spells are associated with poor seasonal rainfall distribution that is common in most parts of the world (Mzezewa et al., 2010). However, some studies attribute the recent drying trends to SST anomalies over the Indian Ocean induced by anthropogenic forcing (Funk et al., 2008; Williams and Funk 2011), signifying the possible escalation of drier conditions in future should human influence continue (Seager and Mark 2015). Shongwe et al. (2011) and Otieno and Anyah (2013) are, however, optimistic that the dry conditions will be, at least partly, ameliorated soon. They base their argument in model projections from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) and the phase 5 of the Coupled Model Inter-comparison Project (CMIP5), that precipitation over East Africa will increase (Taylor et al., 2012).

**Table 7.** Dry spell variation across the counties for both long and short rains from 1997 to 2015.

| County | Seasonal dry spell variation | | | | |
| --- | --- | --- | --- | --- | --- |
| | LR | | | SR | |
| | Dry spell Frequency | CV | | Dry spell Frequency | CV |
| Embu | 83 | 0.19 | | 69 | 0.19 |
| Kiambu | 49 | 0.29 | | 82 | 0.35 |
| Kirinyaga | 66 | 0.32 | | 74 | 0.47 |
| Murang'a | 57 | 0.50 | | 72 | 0.53 |
| Meru | 74 | 0.22 | | 74 | 0.25 |
| Nyeri | 63 | 0.44 | | 88 | 0.25 |
| Tharaka-Nithi | 67 | 0.19 | | 75 | 0.28 |

**Table 8.** Dry spell probability analysis for both long and short rains seasons across the counties.

| County | Dry spell probabilities | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | P* | | R** | | Q*** | | L**** | |
| | LR | SR | LR | SR | LR | SR | LR | SR |
| Embu | 0.05 | 0.04 | 0.95 | 0.96 | 0.01 | 0.02 | 0.99 | 0.98 |
| Kiambu | 0.04 | 0.04 | 0.96 | 0.96 | 0.03 | 0.01 | 0.97 | 0.99 |
| Kirinyaga | 0.04 | 0.04 | 0.96 | 0.96 | 0.03 | 0.02 | 0.97 | 0.98 |
| Murang'a | 0.04 | 0.04 | 0.96 | 0.96 | 0.05 | 0.02 | 0.95 | 0.98 |
| Meru | 0.05 | 0.04 | 0.95 | 0.96 | 0.02 | 0.02 | 0.98 | 0.98 |
| Nyeri | 0.04 | 0.04 | 0.96 | 0.96 | 0.03 | 0.01 | 0.97 | 0.99 |
| Tharaka-Nithi | 0.04 | 0.04 | 0.96 | 0.96 | 0.03 | 0.02 | 0.97 | 0.98 |

* Probability that a dry-spell starts on a particular day within a growing season.
** Probability that a dry-spell less than 5 does not occur at a certain day in a growing season.
*** Probability that a dry-spell longer than 5 days will not occur in a growing season.
**** Probability that a dry-spell exceeding 5 days would occur at least once in a growing season.

Even though the most frequently observed dry spell across the counties was of low magnitude, farmers should cushion themselves from the drought-related calamities by adopting some of the cost-effective soil moisture conservation practices that are being promoted in the regions. Some of the strategies include the use of supplemental irrigation where water resources are available or planting of drought-resistant crop varieties in water-scarce areas. Use of organic inputs that have the potential of improving soil moisture retention and reducing soil moisture loss through evaporation can be considered in ameliorating the impact of a dry spell in crop production (Cai and Wang 2002; Huang et al., 2003; Wang et al., 2003; Lenssen et al., 2007).

### 3.6. Comparison between satellite rainfall estimates and the observed rain gauge data

The visual and statistical trend portrayed by the cumulative departure index (Figure 7) show the satellite data consistently underestimating observed rain gauge values. However, the data sets had similar trend indicating they agree aside from the underestimation of the satellite estimate data.

Pearson correlation of the onset, cessation and the length of the growing period between the satellite and observed gauge data were as per Tables 9, 10, and 11. In Embu County, short rains showed weak agreements on the onset, cessation and the length of growing period of the two data sets where the correlation coefficients were 0.20, 0.04 and 0.03, respectively. However, the two sets of the dates were not significantly different at $p < 0.05$ (Table 9). For the short rains, the correlation coefficient for the onset, cessation and the length of growing period of the two data sets were 0.56, 0.59 and 0.58, respectively with the two sets of dates not significantly different at $p < 0.05$ (Table 9). An almost similar pattern was observed in Meru County. The long rains had the correlation

coefficient for onset, cessation and length of growing period of 0.08, 0.16 and 0.36, respectively, with the two sets of dates not significantly different at $p < 0.05$ (Table 10). The CV for short rains onset, cessation and the length of growing period were 0.17, 0.57 and 0.63, respectively, with the two sets of dates not significantly different at $p < 0.05$ (Table 10). In Tharaka-Nithi County, the long rains had correlation coefficients for the onset, cessation and the length of crop growth period as 0.55, 0.83 and 0.33, respectively with the two sets of dates not significantly different, except on cessation dates at $p < 0.05$ (Table 11). For the short rains, correlation coefficients for the onset, cessation and the length of the growing period were 0.54, 0.63 and 0.16, respectively, with the two sets of dates not significantly different at $p < 0.05$. Generally, the long rains had a weak agreement for the onset, cessation and the length of the growing period between the two data sets. Short rains, however, had a strong agreement on the onset, cessation and the length of the growing period between the two data sets. This shows that the onset, cessation and the length of growing period of satellite estimates cannot effectively substitute the prediction of the observed rainfall data during the long rains but can represent the short rains effectively.

The daily correlation comparison between the two datasets indicated that there was an agreement between the two data sets though not very strong. The correlation coefficient ranged from 0.44 to 0.62 with the t-test showing the datasets were not significantly different from each other across all the three counties at $p = 0.05$ (Table 12). Root mean square error showed high positive values indicating the satellite underestimate the observed rain gauge data and are in agreement (Table 12). The values ranged from 2.82 to 4.31 across the three counties under the study. Scatter plot shows low agreement between the daily observed and satellite estimates rainfall datasets with the coefficient of determination ($R^2$) ranging from $R^2 = 0.19$ to 0.37 (Figure 8). On the monthly scale, however, there was strong agreement with the $R^2$ ranging from $R^2 = 0.62$ to 0.98. This indicates that at the daily scale, the satellite rainfall
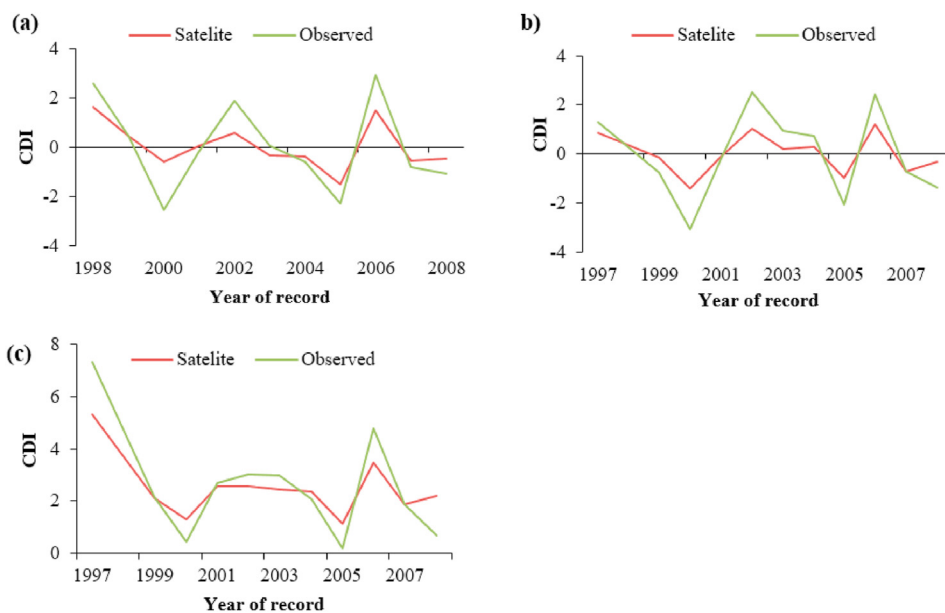
**Figure 7.** Times series of Cumulative departure index for observed and satellite estimates in Embu (a), Meru (b), and Tharaka-Nithi (c) counties across the years.

**Table 9.** Comparison of satellite rainfall estimate and observed rain gauge on onset, cessation and length of growing period during LR and SR in Embu County.

| Year | Long rains | | | | | | Short rains | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Onset (J[th] day) | | Cessation (J[th] day) | | Length (J days) | | Onset (J[th] day) | | Cessation (J[th] day) | | Length (J days) | |
| | Obs** | Sat*** | Obs** | Sat*** | Obs** | Sat*** | Obs** | Sat*** | Obs** | Sat*** | Obs** | Sat*** |
| 1999 | 62 | 71 | 154 | 134 | 92 | 63 | 279 | 269 | 387 | 371 | 108 | 102 |
| 2000 | 78 | 64 | 146 | 134 | 68 | 70 | 280 | 269 | 367 | 367 | 87 | 98 |
| 2001 | 83 | 53 | 150 | 134 | 67 | 81 | 277 | 265 | 359 | 367 | 82 | 102 |
| 2002 | 78 | 62 | 150 | 142 | 72 | 80 | 280 | 275 | 387 | 375 | 107 | 100 |
| 2003 | 78 | 43 | 162 | 139 | 84 | 96 | 278 | 275 | 359 | 367 | 81 | 92 |
| 2004 | 58 | 54 | 146 | 134 | 88 | 80 | 280 | 273 | 355 | 367 | 75 | 94 |
| 2005 | 82 | 60 | 166 | 134 | 84 | 74 | 280 | 273 | 355 | 367 | 75 | 94 |
| 2006 | 57 | 60 | 147 | 138 | 90 | 78 | 277 | 272 | 379 | 379 | 102 | 107 |
| 2007 | 83 | 60 | 166 | 134 | 83 | 74 | 280 | 275 | 355 | 375 | 75 | 100 |
| 2008 | 82 | 60 | 146 | 134 | 64 | 74 | 277 | 266 | 355 | 367 | 78 | 101 |
| **Mean** | **74** | **59** | **153** | **136** | **79** | **77** | **279** | **271** | **366** | **370** | **87** | **99** |
| **CC*** | **-0.20** | | **-0.04** | | **-0.03** | | **0.56** | | **0.59** | | **0.58** | |
| **P-value** | **ns** | | **ns** | | **ns** | | **ns** | | **ns** | | **ns** | |

* Correlation Coefficient.
** Observed rain data.
*** Satellite estimates.

estimates cannot represent the observed rainfall adequately while at monthly scale, the observed rainfall can be well represented by the satellite rainfall estimates.

The two data sets showed consistency in the pattern of behaviour as portrayed by the visual graphical representation of the cumulative departure index. This is further supported by the Pearson correlation that also showed an agreement between the datasets with a high significance level (p = 0.001). The correlation coefficient of onset cessation and the length of the growing period also showed agreement between the datasets during the short rains, implying that the satellite estimates can be used as a substitute of the observed gauge data in the prediction of onset, cessation and the length of the growing period during the short rain period. This can be a solution to the data scarcity problem that has been experienced in the central highlands of Kenya and other regions that are considered remote because the satellite estimate can give rainfall data of any point on the surface of the earth.

Scatter plot showed an agreement between the data sets that were stronger at the monthly scale while weak at daily scale corroborating the findings by Lu et al. (2016) and Sungmin et al. (2016). This indicated that at a daily scale, satellite estimates are not a reliable representation of rainfall, but at monthly scale, they can be used as either a substitute or complementary to the observed rain gauge data depending on how well such data are processed. Various studies have also established the existence of an agreement between the satellite estimates and observed rain gauge data (Mohamed 2013; Lu et al., 2016; Sungmin et al., 2016; Macharia et al., 2020). This indicates that the satellite estimates can be used not only as a complementary to the observed rain gauge data but as a substitute when adequately corrected. However, correction is site-specific and should be customised as per the agro-ecological zone.

The variations in the degree of agreement observed across the counties could be attributed to the findings of various studies that reported the agreement to be affected by factors such as proximity to large

**Table 10.** Comparison of satellite rainfall estimate and observed rain gauge on onset, cessation and length of growing period during LR and SR in Meru County.

| Year | LR | | | | | | SR | | | | | |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| | Onset (Jth day) | | Cessation (Jth day) | | Length (J days) | | Onset (Jth day) | | Cessation (Jth day) | | Length (J days) | |
| | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat |
| 1999 | 76 | 76 | 145 | 146 | 86 | 70 | 284 | 269 | 378 | 358 | 94 | 89 |
| 2000 | 76 | 76 | 141 | 146 | 75 | 70 | 291 | 269 | 369 | 358 | 78 | 89 |
| 2001 | 76 | 76 | 141 | 146 | 85 | 70 | 283 | 269 | 365 | 362 | 82 | 93 |
| 2002 | 62 | 62 | 146 | 146 | 93 | 84 | 280 | 269 | 389 | 370 | 109 | 101 |
| 2003 | 62 | 62 | 141 | 146 | 84 | 84 | 290 | 269 | 361 | 358 | 71 | 89 |
| 2004 | 72 | 72 | 141 | 146 | 101 | 74 | 287 | 269 | 393 | 359 | 106 | 90 |
| 2005 | 60 | 60 | 141 | 159 | 73 | 99 | 291 | 272 | 357 | 358 | 66 | 86 |
| 2006 | 74 | 74 | 161 | 146 | 83 | 72 | 262 | 266 | 397 | 370 | 135 | 104 |
| 2007 | 60 | 60 | 141 | 146 | 83 | 86 | 280 | 275 | 389 | 358 | 109 | 83 |
| 2008 | 60 | 60 | 141 | 146 | 74 | 86 | 277 | 275 | 357 | 358 | 80 | 83 |
| **Mean** | **57** | **68** | **141** | **147** | **84** | **79** | **283** | **270** | **376** | **361** | **93** | **91** |
| **CC** | **-0.08** | | **-0.16** | | **-0.36** | | **0.17** | | **0.57** | | **0.63** | |
| **P-value** | **ns** | | **ns** | | **ns** | | **ns** | | **ns** | | **ns** | |

**Table 11.** Comparison of satellite rainfall estimate and observed rain gauge on onset, cessation and length of the growing period during LR and SR in Tharaka-Nithi County.

| Year | LR | | | | | | SR | | | | | |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| | Onset (Jth day) | | Cessation (Jth day) | | Length (J days) | | Onset (Jth day) | | Cessation (Jth day) | | Length (J days) | |
| | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat | Obs | Sat |
| 1999 | 47 | 76 | 168 | 144 | 121 | 68 | 292 | 281 | 384 | 364 | 92 | 83 |
| 2000 | 47 | 76 | 176 | 144 | 129 | 68 | 271 | 281 | 368 | 360 | 97 | 79 |
| 2001 | 65 | 76 | 164 | 144 | 99 | 68 | 273 | 281 | 361 | 360 | 88 | 79 |
| 2002 | 61 | 62 | 164 | 144 | 103 | 82 | 279 | 278 | 376 | 369 | 97 | 91 |
| 2003 | 61 | 62 | 164 | 144 | 103 | 82 | 290 | 278 | 356 | 360 | 66 | 82 |
| 2004 | 77 | 72 | 164 | 144 | 87 | 72 | 290 | 278 | 360 | 360 | 70 | 82 |
| 2005 | 80 | 60 | 184 | 160 | 104 | 100 | 290 | 272 | 356 | 360 | 66 | 88 |
| 2006 | 58 | 74 | 164 | 144 | 106 | 70 | 289 | 272 | 404 | 369 | 115 | 97 |
| 2007 | 61 | 60 | 164 | 144 | 103 | 84 | 278 | 283 | 396 | 360 | 118 | 77 |
| 2008 | 82 | 60 | 164 | 144 | 82 | 84 | 275 | 279 | 356 | 360 | 81 | 81 |
| **Mean** | **64** | **68** | **168** | **146** | **104** | **78** | **283** | **278** | **372** | **362** | **89** | **84** |
| **CC** | **-0.55** | | **0.83** | | **-0.33** | | **-0.54** | | **0.63** | | **0.16** | |
| **P value** | **ns** | | **<0.00** | | **ns** | | **ns** | | **ns** | | **ns** | |

**Table 12.** Pearson correlation and Root mean square error comparison of daily satellite rainfall estimates and observed rain gauge data.

| County | Correlation analysis | | RMSE |
|--------|-----|-----|------|
| | Correlation Coefficient | P value | |
| Embu | 0.44 | 0.0001 | 4.31 |
| Meru | 0.59 | 0.0001 | 2.98 |
| Tharaka-Nithi | 0.62 | 0.0001 | 2.84 |

water bodies like oceans (Mohamed 2013), satellite-ground misregistration and spatial and temporal resolution (Kidd et al., 2003). For instance, satellite-ground misregistration and low spatial and temporal resolution can cause a change in both place and time of precipitation. This could result in significant differences between the satellite estimates and observed rain gauge data. Displacement in time of the precipitation leads to differences observed in the onset, cessation and length of the growing period. Spatial displacement of the precipitation might also mean precipitation reading recorded for one region might be received in another region. The poor temporal resolution also explains the stronger agreement of the data sets on a monthly scale than at daily scale. This is because, at a monthly scale, the systematic error arising from the low temporal resolution is reduced by the averaging the daily readings. Reducing the causes of such errors is essential in improving the reliability of satellite estimates.

Satellite rainfall estimate was observed to underestimate rainfall values as portrayed visually by cumulative departure index and statistically by the root mean square error that had high positive values. The finding supports the observation made by Sungmin et al. (2016) in southeast Austria while comparing the daily rainfall data from WegenerNet and observed rain gauge data, where WegenerNet data underestimated the observed rainfall data. Mohamed (2013) reported similar
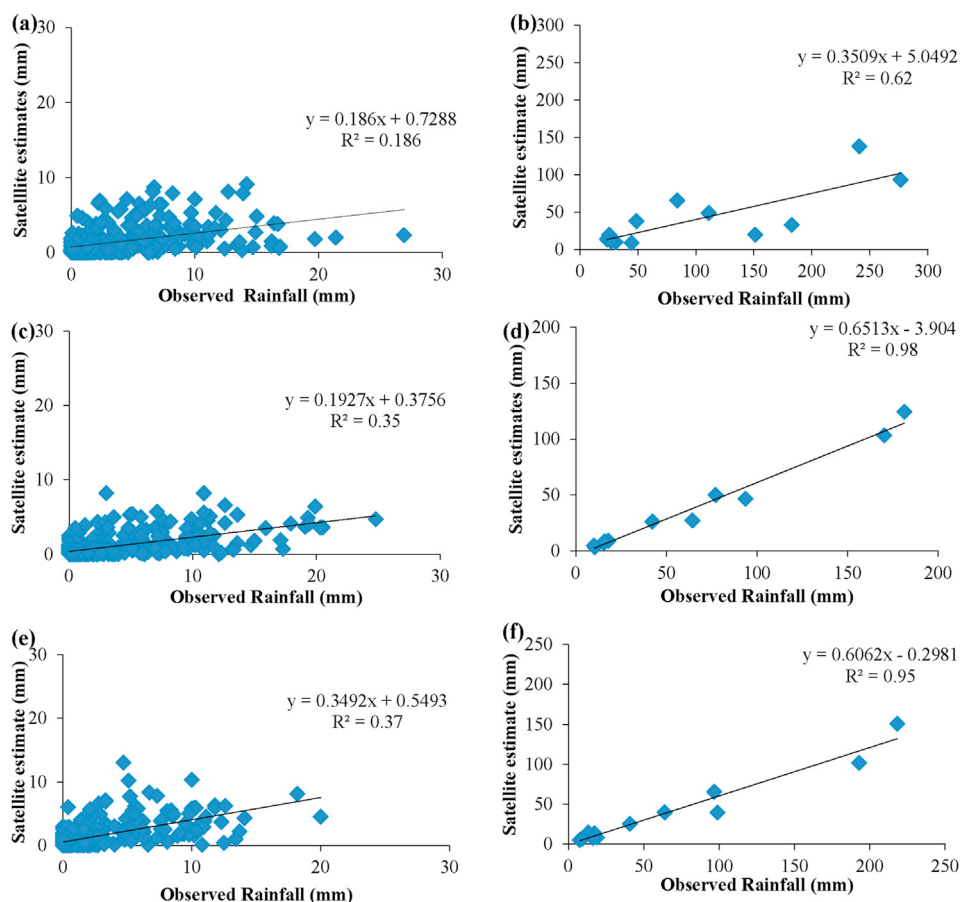
**Figure 8.** Scatter plots comparing satellite estimates and rain gauge based data sets at daily (a), (c) and (e) for Embu, Meru and Tharaka-Nithi respectively and monthly (b), (d) and (f) for Embu, Meru and Tharaka-Nithi respectively from 1999 to 2008.

findings while comparing the satellite estimates from African Rainfall Climatology Project of the Climate Prediction Centre and the observed rain gauge from various regions of Tanzania. The underestimation by the satellite-based rainfall estimation was also observed by Sanchez-Moreno et al. (2014) when comparing the rainfall estimates from TRMM with observed rain gauge data in Cape Verde Islands. These reports indicate that all satellite-based rainfall estimates tend to underestimate the observed rainfall. The underestimation could be as a result of physical differences between satellite retrievals and validation retrievals (Mohamed, 2013), among other factors, both statistical and environmental. While some of these causes can be improved by statistical adjustment of the various parameters involved, others are as a result of the surrounding environment, and thus correction should be environment-specific. This, therefore, requires further investigation to accurately come up with the ideal correction factor as per the region of interest.

## 4. Conclusion

Rainfall onset across the seven counties under consideration ranged from 25th of February to 3rd of April during long rains and from 12th of September to 10th of October during short rains. Cessation dates ranged from 21$^{st}$ May to 2$^{nd}$ June for LR and from 3$^{rd}$ to 26$^{th}$ of January for SR. The length of the growing period was between 81 to 92 and 97–133 days for LR and SR, respectively. Both the onset and cessation dates showed high variation indicating difficulties in the timing of the planting date among farmers. The length of the growing period also showed high variation with the short rains being more variable than the long rains. However, the short rains proved to be more reliable than the long rains due to a longer length of growing period across the counties and years,

thus the primary cropping season. Farmers in Central highlands of Kenya should, therefore, be ready to plant at the first rains received around the projected onset period to maximize on the length of a crop growth period. They should also focus more on the short rains as their main growing season.

Generally, rainfall in the CHK showed high temporal variation across the years with the spatial variation difficult to determine due to the nature of the data used. The satellite rainfall estimate data used in rainfall characterisation, averaged rainfall values for various points on a wider geographical location, thus unreliable when analysing spatial characteristics. Rainfall, however, was fairly distributed temporally with a low intensity that encouraged agricultural production. Thus, the impact of high variability in agricultural production is abridged by good distribution and low rainfall intensity.

While the dry spell was a common occurrence in the region with a high probability of future occurrences, the more frequently experienced dry spells were of low magnitudes that do not have a severe impact on crop production. The most common dry spell experienced was the dry spells of more than five to ten days. These could lower the crop yield depending on the crop stage of growth and the sensitivity of the crop to moisture stress but does not cause serious damages like complete crop failure. However, there is a need for farmers to put mechanisms to ameliorate its impact. Use of soil moisture conservation technologies and supplemental irrigation in case of severe dry spells are some of the potential ameliorative measures. More research needs to be done on efficient use of the available soil moisture and on drought-tolerant crop varieties to reduce the impact of drought on crop productivity.

Validation of the satellite rainfall estimate and observed rain gauge data showed that the two data sets are in agreement especially at the monthly scale where the satellite can substitute the observed rain gauge

data aside from being a complementary source. However, satellite data underestimated the rainfall readings. To ensure more reliability of the satellite estimates even at daily scale, proper correction method of satellite estimates needs to be devised and customised for each region.

## Declarations

### Author contribution statement

N. O. Oduor: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

F. K. Ngetich: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

M. K. Kiboi: Performed the experiments; Wrote the paper.

A. Muriuki: Contributed reagents, materials, analysis tools or data; Wrote the paper.

N. Adamtey, D. N. Mugendi: Contributed reagents, materials, analysis tools or data; Wrote the paper.

### Competing interest statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

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