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Seasonal rainfall variability and aptness of Geographical-Information-Systems (GIS) interpolation techniques in the arid regions of Embu county, Kenya

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Abstract This study sought to characterize inter/intra seasonal rainfall variability, drought probabilities and assess the efficacy of geo-statistical interpolation techniques for spatio-temporal reconstruction of rainfall data in arid areas of Embu County; Kenya. Gaps in rainfall data from two stations of Embu and Machang'a were filled using multiple imputations. Cumulative Departure Index (CDI), Rainfall Anomaly Index (RAI) and Coefficients-of-Variance (CV) and probabilistic statistics were utilized in the analyses. Data reconstruction utilized ArcGIS environmental tool combined with the digital elevation model (DEM) to generate average spatial rainfall and maps using various interpolation techniques. The efficacy of interpolation techniques was assessed using root mean square errors (RMSE), mean absolute errors (MAE) statistics plus gauged-data for validation. Rainfall homogeneity was accepted at 99% probabilities. Probabilities of rainfall exceeding cropping threshold were 50% (506.8mm) at Embu and 30% (523.7mm) at Machang'a during Long-Rains (LRs) and Short-Rains (SRs) respectively. High variability was observed in rainfall amounts (CV=0.41 and 0.36) during LRs and (CV=0.56 and 0.38) during SRs in Machang'a and Embu respectively. Daily rainfall distribution depths were highly skewed; small proportion of rainy days supplying a high proportion of rainfall. Variabilities in rainy days were CV=0.26 and 0.08 (LRs) and CV=0.88 and 0.27 (SRs) in respective stations above. High variability were observably in March (onset) (CV=0.98 and 0.61) and October (onset) (CV=0.80 and 0.66) respectively. Dry-spell probabilities within growing months were high (81%) and (60%) in Machang'a and Embu respectively. Kriging technique was identified as the most appropriate Geo-statistical and deterministic interpolation techniques that can be used in the region. To optimize yield in the area, use of soil-water conservation and supplementary irrigation, crop selection and timely accurate rainfall forecasting should be prioritized.

Key words: Cumulative-Departure-Index, GIS, Interpolation, Kriging, Rainfall-Anomaly-Index, Rainfall-variability

Introduction

Understanding spatio-temporal rainfall patterns of rainfall has been directly linked to combating extreme poverty and hunger through agricultural enhancement (IPPC, 2007). The amount of soil-water available to crops depends on rainfall onset, length and cessation which influence the success or failure of a growing season (Ati *et al.,* 2002). According to Khuram & Rasul (2011), soil-water is an indispensable requirement for crop growth from sowing to maturity. It's thus palpable that, climatic parameters and rainfall in particular are prime inputs of improving the socio-economic well being of smallholder farmers. This is particularly important in Sub-Saharan Africa (SSA) where agricultural productivity is principally rain-fed yet highly variable (Jury 2002). Drier parts of Mbeere sub-county; Embu County in Kenya continue to experience elevated rainfall variations, persistent dry spells, prolonged droughts and high annual potential evapo-transpiration ranging between 2000 and 2300mmyear^{-1} (Micheni *et al.,* 2004). Generally, there is enough water on the total; but, it is poorly re-distributed over time (Kimani *et al.,* 2003) with 25% of the annual rain often falling within a couple of rainstorms, allowing crops to suffer from water stress for the bigger part of the season, often leading to complete crop failure (Meehl *et al.,* 2007). Quite often, analyses on rainfall patterns erroneously have been based on annual averages, thus missing on characteristics of seasonal variations (Barron *et al.,* 2003). Sivakumar *et al.* (1993) reported that, understanding the average amount of rain per rainy day is essential in assessing inter/intra seasonal variability. Similarly evaluating mean duration between successive rain events also aids in understanding these variabilities (Akponikpè *et al.,* 2008). Recha *et al.* (2011) noted that, most studies do not provide information on the much-needed character of within-season variability despite its implication on soil-water distribution and productivity. There has been growing interest in understanding seasonal rainfall patterns by evaluation of its variables including rainfall amount, rainy days, lengths of growing seasons and even dry-spell frequencies. Studies by Sivakumar (1991), Seleshi & Zanke (2004) and Tilahun (2006) noted high variations in annual and seasonal rainfall totals and rainy days in Ethiopia and Sudano-Sahelian regions. Mugalavai *et al.* (2008) analyzed onset and cessation of rainfall in Kenya and linked their variation to atmospheric, oceanic and local geographic conditions. Hitherto, the much-needed information on inter/intra seasonal variability of rainfall in Embu County is still inadequate despite its critical implication on soil-water distribution, Water Use Efficiency (WUE), Nutrient Use efficiency (NUE) and final crop yield.

Recently geographic information systems (GIS) and modelling have become dominant tools in agricultural research and, natural resource management (NRM). Thus, spatial and temporal estimates of climatic data are increasingly utilizing GIS modelling and applications (Collins & Bolstad, 1996) with prime intent of optimizing agricultural production. There is need for accurate and inexpensive quantitative approaches to spatial data acquisition and interpolation. To optimize rain-fed agricultural productivity, understanding its occurrence, patterns and distribution both temporally and spatially through hydrological and meteorological analysis is required. Unfortunately, most data in the meteorological stations in Mbeere are inconsistent, unrecorded or missing; leading to more discrete and unreliable data for analysis apart from the main stations themselves being several kilometres from the target area.

There is need to quantify rainfall variability at a local level as a first step for optimal on-farm management in this area.Utilization of the spatial tools, like Inverse Distance Weighted (IDW), Spline and Kriging interpolation techniques are some of the applications exhausted in the ArcGIS tool which are essential for data reconstruction. Kriging is a Geo-statistical gridding and flexible technique that has proven useful and popular in many fields and is supported by the ArcGIS software. This technique generates visually appealing maps from intermittently spaced data. Kriging attempts to convey the trends produced by data, so that, for instance, high points being joined along a ridge rather than be isolated by bull's-eye form of contours. This depends on the user-specified parameters during data input. It integrates anisotropy as well as the underlying trends in an efficient and natural way (Yang *et al*., 2006). Unlike the other interpolation techniques supported by the ArcGIS Spatial Analyst, Kriging utilizes an interactive analysis of the spatial trends of the events represented by the z-values before selecting the accurate estimation technique for spawning the output surface. For IDW, interpolation overtly implements the premise that things that are close to each other are more identical than those that are farther apart. Thus, predictably, values close to the gauged point have predominant influence on the generated value on the assumption that the gauged value has a local influence which diminishes with distance. Spline technique estimates values via a mathematical function which minimizes general surface curvature, resulting into an even surface that interconnects all the input points. Conceptually, the gauged points are extruded up to the height of their magnitude.

Since climate (and rainfall in particular) is the most critical factor determining rain-fed agriculture yet not homogeneous, knowledge of its statistical properties derived from long-term observation can be utilized in developing variability and drought mitigation strategies in the area. This study to quantified and characterised inter/intra seasonal rainfall variability and drought probabilities as the first step towards improving agricultural productivity in the study area. The study further utilized computer applications of ArcGIS tools to reconstruct rainfall data through appropriate and reliable techniques that employ geo-statistical or deterministic interpolation techniques.

Materials and methods

Study area. The study was conducted in Mbeere South (of Embu County) District locate in the Central highlands of Kenya (Fig. 1). Mbeere South District lies in the lower midland (LM) 3, 4 and 5 (LM 3, LM 4 and LM 5), Upper midland (UP) 1,2,3 and 4 (UM 1, UM 2, UM 3 and UM 4), and Inner lowland (IL) 5(IL 5) (Jaetzold *et al.,* 2006) at an altitude of approximately 500 m-1200 m above sea level. Its temperature ranges of 21.7 to 22.5^{o}C; and average annual rainfall of 700 to 900 mm. It has a population density of 82 persons per km^{2} with an average farm size of less than 5.0

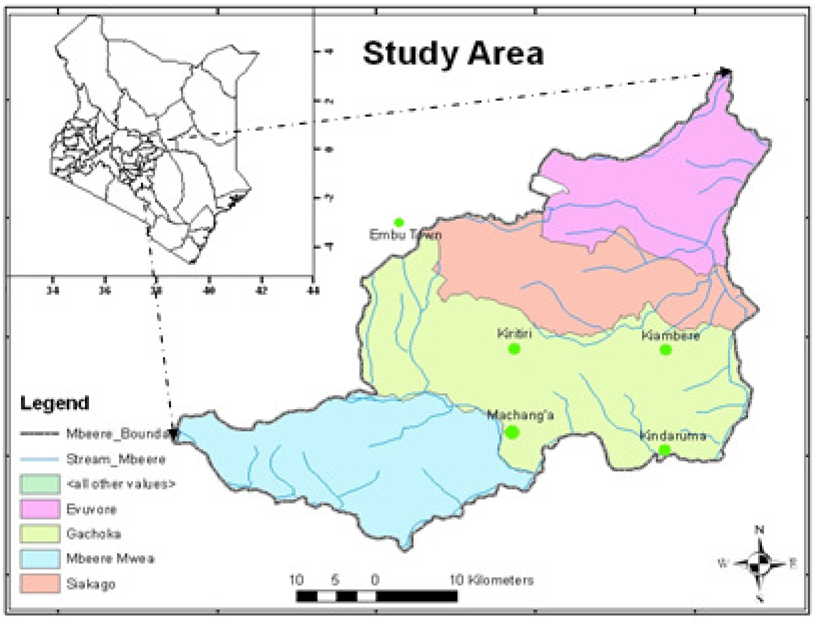

Figure 1. Map showing the study area with the point gauged rainfall data; Machang'a and Embu.

Table 1. Selected characteristics of the meteorological Station (Embu and Machang'a) used in the study.

Station	AEZ	Lat	Long	Alt	Rainfall	Climate
Embu	1 and 2	0°30'S	37°27'E	1409	1210	humid
Machang'a	4 and 5	0°46'S	37°39'E	1106	781	s-humid

AEZ = Agro-Ecological Zone, Lat = Latitude, Long = Longitude, Alt = Altitude

ha. The rainfall is bimodal with long rains (LR) from mid March to June and short rains (SR) from late October to December hence two cropping seasons per year. The soils are predominantly Ferralsols, Cambisols and Acrisols (Jaetzold *et al.,* 2006). There is generally a secure land tenure system but often the area underscores in agricultural productivity.

Rainfall data. Daily rainfall was sourced from the Kenya Meteorology Department (KMD) alongside on-going primary recording at a gauged station in Machang'a, Kamburu, Kindaruma, Kiritiri and Embu. The choice of these stations was guided by their agro-ecological zones and percentage of missing data, (less than 10% for a given year as required by the World Meteorological Organization (WMO).

Rainfall variability. Rainfall dailies were captured into MS Excel spreadsheet where seasonal rainfall totals for (SRs and LRs), annual average and number of rainy days were computed. Multiple imputations were utilized to fill in missing daily data through creation of several copies of datasets with different possible estimates. The method was preferred as it appropriately adjusted the standard error for missing data yielding complete data sets with known sampling errors for analysis (Enders (2010). A rainy day was considered to be any day that received more than 0.5 mm of rainfall. The rainfall dailies were captured into *RAINBOW Software* for homogeneity testing based on cumulative deviations from the mean to check whether numerical values came from the same population. The cumulative deviations were then rescaled by dividing the initial and last values of the standard deviation by the sample standard deviation values (Equation (1).

$$S_k = \sum_{i=1}^{k}(X_i - \bar{X}) \qquad \text{Equation (1)}$$

$$\text{when} \quad k = 1, \ldots, n$$

Where S_k is the rescaled Cumulative Deviation; n represents the period of record for K=1 and also when K=13.

The maximum (Q) and the range (R) of the rescaled cumulative deviations from the mean were evaluated based on number of Nil Values, Non-Nil values, Mean and Standard deviations and Kolmogorov Smirnov (K-S) values (Equations (2) and (3)) to test homogeneity. Low values of Q and R indicated that data was homogeneous.

$$Q = max\left[{}^{S_k}/_{S}\right] \qquad \text{Equation (2)}$$

$$R = max\left[{}^{S_k}/_{S}\right] - min\left[{}^{S_k}/_{S}\right] \qquad \text{Equation (3)}$$

Where Q is maximum (max) of S_K and R in the range of S_K and min is Minimum

The seasonal rainfall frequency analyses were based on normal probability distribution with $\log_{10}$ transformation. The Weibull method was used to estimate probabilities while the Maximum Likelihood Method (MOM) was utilized as a parameter estimation statistic. Homogeneous seasonal rainfall totals were subjected to trend and variability analyses using Cumulative Departure Index (CDI) and Rainfall Anomaly Index (RAI), (described in Tilahun, 2006). Trend analyses based on CDI utilized normalized arithmetic means for seasonal and annual rainfall recorded for the period of 13 years (Equation (4).

$$CDI = (r - R)/S \qquad \text{Equation (4)}$$

Where: r is actual rainfall (seasonal or annual), R is the mean rainfall of the total length of period recorded (2001-2013), S is the standard deviation of the total length of period of record.

Seasonal variability was computed in tandem with annual averages for both positive (Equation (5)) and negative anomalies (Equation (6)) using RAI

$$RAI = +3\left(\frac{RF - M_{RF}}{M_{H10} - M_{RF}}\right) \qquad \text{Equation (5)}$$

$$RAI = -3\left(\frac{RF - M_{RF}}{M_{L10} - M_{RF}}\right) \qquad \text{Equation (6)}$$

Where: M_{RF} is mean of the total length of record, M_{H10} is mean of 10 highest values of rainfall of the period of record, M_{L10} is the lowest 10 values of rainfall of the period of record

The Coefficient of Variance (CV) statistics were utilized to test the level of mean variations in LR and SR seasonal rainfall, number of rainy days (RD) and Rainfall Amounts (RA) and T-test statistic to evaluate the significance of variation.

Drought probability. A day that received less than 0.2 mm rainfall was considered dry. A dry-spell was considered as sequence of dry days bracketed by wet days on both sides (Kumar & Rao, 2005). Frequency analysis of dry-spells was adapted from Belachew (2002) as follows: in the *Y* years of records, the number of times (*i*) that a dry-spell of duration (*t*) days occurs was counted on a monthly basis. Then the number of times (*I*) that a dry spell of duration longer than or equal to t occurs was computed through accumulation. The consecutive dry days (1 d, 2 d, 3 d …) were prepared from historical data. Probabilities of occurrence of consecutive dry-days were estimated by taking into account the number of days in a given month n. The total possible number of days, N, for that month over the analysis period was computed as, $N = n*Y$. Subsequently, the probability p that a dry-spell may be equal to or longer than t days was given by Equation (*7*): The probability q that a dry-spell not longer than t does not occur at a certain day in a growing season was computed by Equation (*8*); and probability Q that a dry-spell longer than t days will occur in a growing season was calculated by Equation (*9*) and probability that a dry-spell exceeding t days would occur within a growing season was computed by equation (x). The contour feature was converted to point feature to generate spatially distributed elevation points using the ArcGIS attribute field calculator to generate modeled rainfall data. Inverse Weighted Mean, Spline and Kriging interpolation techniques in the spatial analysis tools were applied to generate 12 average rainfall maps for the specific years stepwise finally, averaging of the 12 maps was done using map algebra tools yielding the average rainfall map for each technique.

$$P = {}^{I}/_{N} \qquad \text{Equation (7)}$$

$$q = (1 - p) = [1 - \tfrac{1}{N}] \qquad \text{Equation (8)}$$

$$Q = \left[1 - \tfrac{1}{N}\right]^{n} \qquad \text{Equation (9)}$$

$$p = (1 - Q) = 1 - \left[1 - \tfrac{1}{N}\right]^{n} \qquad \text{Equation (10)}$$

Rainfall data interpolation. Rainfall data of the neighboring stations were acquired and captured in the Microsoft Excel spreadsheet where missing data gaps were generated by utilizing either linear or different orders of polynomial relationships. Appropriate mathematical functions were derived from elevation versus recorded rainfall amounts where the best-fitted of individual specific years were generated using the scatter plot and trend lines Generated linear functions were used in ArcGIS environment in conjunction with digital elevation model (DEM) for orographic construction of monthly average maps starting from January 2001 to April2013 using inverted weighted mean, Spline, and Kriging interpolation techniques (Fig. 2).

Results

Homogeneity testing and frequency analyses

Homogeneity test. Results showed the rescaled cumulative deviations (RCD) having zero outliers and NIL values that restricted homogeneity around the zero mark in both stations and seasons (Table 2). The standard deviations (SD) from the normalized means for both LR

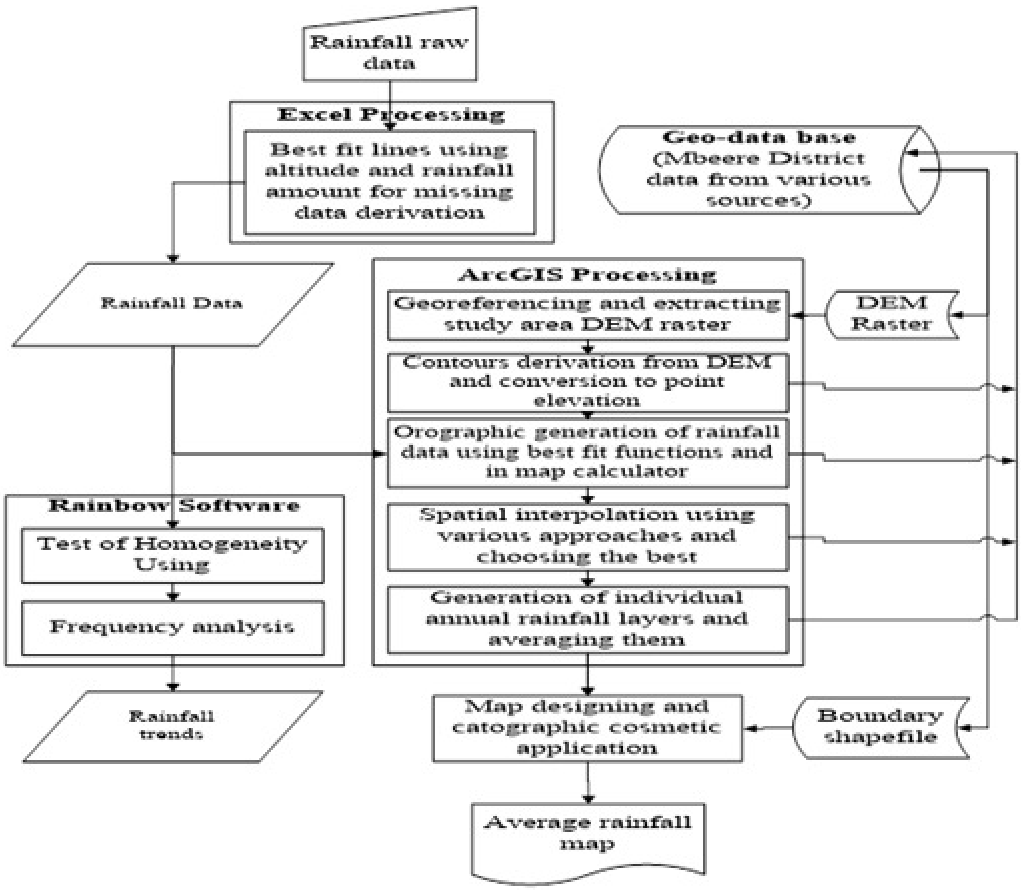

Figure 2. Flow chart showing stepwise implementation of the study and the expected output.

and SR seasons recorded minimal variations (SD=0.2 for means of 2.4 and 2.6 at Machang'a) and of SD= 0.9 and 0.1(for means of 3.2 and 2.6 at Embu) indicating high homogeneity. An R^2 of 96% for LRs at Machang'a indicated the highest best-fit of the RCDs from the normalized mean while R^2 of 92% the least best-fit for SRs of Embu.

A plot of homogeneity showed deviations from the zero mark of the RCDs not crossing probability lines (thus homogeneity was accepted at 90%, 95% and 99% probabilities) (Fig. 3).

A Kolmogorov Smirnov (K-S) value (one sided sample K-S test) for both LR and SR seasons were 0.1479 and 0.1900 (Machang'a) and 0.2330 and 0.1722 (Embu) stations respectively (Table 3). The K-S table value for n=13 at α= 0.005 probability was found to be 0.302; indicating acceptance of an exponential distribution (Table 3).

Seasonal rainfall frequency analyses, probability of exceedance and return periods. The probability of exceeding various amounts of rainfall for both LRs and SRs diminished as threshold rainfall amount increased. There was 90% chance of receiving rainfall greater than 172.2mm and 213.5mm during LRs in Machang'a and Embu respectively. This probability also indicated receiving rainfall amounts exceeding 258.1 mm and 262.5mm during the SRs at both Machang'a and Embu respectively. However, the chance of having more than 449.8mm and 763.0mm during LRs and 628.8mm and 994.7mm during SRs in Machang'a and Embu respectively was 10% (Table 4).

Trend analyses of rainfall events. Fluctuations around, above and below the CDI zero mark corresponded to

Table 2. Homogeneity test values on K-S, nil values, mean, standard deviation and R^2 for both Embu and Machang'a rainfall Stations.

Season	Transformation	Nil values		Mean		SD		R^2 (%)	
		Mac	Emb	Mac	Emb	Mac	Emb	Mac	Emb
LRs	Log_{10}	0	0	2.4	3.2	0.2	0.9	96	94
SRs	Log_{10}	0	0	2.6	2.6	0.2	0.1	94	92

Mac=Machang'a, Emb=Embu and SD= Standard Deviation; LRs=Long Rains and SRs=Short Rains.

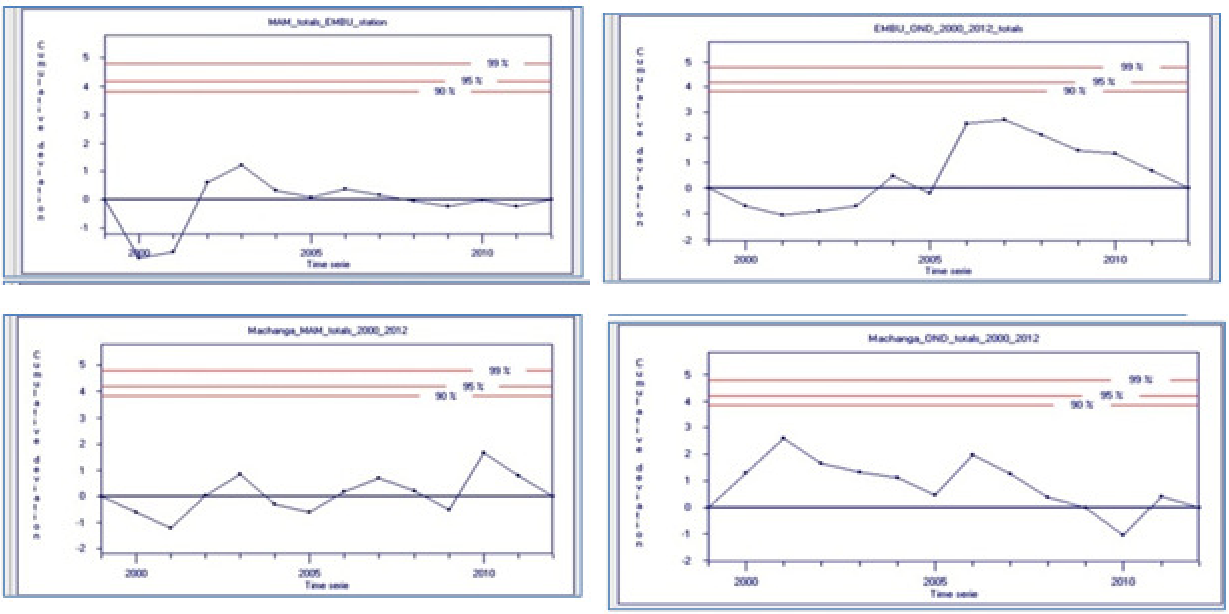

Figure 3. Rescaled cumulative deviations for LRs and SRs (Left-Right) seasons; Embu (Above) and Machang'a (below).

Table 3. Homogeneity test values on K-S, and non-nil values (n), for both Embu and Machang'a rainfall Stations.

Month	Transformation	(K-S)		n		K-S: T. value	
		Mac	Emb	Mac	Emb	Mac	Emb
LRs	Log10	0.1479	0.2330	13	13	0.302*	0.302*
SRs	Log10	0.1900	0.1722	13	13	0.302*	0.302*

K-S=Kolmogorov Smirnov Test; TableV= Table Value; (0.302* exponential distribution applies and accepted) Mac=Machang'a, Emb=Embu and LRs=Long Rains and SRs=Short Rains deviations from the average rainfall over time. Machang'a station experienced near and above average rainfall between 2001 and 2003 for both SRs and the annual average rainfall (CDI >+1). Periods after 2004 recorded below average rainfall amounts (Fig. 2). SRs in both Machang'a and Embu received relatively above average rainfall throughout the decade (Figs. 4 and 5).

Analyses of seasonal rainfall variability and its anomalies. There was observably high decadal seasonal rainfall variability (Fig. 6). There were more negative anomalies in Machang'a (more during LRs; RAI= -8) than positive anomalies (RAI=+4). Embu had more positive anomalies during LRs (RAI= +6) and more negative anomalies (RAI=-7) during SRs (Fig. 6).

Variability in seasonal rainfall and rain days. Rainfall amounts recorded high Coefficients of Variation (CV of 0.41 and 0.36)) compared to rainy days (CV of 0.26 and 0.08) (Table 5) implying high variability in rainfall amounts than rainy days. At Machang'a rainfall amounts during LRs (CV=0.408) were highly variable than those in Embu (CV=0.361).

At monthly level, CV of rainfall amount (RA-CV) exceeded 30% for all the seasonal months (high variability in March (RA-CV=0.979) and December (RA-CV=0.857) at

Table 4. Probability of rainfall exceedance and return periods for both LRs and SRs at Machang'a and Embu.

Probability of exceedance (%)	Return period (year)	Magnitude of anticipated rainfall (mm)			
		LRs		SRs	
		Machang'a	Embu	Machang'a	Embu
10	10	449.8	994.7	763.0	628.8
20	5	381.4	788.9	613.1	541.2
30	3.33	338.7	667.5	523.7	485.7
40	2.50	306.0	578.8	457.7	442.9
50	2	278.2	506.8	403.6	406.3
60	1.67	253.2	443.5	356.0	372.8
70	1.43	22.8	384.5	311.1	339.9
80	1.25	203.1	325.4	265.7	305.0
90	1.11	172.2	258.1	213.5	262.5

LRs=Long Rains and SRs=Short Rains and (mm) =millimetres.

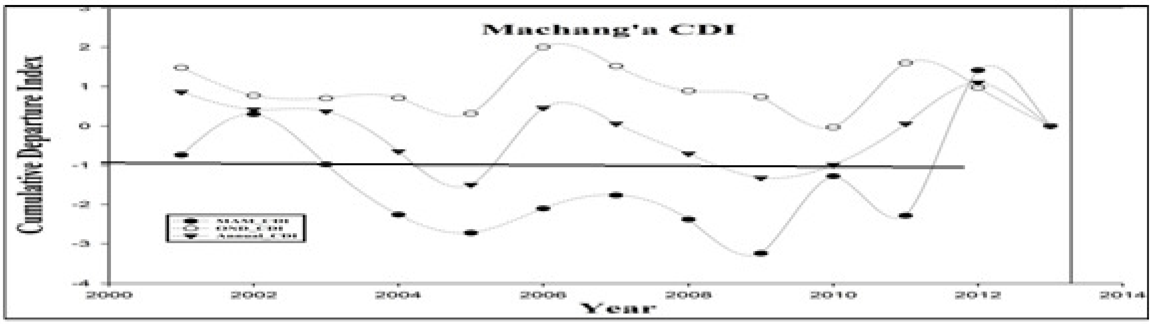

Figure 4. Trend analyses based on Cumulative Departure Index for Machang'a Stations (Agro-Ecological Zone 4 and 5): Key: MAM=LRs, OND=SRs.

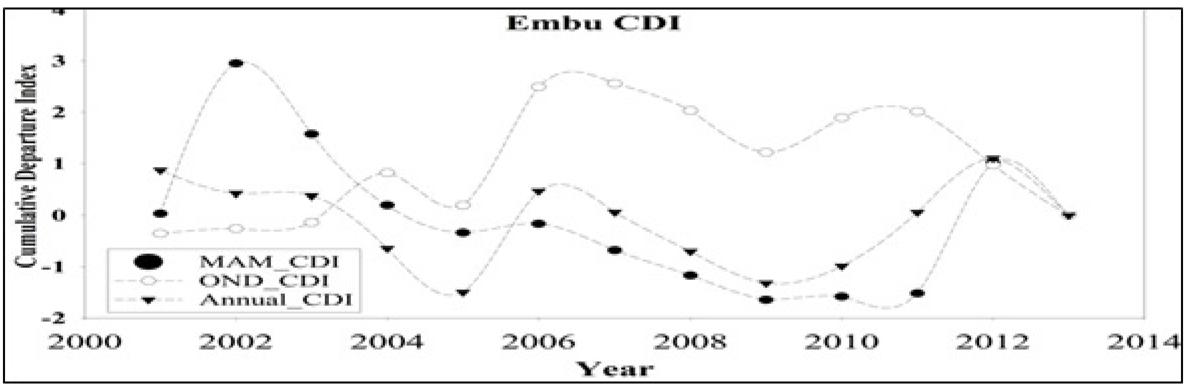

Figure 5. Trend analyses based on Cumulative Departure Index for Embu Station; CDI=Cumulative Departure Index.

Machang'a; and October (RA-CV=0.66) and December (RA-CV=0.97) at Embu. Least variability in rainfall amounts was recorded in April (RA-CV=0.420) and November (RA-CV=0.426) in Machang'a and Embu (Table 6).

Drought probability, frequency of dry spells and implications on crop productivity. Lowest probabilities of dry-spells occurrence of all durations would be in April (LRs) and November (SRs). High probabilities of dry-spells were in March (0.72 and 0.55) and December (0.8 and 0.6) in Machang'a and Embu respectively. The probability of having a dry-spell increased with shorter periods (more chance of having a 3 than a 10 or 21 day dry-spell) (Figs. 8 and 9). Probabilities of a 15-day dry-

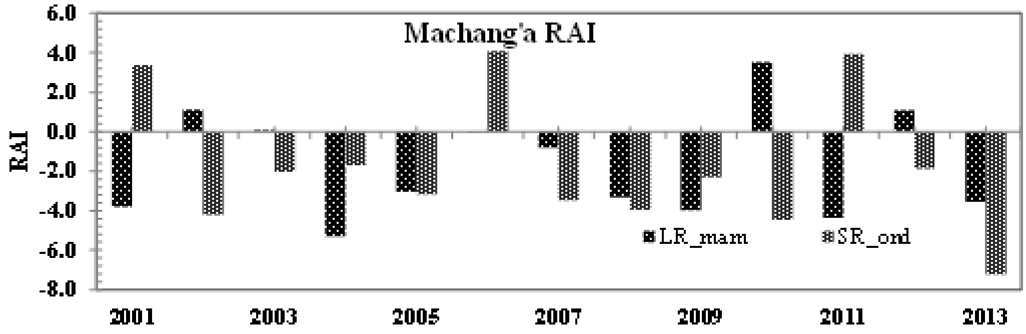

Figure 6. Rainfall Anomaly Index (RAI) for Both LRs and SRs (Machang'a).

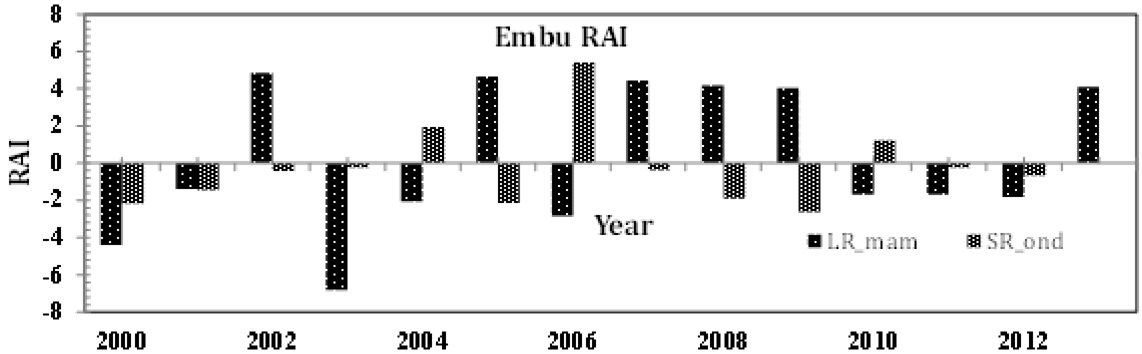

Figure 7. Rainfall Anomaly Index (RAI) for Both LRs and SRs (Embu).

Table 5. Variability analyses: Coefficient of variations in seasonal rainfall amounts and number of rainy days.

Station	LRs				SRs				M.variations
	RA	CV	RD	CV	RA	CV	RD	CV	T-test values
Machang'a	314.9	0.408	24	0.264	438.7	0.56	53	0.881	0.111
Embu	586.3	0.361	46	0.079	497.1	0.381	40	0.272	0.035*

RA=Rainfall Amount in (mm), RD=Rainy Days CV=Coefficient of Variation and M.variations=mean variations; *=Significant at 0.05 Level

Table 6. Variability in seasonal months: Coefficient of variation in rainfall amounts and rainy days.

Machang'a	March	April	May	October	November	December
RA (mm)	85.5	160.2	69.2	98.9	267.9	72.0
RA-CV	0.979	0.420	0.687	0.798	0.765	0.857
RD	8	11	5	14	29	10
RD-CV	0.606	0.223	0.606	0.353	0.229	0.335
Embu						
RA (mm)	110.1	300.8	175.6	175.1	250.3	71.8
RA-CV	0.610	0.480	0.542	0.660	0.426	0.967
RD	20	14	12	10	13	17
RD-CV	0.468	0.269	0.266	0.588	0.246	0.833

RA (mm) = Rainfall Amount in millimetres; RA-CV= Coefficient of Variation in Rainfall Amounts, RD=Number of Rainy Days; RD-CV= Coefficient of Variation in Rainy Days.

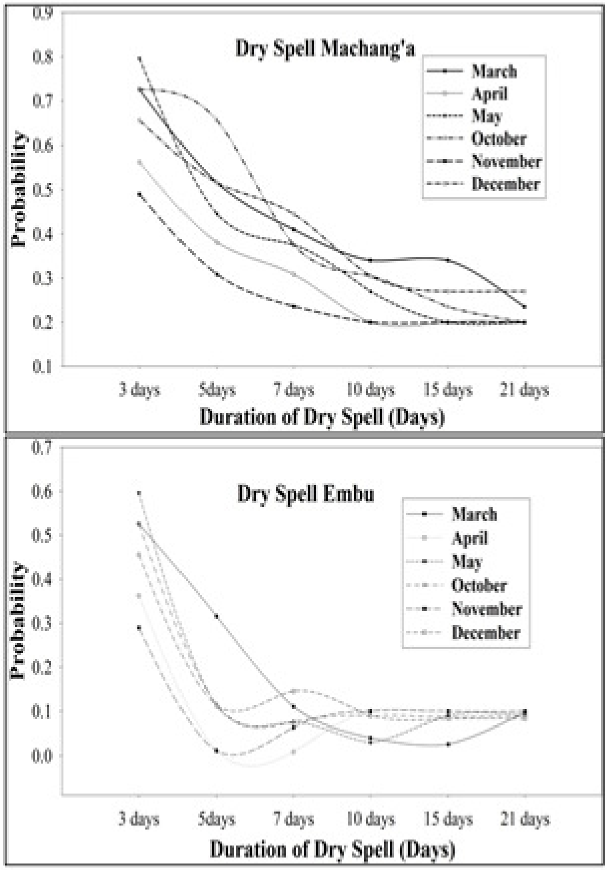

Figure 8. Probability of a dry spell of length e"n days, for n=3, 5, 7, 15, 21, in each month, estimated using the raw data from 2000 to 2013.

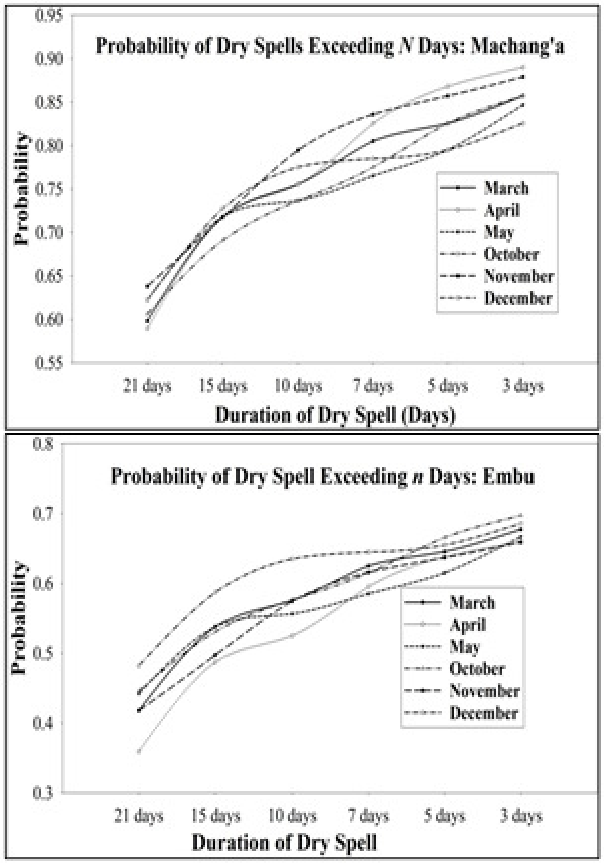

Figure 9. Probability of Dry Spell Exceeding the *n (3, 5, 7, 10, 15 and 21)* Length of Days for both Machang'a and Embu Stations.

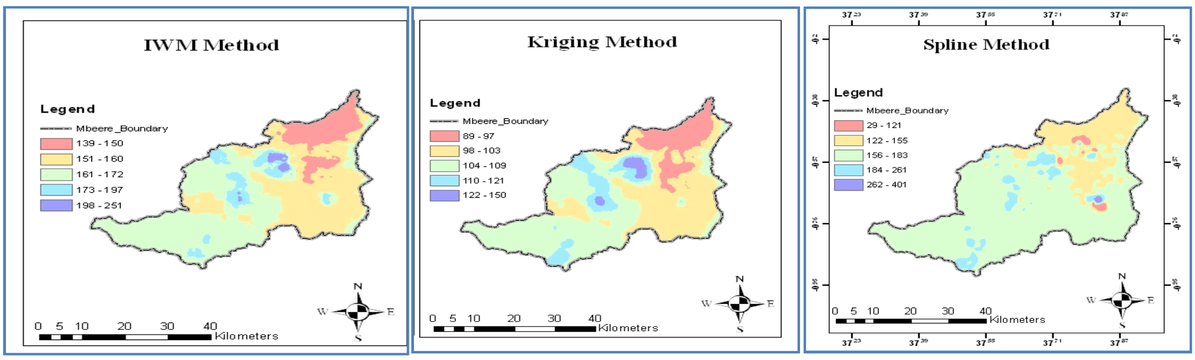

Figure 10. Annual rainfall maps derived by using IWM, Kriging and Spline methods.

spell were relatively lower (0.1 to 0.4) in both stations. The probability of dry spell exceeding the n length of days in the two stations is captioned in Figure 9.

The resultant annual rainfall maps of the three spatial interpolation methods are shown in Figure 10 whose source is ArcGIS 9.0 version. The patterns in the maps resulted mainly from the patterns generated from the mapping of the index value (the mean annual precipitation) and were influenced also by the special local conditions (elevation) including the nonexistence of altitudinal variability of the parameters of the distribution function and the interpolation methods used. From a statistical point of view, the spatial distribution of quantiles was theoretically better underpinned in the regional Kriging approach than in the other methods tested.

Discussion

According to Raes *et al.* (2006), restriction of the rescaled cumulative deviations (RCDs) around the zero mark, with zero number of outliers not crossing the probability level lines (at 95% and 99%) indicates high homogeneity in a recorded time-series (Table 1 and Fig. 1). Frequency analyses of meteorological data require that the time series be homogenous, to gain in-depth and representative of its trends over time (Raes *et al.,* 2006). According to MATLAB Central (2013), K-S test evaluates whether tested dataset comes from a continuous distribution, often based on the empirical cumulative distribution function (ECDF). This (ECDF) is derived from the largest vertical difference between the extracted (observed k-s value) and the table value. During this study, table value (0.302) was high than extracted values (*n*) (0.1479 and 0.1900); showing acceptance of an exponential homogenous distribution amid entire versus extracted dataset (Botha *et al.,* 2003; Mzezewa, 2010; and MATLAB, 2013). This is owed to fact that tested dailies were extracted from raw time series for a selected time period only.

Analyses of probability of exceedance and return periods projected when a given amount of rainfall would be exceeded with time. This information serves in advising farmers on crop selection in tandem with its water requirements during the growth cycle and optimize on SWC technologies ((Rappold, 2005). Both study stations could receive rainfall exceeding most crops' threshold requirements (>315mm) after 3.33 years (30% probability). Rainfall amounts exceeding 270mm can only occur after 1.11 (probability of 90%). Both scenarios showed very low amounts and probabilities of optimal anticipated rainfall. Echoing these findings was Mzezewa (2010) while studying the semi-arid Ecotope of Limpopo, South Africa. Mzezewa (2010) observed that, the probabilities of exceeding average annual rainfall (800mm) was only 47% after 5 years while exceeding total annual was 0% (no increase).

Decadal rainfall trends studied here supported indicated that the 20th century desiccation trends of annual rainfall by Dai *et al*. (2004), Hulme (2001) and Nicholson (1993) in Sub Saharan Africa (SSA) have in part affected the Central Highlands of Kenya; including Embu County. Evidently, LRs varied minimally from annual averages (CDI and RAI analyses) but consistently below the areas' average rainfall (drying). SRs recorded highly variable positive anomalies in both stations. Consistent below average rainfall could indicate a probable shift towards aridity especially during LRs. Similar trends were observed in the studies by Ovuka & Lindqvist (2000), Tucker (2005), Tilahun (2006), and Recha *et al.* (2012). Ovuka & Lindqvist (2000) for example, noted a decreasing annual rainfall trend for the period 1963–1996 in Murang'a district (AEZ 1, 2 and 3). Even Tilahun (2006) who utilized CDI established that parts of Northern and Central Ethiopia had persistently received below average rainfall from early periods as 1970.

Intra station-seasonal rainfall variability showed that LRs in Embu (AEZ 1 and 2) were wetter than SRs. A reverse trend was observed in Machang'a (AEZ 4 and 5) but both recorded high variance during SRs. It could be deduced that SRs were not reliable in Embu but more reliable in Machang'a. Evidence of high rainfall variability during SRs and drying LRs in arid regions (AEZ 4 and 5) are documented by Cohen (1987); Hutchinson (1996); Shisanya (1990) and Recha *et al.* (2012). Shisanya (1990), Anyamba *et al.* (2001) and Amissah- Arthur *et al.* (2002) attributed La Nina events to persistent droughts (LRs) and El Nino events (e.g. 1997) as inputs to variations in SR storms. This studied proved that rainy days and rainfall amounts were highly variable during SRs in Machang'a. high variability during SRs were also established by Barron *et al.* (2003) who recorded CV as 53% and 45% for SRs and LRs respectively at a station in Machakos (AEZ 3). Seleshi and Zanke (2004) further showed that annual and seasonal rainfall in Ethiopia was highly variable (CV range: 0.1 to 0.5) during SRs seasonal phases.

Rainfall being a prime input and requirement for plant life in rain-fed agriculture, occurrence of dry-spells has particular relevance to rain-fed agricultural productivity (Belachew, 2002; Rockstrom *et al.,* 2002). Probabilities of dry-spell occurrence during cropping season were markedly high in Machang'a than Embu. The probabilities of experiencing dry-spells (in November) exceeding 3 days were 0.7 and 0.5 and 12 days were 0.3 and 0.1 in Machang'a and Embu respectively. Relatively high dry-spell probabilities especially in arid areas were also reported by Sivakumar (1992), Aghajani (2007), Kosgei (2009) and Njiru *et al.* (2010). Njiru *et al.* (2010) observed high dry-spell probabilities (88%) in October in the lower eastern parts (Makindu and Katumani) in Kenya which is a SR month. This study established dry-spell probabilities of 0.79 (79%) during the same month.

Conclusion and recommendations

The objective of this study was to characterize inter/intra seasonal rainfall variability of AEZs 1 and 2, and 4 and 5. There is palpable increase of rainfall variability from AEZ 1 and 2 towards AEZ 4 and 5 and highly pronounced during SRs. Nonetheless, both zones have continued to receive below average LRs and annual rainfall since 2000 to date; showing probabilities of their shift towards aridity. Despite high variability during SRs (attributed to El Nino events), the season appeared to receive more total amount of rainfall in AEZ 4&5 than that received in AEZ 1 and 2. The former however stands high chances of experiencing dry-spells exceeding 21 days (crop desiccation) within cropping months; more likely during SRs in AEZ 1 and 2, and LRs in AEZ 4 and 5. Thus, chances of harvesting crops during SRs were relatively high in AEZ 4 and 5, and LRs in AEZ 1 and 2. However, the scope of optimizing crop production and sustainability in the region lies in adoption of rain-water conservation strategies (at field level) and probably supplementary irrigation. There is also need for careful selection of crop types and varieties. Reliably and timely information on rainfall on-set, cessation, planting dates and lengths of growing season is essential. Nonetheless, information on probabilities of dry spells would aid in designing risk aversion strategies. In follow up investigations the mapped information could be further processed by different interpolation methods such as IDW, Spline and Kriging for temporal and spatial reconstruction of precipitation values. Kriging appeared to be the best technique despite showing high sensitivity to inconsistent density of the stations in the district, which was an initial limitation hence Kriging, this technique could be the method of choice. However, it still has some limitations including the high amount of required calculations, the need for expert judgment and the impossibility of normalizing the indices for a few months. Finally, it is recommended that within the month's rainfall frequency analysis might be essential in order to better understand rainfall characteristics such as onset and cessation. Understanding these patterns is crucial especially for better farm management practices by the small scale farmers of Mbeere district and in the Central Highlands at large

Interpolation. The resultant annual rainfall maps of various spatial interpolation methods are shown in figures 2, 3, & 4. The resultant patterns of spatial distribution for each map were an outcome of the generated patterns from the mapping of the index value (the mean annual precipitation). Besides, they were influenced by the spatial local conditions (elevation) including the nonexistence of altitudinal variability of the parameters of the distribution function and the interpolation methods used. From a statistical point of view, the spatial distribution of quantiles is theoretically better underpinned in the regional Kriging (Fig. 3) approach than in the other methods tested. For this study, Kriging was extended by the regional regression for each index value for areas whose terrain or other controls could have contributed to the spatial variability of the trends. Despite the fact that usual mapping methods like Spline and IDW are considered ample only for simple climate patterns, here, their application was considered justified both by the properties of the data and the respective maps generated. Both methods presume that the modelled value is not dependent on spatial location. Additionally, they premise that variance of the differences amid two values predominantly is dictated by the distance between them but not local variability. On the other hand this common feature showed that the results of both methods exhibit visually and numerically similar results (Fig. 10).

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References

Akponikpè, P.B.I., Michels, K. & Bielders, C.L. 2008. Integrated nutrient management of pearl millet in the Sahel using combined application of cattle manure, crop residues and mineral fertilizer. Experimental Agriculture **46,** 333-334.

Burroughs, P. & McDonald, A. 1998. Principles of Geographical Information Systems: Land Resources Assessment. New York: Oxford University Press.

Dai, A.G., Lamb, P. J., Trenberth, K. E., Hulme, M., Jones, P. D. & Xie, P. P. 2004 . The recent Sahel drought is real. International Journal of Climatology **24,** 1323-1331.

Enders, C.K. 2010. Applied missing data analysis. The Guilford Press: New York. ISBN 978-1-60623-639-0.

Heine, G.W. 1986. A controlled study of some two-dimensional interpolation methods. COGS Computer Contributions **3(2),** 60-72.

Hulme, M. 2001. Climatic perspectives on SSA desiccation: 1973-1998. Global Environmental Change **11,** 19-29.

IPCC, 2007. Climate Change 2007. Fourth Assessment Report. Cambridge University Press: Cambridge.

Jaetzold, R., Schmidt, H., Hornet, Z.B. & Shisanya, C.A. 2006. Farm Management Handbook of Kenya: Natural Conditions and Farm Information, vol 11/C, 2nd edn. Ministry of agriculture/GTZ: Nairobi (Eastern province), Kenya.

Jury, M.R. 2002. Economic impacts of climate variability in South Africa and development of resource prediction models. Journal of Applied Meteorology **41,** 46-55.

Khuram, R. & Rasul, G. 2011. Rainfall variability and maize production over the Potohar plateau of Pakistan. Pakistan Journal of Meteorology **8,** 15, 63-70.

Kimani, S.K., Nandwa, S.M., Mugendi, D.N., Obanyi, S.N., Ojiem, J., Murwira, H.K. & Bationo, A. 2003. Principles of integrated soil fertility management. pp. 51-72. In: Gichuri, M. P., Bationo, A., Bekunda, M.A., Goma, H.C., Mafongoya, P. L., Mugendi, D. N., Murwuira, H. K., Nandwa, S. M., Nyathi, P. & Swift, M. J. (Eds.). Soil fertility management in Africa: A regional perspective. Academy Science Publishers (ASP); Centro Internacional de Agricultura Tropical (CIAT); Tropical Soil Biology and Fertility (TSBF), Nairobi, Kenya.

Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P. Gaye, A.T., Gregory, J.M., Kitoh, A., Knutti, R., Murphy, J.M., Noda, A., Raper, R.L., Watterson, I.G. & Zhao, Z.C. 2007. Global climate projections. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. & Miller, H.L. (Eds.). Climate change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge.

Micheni, A.N., Kihanda, F.M., Warren, G.P., & Probert, M.E. 2004. Testing the APSIM Model with experiment data from the long term manure experiment at Machang'a (Embu), Kenya. pp. 110-117. In: Delve, R.J. & Probert, M.E. (Eds.). Modeling nutrient management in tropical cropping systems. Canberra, Australian Center for International Agricultural Research (ACIAR) No 114.

Mucheru-Muna, M., Pypers, P., Mugendi, D., Kung'u, J., Mugwe, J., Merck, R. & Vanlauwe, B. 2009. A staggered maize-legume intercrop arrangement robustly increases crop yields and economic returns in the highlands of Central Kenya. Field Crops Research 115:132-139.

Mugalavai, E.M., Kipkorir, E.C., Raes, D. & Rao, M.S. 2008. Analysis of rainfall onset, cessation and length of growing season for Western Kenya. Agricultural and Forest Meteorology **148,** 1123-1135.

Mugwe, J., Mugendi, D., Odee, D. & Otieno, J. 2007. Evaluation of the potential of organic and inorganic fertilizers of the soil fertility of humic hit soil in the central Highlands of Kenya. Soil Use and Management **25,** 434-440.

Nyikal, R.A. 2003. Commercial and subsistence farming. What is the future for smallholder Kenyan agriculture? In: Nampala, M.P., Tenywa, J.S., Mwangómbe, A.W., Osiru, M., Kawuki, R. & Biruma, M. (Eds.). Harvesting crop technologies to alleviate hunger and poverty in Africa. African Crop Science Conference Proceedings **6,** 991-596.

Oliver, M.A. 1990. Kriging: A Method of interpolation for geographical information systems. International Journal of Geographic Information Systems **4,** 313-332.

Raes, D., Mallants, D. & Song, Z. 2002. Rainbow: A software package for analyzing hydrologic data. pp. 525 - 534. In: Blain, W.R. (Ed.). Hydraulic engineering software VI. Computational Mechanics Publications, Southampton.

Raes, D., Willems, P. & Baguidi, F. 2006. Rainbow: A software package for analyzing data and testing the homogeneity of historical data sets. Proceedings of the 4th International Workshop on Sustainable management of marginal dry lands. Islamabad, Pakistan, 27-31 January 2006.

Rao, N.S.S. 1998. Biofertilizers in agriculture and forestry, 3rd ed. New York: International Science Publishers.

Recha, C., Makokha, G., Traoré, P.S., Shisanya, C. & Sako, A. 2011. Determination of seasonal rainfall variability, onset and cessation in semi-arid Tharaka District.

Seleshi, Y. & Zanke, U. 2004. Recent changes in rainfall and rainy days in Ethiopia. *I*nternational Journal of Climatol **24,** 973-983.

Sivakumar, M.V.K. 1991. Empirical-analysis of dry spells for agricultural applications in SSA Africa. Journal of Climate **5,** 532-539.

Sivakumar, M.V. K., Maidoukia, A. & Stern, R.D. 1993. Agroclimatology of Africa: Information Bulletin no 5. Patancheru, A.P. 502 324, India: International Crops Research Institute for the Semi-Arid Tropics, and: Direction de la meteorology nationale du Niger. 116p.

Tilahun, K. 2006. Analysis of rainfall, climate and evapotranspiration in arid and semi-arid regions of Ethiopia using data over the last half century. Journal of Arid Environments **64,** 474-487.

Yang, C. 2006. Twelve different interpolation methods*:* A case study of SURFER 8.0. In Wiley InterScience.