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Spatio-temporal Drought Characterization for the Upper Tana River Basin, Kenya Using Standardized Precipitation Index (SPI)

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Abstract Drought occurrence in the upper Tana River basin in Kenya has impacted negatively on water resources, hydro-power generation and agricultural production within the basin. Although this is an important river basin in Kenya, there is limited research work that has been done to assess and characterize drought to provide feasible mitigation measures and /or coping mechanics for water resources management. The Standardized Precipitation Index (SPI) was used to assess the spatio-temporal drought characteristics within the upper Tana River basin based on precipitation data for 41 years for eight gauging stations within the basin. The Kriging interpolation technique was applied to estimate spatially drought occurrence within the basin while the non-parametric Mann-Kendall (MK) trend test was used for trend detection. Results show that the south-eastern parts of the basin exhibit the highest drought severities while the north-western parts have the lowest drought values with averages of 2.140 and 4.065, and 2.542 and 4.812 in 1970 and 2010 respectively. The areal-extend of drought severities in both the south-eastern and north-western areas increased from 4868.7 km^2 to 6880 km^2, and 6163.9 km^2 to 6985.5 km^2 from 1970 to 2010 respectively. The drought trend increased in the south-eastern parts of the basin at 90% and 95% significant levels while no significant trend was detected in the north-western areas. The results presented in this paper are useful in formulating a drought early warning system that can be used to assist water resources managers in developing timely mitigation measures in planning and managing water resources within the basin.

Keywords: *Kriging, Mann-Kendall trend test, Spatio-temporal drought, SPI, upper Tana River basin*

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1. Introduction

Although significant research has been done in hydrology and water resources management, research on the effect of drought characteristics on water resources is still limited for numerous river basins in the world. For instance, the upper Tana River basin which is the largest water tower in Kenya has continued to experience frequent drought occurrence due to climate change. This has impacted negatively on the available water for hydro-power generation and yet most of the Kenya's hydro-electric power generation which contributes to 80% of the total power requirement in the country is generated from this basin. The main hydro-electric power stations in the basin include; Gitaru, Kiambere, Kamburu, Kindaruma and Masinga each with installed power capacity of 225, 156, 94.2, 44 and 40 Mega Watts (MW) of electrical power [22]. Due to the importance of this river basin in Kenya, some research work has been done on drought occurrence within the basin. Although from limited research work, some of the authors have indicated that the basin continues to experience frequent droughts. For instance, Agwata *et al*. [1] used the principal component approach to analyse drought severity within the upper Tana River basin with results showing that the severity ranges from 0.63 to 3.89. However, application of Standardized Precipitation index (SPI) has not been applied in the basin for spatial and temporal drought estimation. In addition, the trend of drought occurrence in this basin has not yet been documented. Therefore, this paper addresses the aspects of spatio-temporal and trend of drought in the upper Tana River basin.

Drought may be defined as natural event resulting from significantly low amount of precipitation or water resources quantity for an extended period of time compared with the normal average levels. According to Wang *et al*. [31], the key driver of drought occurrence is the climate change, whose effects on river basins take different dimensions. Drought occurrence in any river basin leads to significant adverse effects such as decrease in surface water and ground water resources, erratic water supply, low agricultural production [5] and decline in socio-economic development. The main characteristics of droughts include; severity, duration, frequency and spatial distribution. These are critical variables in water resources planning and management, and for effective mitigation of drought impacts. The common tools used for drought characterization are the drought indices. These indices are numeric values that are used to define the severity of drought. The indices are classified into two broad categories; satellite based and the data driven drought indices [6].

The Satellite based drought indices are based on satellite remote sensing (RS) data. The RS refers to the science and art of obtaining information of points, objects, areas or phenomena via data analysis from a sensor, which is not in direct physical contact with the target of investigation [26]. The RS gives an aerial view of land, water resources and vegetation cover. This method yields spatial and temporal aspects of measuring drought. In addition, monitoring of vegetation dynamics over large surface areas is conducted. Currently, remotely sensed data at multiple time steps is being collected especially in conducting research for large river basins requiring huge amounts of data sets. Such data are used for conducting a near real time information management [20]. Examples of satellite drought indices are the Vegetation Condition Index (VCI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Water Supply Vegetative Index (WSVI) and Normalized Difference Drought Index (NDDI).

The Data Driven Drought Indices (DDDI) uses hydro-meteorological variables as measured from weather and stream flow gauging stations. These variables are used as input parameters in the selected models or tools to assess drought intensity, duration, severity and magnitude. Some of the data driven indices include; Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Surface Water Supply Index (SWSI), Aggregated Drought Index (ADI), Effective Drought Index (EDI), Reclamation Drought Index (RDI), Crop Moisture Index (CMI) and Murger Index (MuI) [6,33]. However, the application of these indices and their testing for Kenyan conditions has not been done adequately.

Some of the most critical elements of drought which are used for the design of water storage systems to cope with drought impacts include; longest duration, largest severity, highest intensity and spatial and temporal variation of droughts [16]. Drought duration refers to any continuous period of the sequence with deficit, while intensity is the magnitude below a truncation level. The truncation level may be taken as the long-term mean of the drought variable [7,11]. Severity is the cumulative deficit below a truncation level during a drought episode and is defined as the product of the drought intensity and duration.

The Standard Precipitation Index (SPI) was developed by Mckee *et al*. [19] for quantification of the rainfall deficit and monitoring of drought conditions in Colorado, USA. In order to compute SPI values for a given river basin, a long-term historical precipitation record of at least 30 years is integrated into a probability distribution function which is then transformed into a normal distribution. Aggregated monthly precipitation series of 1, 3, 6, 9, 12, 24 and 48 months are normally used. The SPI requires less input data than most other drought indices. This makes it flexible for wide applications in drought forecasting [4,18].

The SPI has numerous advantages which qualify for its application in many river basins in the world. First, it requires precipitation as the only input data and thus makes it ideal for those river basins that do not have widespread hydro-meteorological data records. The use of precipitation is considered a key since in drought studies since it is taken as a critical factor that drives some of the natural hazards such as drought, floods and soil erosion [27]. Secondly, the evaluation of SPI is relatively easy as it uses precipitation data without integrating it with other weather factors. Thirdly, it is a standardized index which is independent of geographical location because average precipitation values derived from the area of interest are determined. The SPI displays a statistical consistency. It can also analyze both short-term and long-term droughts over time scales of precipitation variation [5]. However, the SPI has some demerits. For instance cannot be applied on those river basins that do not have reliable precipitation data to generate the best estimate of the distribution parameters.

To overcome the challenge of simulating and modelling the data for SPI, different probability distribution functions are employed. These include; the Gamma, Pearson type III, Lognormal, Extreme value and Exponential distribution functions [10]. However, the Gamma probability distribution function is preferred in hydrological studies. This distribution function has the advantage of fitting only positive and zero values and therefore becomes more applicable since hydrological variables such as rainfall, runoff and are always positive or equal to zero as lower limit value [2,17]. The Gumbel and Weibull distributions are used in studying extreme hydrological variables. The Gumbel distribution is used for frequency analysis of floods, while Weibull distribution is used for the analysis of low flow values observed in rivers [9]. According to Awass [3], the SPI values are influenced by time scales greater than 6 months and thus should be used to investigate droughts beyond this period. The objective of this research was to assess spatio-temporal drought characteristics using standardized precipitation index (SPI) based on precipitation data from 1970 to 2010 for the upper Tana River basin in Kenya.

2. Materials and Methods

2.1. Description of the upper Tana River Basin

The upper Tana River basin, which is part of Tana River basin; the largest river basin in Kenya [13,32], lies between latitudes 00^0 05' and 01^0 30' south and longitudes 36^0 20' and 37^0 58 east. The upper Tana River basin has an area of 17,420 km^2 (Figure 1). It has fundamental forest and land resources located along the eastern slopes of Mount Kenya and the Aberdares range. The basin plays a critical role in regulating the hydrology of the entire basin [12] and in the process, it controls the hydro-electric power generation within the Seven-Folk dams downstream of the Tana River. The basin is very critical in Kenya as it drives the socio-economic development through hydro-electric power generation, water supply and agricultural production.

The elevation of the upper Tana River basin ranges from approximately 730 m to 4,700 m above mean sea level (a.m.s.l.). These elevations are adjacent to Kindaruma hydropower dam and Mount Kenya respectively. The river basin exhibits heterogeneous soil types, with Andosols, Nitosols, Ferrasols and Vertisols dominating at the higher, middle and lower elevations respectively [13].

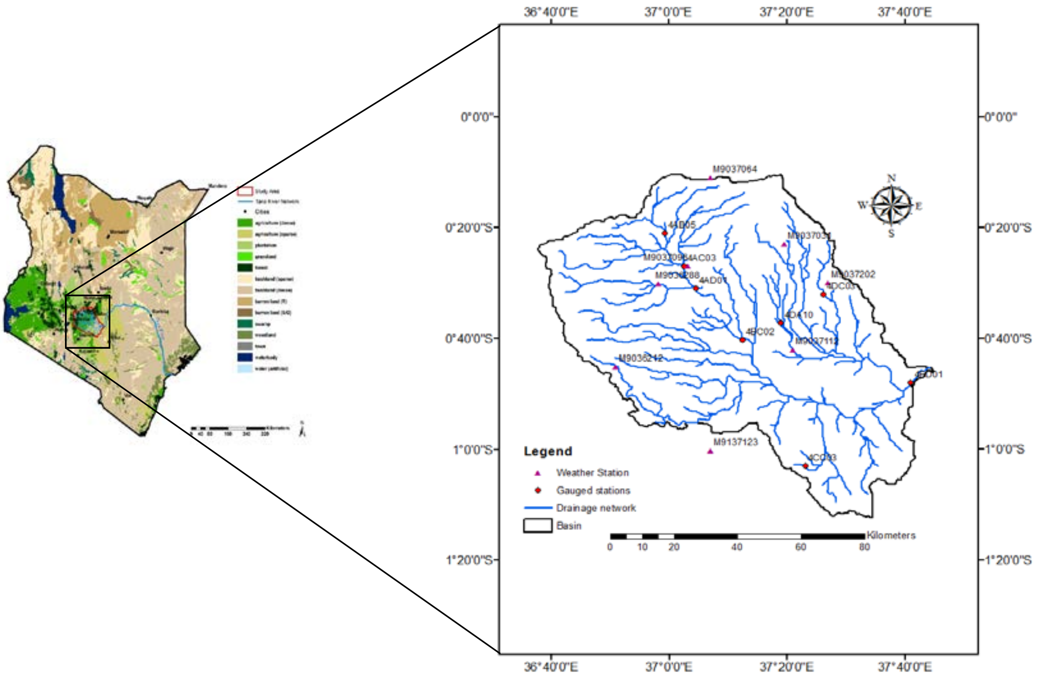


Figure 1. The location of the upper Tana River basin in Kenya

Precipitation and temperature vary across the entire river basin. The annual precipitation at Mount Kenya and the Aberdares ranges is approximately 1800 mm [23]. Within the middle elevations of 1200 to 1800 m a.m.s.l., the annual rainfall ranges from 1000 to 1800 mm or slightly more, while the lower elevations of 1000 m, receive annual rainfall of 700 mm as shown in the spatial distribution map of precipitation (Figure 2).

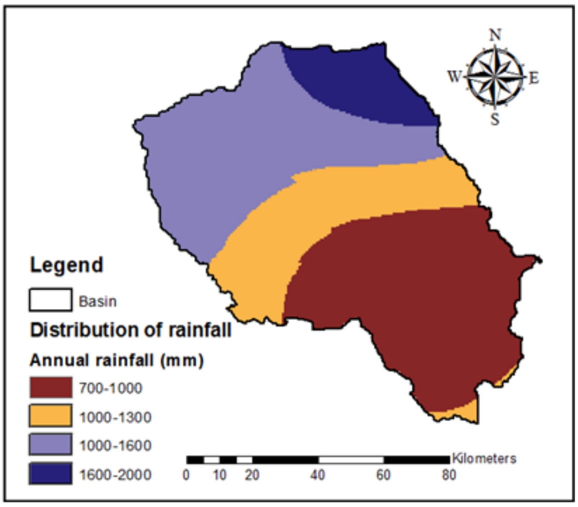


Figure 2. Spatial distribution of precipitation in upper Tana River basin

Although the basin receives significantly high rainfall amounts, it is characterized by seasonal rainfall fluctuations, poor spatial distribution and is highly influenced by orographic forces [25]. Subsequently, this leads to seasonal variation of stream flow in Tana River. Generally the basin experiences bimodal rainfall pattern caused by inter-tropical convergence zone [30]. The rain seasons are distributed in the months of March to June, and September to December.

The maximum and minimum mean annual temperatures in the basin range from 25.5 to 31.0°C and 21.0 to 24.0°C respectively [21]. The average annual river basin evapo-transpiration is approximately 500 mm in the summit area. The major land use types within the upper Tana River basin include; forests, crop land, agriculture and range land. The forests and tea plantations dominate the land use activities at the higher elevations of the basin while range lands dominate the lower elevations.

2.2. Meteorological Data

Monthly rainfall data from 1970-2010 within the upper Tana River basin used used to compute the time series of the SPI values. The selected meteorological stations used in this study are given in Table 1. The data was obtained from the Ministry of Water and Irrigation and also from Water Resources Management Authority (WRMA).

Table 1. The meteorological stations used in the study

S.No	Station name	Station ID	Coordinates		Elevation (m)
			Longitude	Latitude	
1	MIAD	9037112	37.35	-0.7	1246
2	Embu	9037202	37.45	-0.50	1494
3	Kerugoya DWO	9037031	37.327	-0.3824	1598
4	Sagana FCF	9037096	37.054	-0.448	1234
5	Nyeri	9036288	36.97	-0.50	1780
6	Muragua	9036212	36.85	-0.75	2296
7	Naro moru	9037064	37.117	-0.183	2296
8	Mangu	9137123	37.033	-1.10	1630

MIAD: Mwea Irrigation and Agricultural Development Centre, DWO: District Water Office, FCF: Fish Culture Farm, ID: Identification number.

2.3. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was used to quantify rainfall deficit within the basin. To compute the SPI, long-term data for 41 years (1970-2010) was used. The standard procedure first involved fitting the rainfall data into a probability distribution function as described by McKee *et al*. [19]. Aggregated monthly precipitation data series of 3 months was used in the present study. This was then followed by computing the SPI values which were used in drought assessment and classification. The selection of the Gamma distribution function was preferred in this study as it fits well in time series rainfall data [8]. The Gamma distribution is expressed in terms of its probability density function [10] as:

$$g(x)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-x/\beta}\quad for\ x>0 \qquad (1)$$

Where; α is the shape parameter, β is scale parameter, x is the rainfall amount (mm), $\Gamma(\alpha)$ is the value taken by Gamma function and $-x$ is mean rainfall (mm).

The $\Gamma(\alpha)$ is the value defined by a standard mathematical equation called Gamma function. This was determined by applying an integral function adopted from Cacciamani *et al*. [10] which is expressed as:

$$\Gamma(\alpha)=\int_{0}^{\infty}y^{\alpha-1}e^{-y}dy \qquad (2)$$

Where; y is the value computed from Equation 1, that is y is equal to g(x). The Gamma function given in Equation 2 was evaluated using the numerical method by using tabulated values that depended on the value taken by the shape parameter α. A maximum probability was used to estimate the optimal values of α and β using Equations 3 and 4 given as:

$$\alpha=\frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right) \qquad (3)$$

$$\beta=\frac{\bar{x}}{\alpha} \qquad (4)$$

Where; α, β, $\bar{x}$ have the same meaning as given in Equation 1, and A is a sample statistic. The sample statistic is determined using the relation:

$$A=\ln(\bar{x})=\frac{\ln x}{n} \qquad (5)$$

Where; n is the number of observations. The density probability function $g(x)$ in Equation 1 is integrated with respect to x to get an expression for cumulative probability $G(x)$. This function is defined when a certain amount of rain is received for a given month and for a specific time duration. Thus, the calculated values of the cumulative probability for non-zero rainfall are determined using Equations 6 and 7 respectively:

$$G(x)=\int_{0}^{x}x^{\alpha-1}e^{\frac{-x}{\beta}}dx \qquad (6)$$

Where; $G(x)$ is the cumulative probability for non-zero rainfall. The Gamma function applies for values of rainfall $x > 0$ for the rainfall time series of the basin under study. In case of non-zero values, cumulative probability of both zero and non-zero values are computed. This probability is represented by a function $H(x)$ defined as:

$$H(x)=q+(1+q)F(x;\alpha,\beta) \qquad (7)$$

Where; $H(x)$ is the Cumulative probability and q is the probability of zero rainfall. In this case, when m was taken as the number of zero entries in the time series rainfall data, then q was estimated by the ratio m/n. The cumulative probability was then transformed into a standard normal distribution in such a way that the mean and variance of the *SPI* values were zero and one respectively. To carry out this step, an approximate transformation according to Mishra and Desai was adopted. This was achieved using Equations 8 and 9 given as:

$$SPI=-\left(k-\frac{c_0+c_1k+c_2k^2}{1+d_1k+d_2k^2+d_3k^3}\right)\ for\ 0<H(x)\le 0.5 \qquad (8)$$

$$SPI=+\left(k-\frac{c_0+c_1k+c_2k^2}{1+d_1k+d_2k^2+d_3k^3}\right)\ for\ 0.5<H(x)<1. \qquad (9)$$

The value of k in Equations 8 and 9 were determined using Equations 10 and 11 given as:

$$k=\sqrt{\ln\left(\frac{1}{H(x)^2}\right)}\quad for\ 0<H(x)\le 0.5 \qquad (10)$$

$$k=\sqrt{\ln\left(\frac{1}{1-H(x)^2}\right)}\quad for\ 0.5<H(x)<1. \qquad (11)$$

Where; c_0=2.515517, c_1= 0.802853, c_2= 0.010328, d_1=1.432788, d_2= 0.189269 and d_3= 0.001308

In this study, the *SPI* values were calculated using a monthly time step and the threshold criterion as presented in Table 2 were used to define drought conditions [19].

Table 2. Drought classification based on SPI

State	Criterion	Drought classification
1	2.00 or more	Extremely wet
2	1.50 to 1.99	Very wet
3	1.00 to-1.49	Moderate wet
4	0.99 to -0.99	Near normal
5	-1.00 to -1.49	Moderate drought
6	-1.50 to -1.99	Severe drought
7	-2.00 or less	Extreme drought

The steps that were followed in computing the monthly series of SPI are summarised in Figure 3.

The absolute severity was calculated as a product of the sum of SPI values less than zero and its probability for a given year. The probability of drought occurrence is taken as the ratio of the number of months with negative SPI values for twelve months in a year. The computation was based on ten-year intervals from 1970 to 2010.

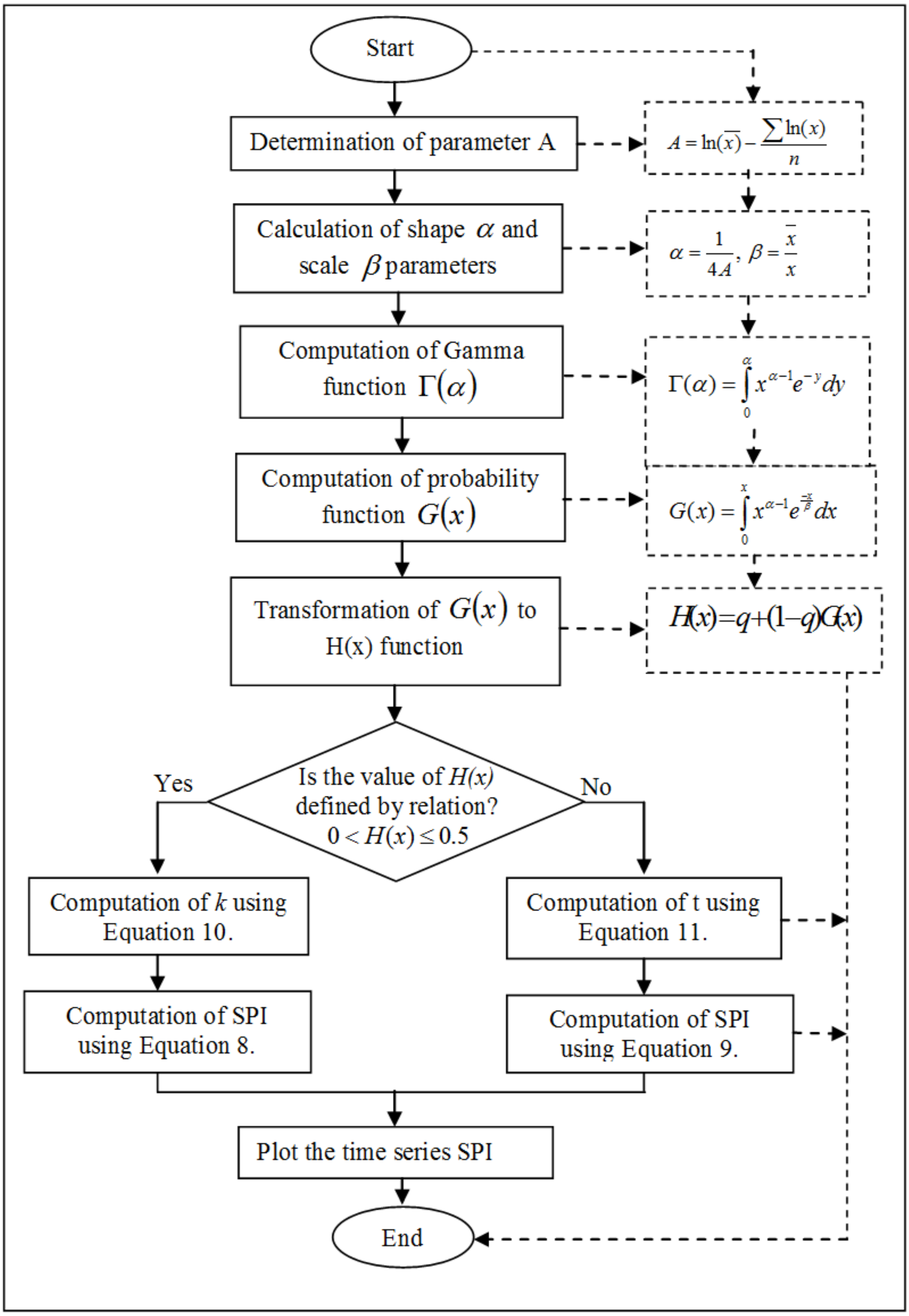


Figure 3. The flow chart of the procedure used in computation of the time series SPI

2.4. Mann-Kendall Based Drought Trends

The Mann-Kendall trend test which is a non-parametric technique was applied to test for trend in the drought severity within the upper Tana River basin. This test has the capacity to test for increasing, decreasing or no trend. The data was evaluated using ordered time series. In this test, the sum of decrements and increments results to a Mann-Kendall statistical value *S*. The data sets were organized in form of $x_1, x_2, x_3, \ldots, x_j$ *n*-data points where x_i represents data point at time *j*. Then the Mann-Kendall statistical trend *S* was determined using the relation:

$$S=\sum_{k=1}^{n-1}\left[\sum_{j=k+1}^{n} sign\left(x_i-x_k\right)\right] \tag{12}$$

The right hand side of Equation 12 is simplified using Equation13 given as:

$$sign\left(x_j-x_k\right)=\begin{cases} 1 \; if \; (x_j-x_k)>0 \\ 0 \; if \; (x_j-x_k)=0 \\ -1 \; if \; (x_j-x_k)<0 \end{cases} \tag{13}$$

Figure 3 presents a summary of the procedure that was use in computing the time series SPI for the upper Tana River basin.

The probability linked to the Mann-Kendall statistic *S* and the selected *n*-data were determined to quantify the level of significance of the trend. The variance of data set *VAR(S)* was calculated and then the normalized test statistic *Z* was computed using Equations 14 and 15 respectively:

$$VAR(S) = n(n-1)(2n+5) - \sum_t \frac{t(t-1)(2t+5)}{18} \quad (14)$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \frac{S-1}{\sqrt{VAR(S)}} & if\ S < 0 \end{cases} \quad (15)$$

Where; *VAR(S)* is the variance of the data set [14], *n* is the number of data points. Equation 14 was used to qualify the drought trend in the basin as, no trend, increasing trend and decreasing trend when *S*=0, *S*>0 and *S*<0 respectively. In order to determine whether or not the drought trend in the upper Tana River basin was significant or insignificant, significance levels at 90% and 95% were used. At these significance levels, the null hypothesis of no trend was rejected when $|Z| > 1.645$ and $|Z| > 1.96$ respectively where the values of *Z* were adopted from Sneyers [28].

2.5. Spatial Distribution of Drought

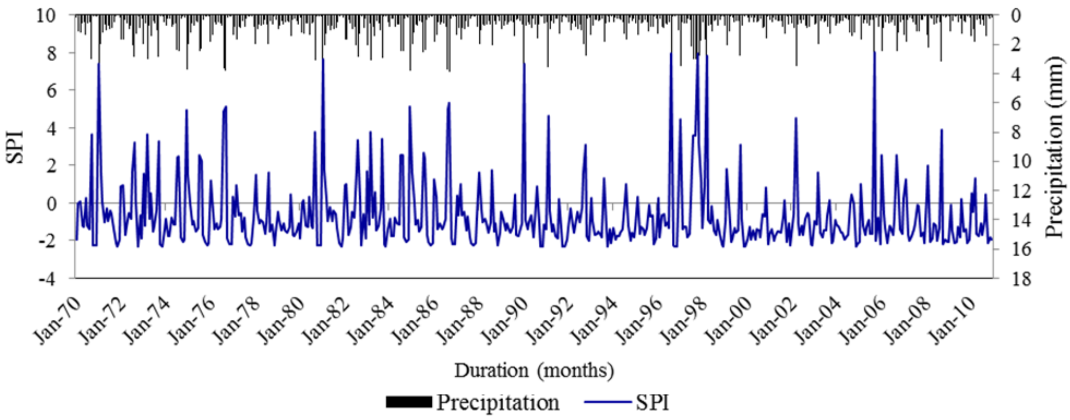
The spatial distribution of drought conditions was estimated using the standard Kriging interpolation technique using the point data. The Kriging technique is described using the various parameters and functions that are applied in the interpolation of values according to Kim and Valdes [22]. In this study, the application of Kriging technique was achieved within the geo-statistical analysis tool of ArcGIS 10.1. This method was selected because it is a reliable approach for any surface interpolation of point data. The Kriging method has also been tested for accuracy in previous studies in other river basins, for instance by Robinson and Matternicht [24].

3. Results and Discussions

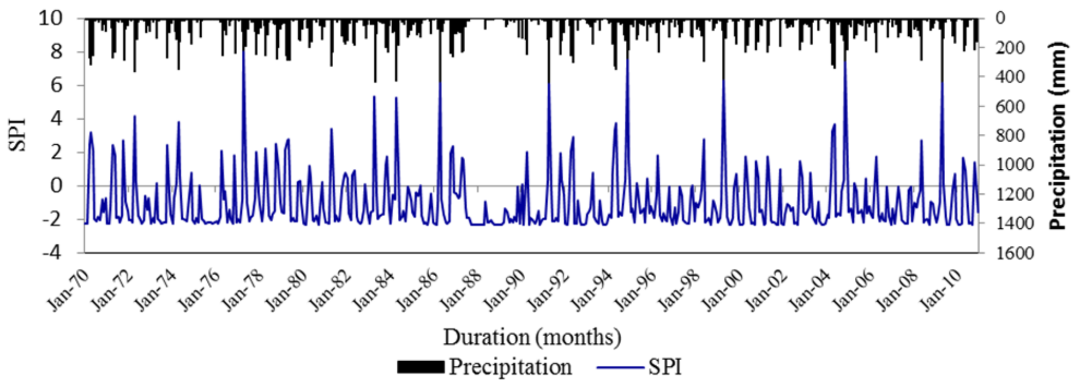
The results for monthly time series SPI and the spatial characteristics of droughts in the upper Tana River basin are presented where different meteorological stations were used to represent different elevations bands of the basin; lower, lower-middle, middle and higher elevations.

3.1. Drought based on SPI time Series

For illustration purposes, Figure 4 shows drought conditions on monthly time series for selected rainfall gauging stations at Mwea Irrigation and Agricultural Development (MIAD) Centre and Naro-Moru located at the lower and higher elevations of the basin respectively.



(a)



(b)

Figure 4. Monthly Time series SPI and precipitation at (a) MIAD (b) Naro-moru meteorological stations

Both the time series SPI and the precipitation were plotted for ease of comparison as given in Figure 4 for the selected meteorological stations. The time series plot show that the SPI varies with the monthly precipitation within the study period. The SPI for meteorological stations presented are objectively selected to represent different elevation bands of the basin where; MIAD, Kerugoya DWO, Nyeri and Naro-moru stations are located in the lower, lower-middle, middle and higher elevation bands of the basin respectively. For all the stations, extreme droughts based on values given in Table 1 were detected using the SPI for the periods 1972-1974, 1983-1984, 1987-1988, 1999-2000 and 2010 within which the monthly SPI values were consistently below -2.00. The SPI is normally used to detect the occurrence both the drought (negative values of SPI) and the wetness (positive values of SPI) in a river basin. The other drought conditions characterized using the SPI for the upper Tana River basin as defined in Table 1 include severe drought, moderate drought, near normal, moderate wet, very wet and extremely wet conditions (Figure 4). The SPI time series results that show extreme wetness within the basin 1985-1886, 1992, 1998 are extremely wet with the SPI values being constantly above +2.00.

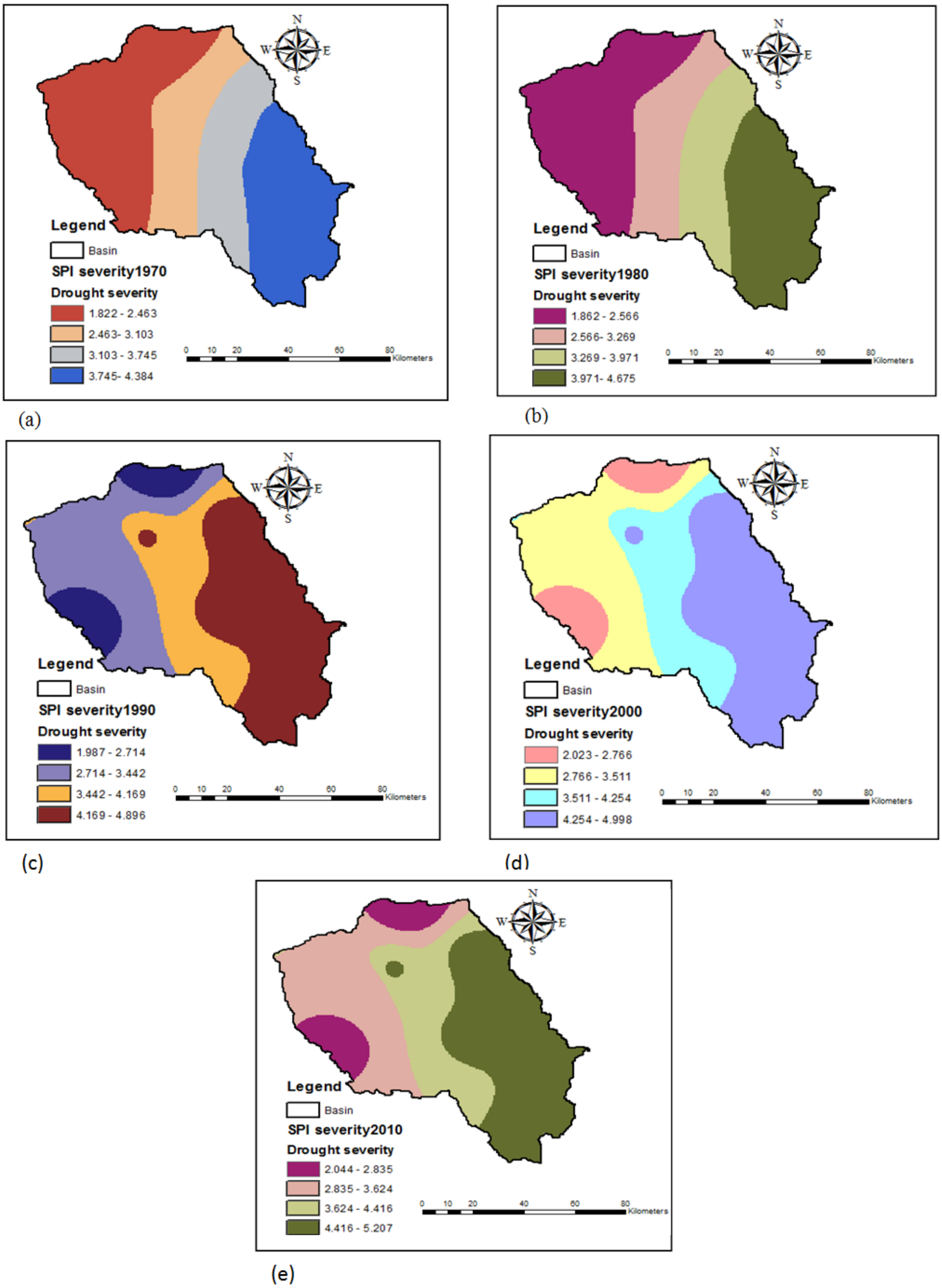


Figure 5. Spatial distribution of drought severity for the period 1970-2010

3.2. Spatial Distribution of Drought

Drought severities for the upper Tana River basin were computed and mapped using the Kriging approach for the selected years, that is; 1970, 1980, 1980, 1990 and 2010. Results show that the south-eastern parts of the basin exhibit the highest drought severities while the north-western areas have the lowest with an average of 2.140 (1.822-2.463) and 4.065(3.745-4.384), and 2.542 (2.044-2.835) and 4.812) (4.416-5.207) in 1970 and 2010 respectively as given in Figure 5*a* and *b*. Most of south-eastern parts of the basin are arid and semi-arid areas (ASALs) that fall in zones V and IV of Kenya's agro-climatic zones. These areas are at lower elevations (700-2700 m a.s.l.) and are considered to be most prone to drought risks. On the other hand, the north-western parts which are at higher elevations (2700-4700 m a.s.l.), are humid and fall within zones III to I (Table 3). The corresponding rainfall to potential evapo-transpiration (R/E_0) ratio values of the south-eastern and north-western areas are 25-50 and 50-80 respectively.

Table 3. The agro-climatic zones of Kenya

Zone	Clasiification	Annual rainfall R (mm)	Potentail Evapo-transpiration E_0 (mm)	R/E_0 ratio
I	Humid	1400-2700	1200-2000	>80
II	Sub-Humid	1000-1600	1300-2100	65-80
III	Semi-Humid	800-1400	1450-2200	50-65
IV	Medium to Semi-Arid	600-700	1500-2200	40-50
V	Semi-Arid	500-600	1650-2300	25-40
VI	Arid	300-550	1900-2400	15-25
VII	Very Arid	<300	2100-2500	<15

Source: [29].

The average values of drought severities for the ten-year interval within the study period was also plotted to illustrate the trend of the drought severity with time in years. Results show that both the south-eastern and north-western parts of the basin exhibit notable increment in drought severity. The former shows the highest increment in drought severity while the latter has lowest change within the study period (Figure 6).

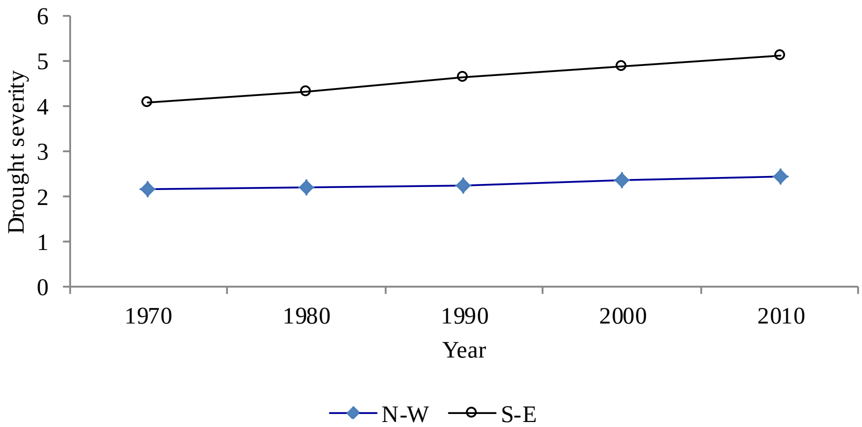


Figure 6. Average drought severity between 1970 and 2010 for both south-eastern (S-E) and north-western (N-W) areas

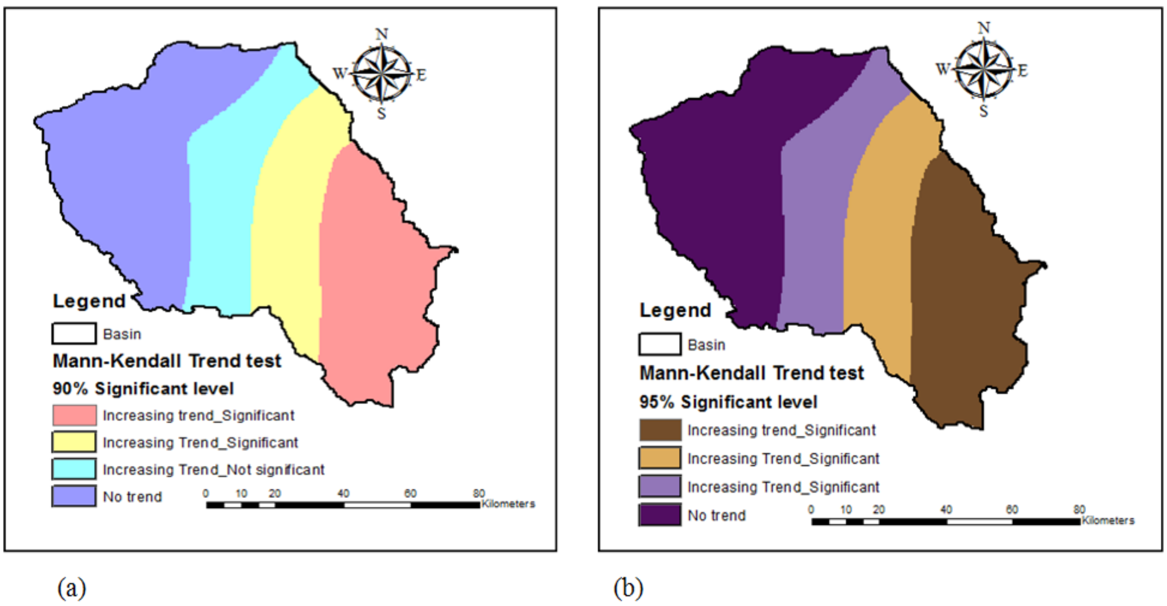


Figure 7. Spatial distribution of Mann-Kendall drought trend test at (a) 90% and (b) 95% significant levels for the upper Tana River basin

The areal-extend of maximum and minimum drought severities increased in both the south-eastern and north-western areas from 4868.7 km^2 to 6880 km^2, and 6163.9km^2 to 6985.5 km^2 from 1970 to 2010 respectively. Between 1970 and 1980, the drought areal-extend is almost the same but significant increase in areal-extend occurred between 1980 and 2010. The drought characteristics were also studied in terms of their trend in different parts of the river basin. The Mann-Kendall trend test shows that there was an increase in drought trend in the south-eastern parts of the basin at 90% and 95% significant levels while no significant trend was detected in the north-western areas. The results show that there is an increase in trend in drought which is significant at 95% significant level and insignificant at 90% significant level for middle elevations as given in Figure 6.

4. Conclusion and Recommendations

This study assessed the spatio-temporal drought characteristics for the upper Tana River basin using the SPI drought index. The results show that the SPI detected the monthly drought severities for the study period. It was also found out that the south-eastern parts of the river basin located in lower elevations and within the Arid and Semi-Arid Lands (ASALs) experience the most severe droughts. On the other hand, the north-western areas located in humid areas of Mt. Kenya and the Aberdares ranges have the lowest drought severity. Generally, the south-eastern areas exhibit increasing drought trend as detected using the Mann-Kendall trend test, while the north-western areas show no trend. It can therefore be concluded that the south-eastern areas of the basin are more vulnerable to droughts than the north-western areas.

The authors of this work propose adoption of sustainable water harvesting and conservation methods for drought mitigation especially in the drought prone areas in the south-eastern parts of the basin. For drought planning and implementation of drought mitigation programmes, the south-eastern areas of the basin should be given a priority since it is vulnerable to drought. In addition, the authors propose future research to focus on drought forecasting aspects at different lead times for timely planning and management of water resources.

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References

[1] Agwata, J. F., Wamicha, W. N. and Ondieki, C. N. (2015). Analysis of hydrological drought events in Upper Tana basin of Kenya, *Journal of environment and earth science*, 5(2): 22-31.

[2] Aksoy, H. (2000). Use of Gamma distribution in hydrological analysis, *Turk Journal of Engineering Sci*., 24: 419-428.

[3] Awass, A. A. (2009). Hydrological drought analysis-occurrence, severity and risks, the case of Wabi Shebele River Basin, Ethiopia PhD thesis Universität Siegen.

[4] Bacanli, U. G., Firat, M. and Dikbas, F. (2008). Adaptive neuro-fuzzy inference system for drought forecasting, *Journal of stochastic environmental research and risk assessment*, 23(8): 1143-1154.

[5] Belayneh, A. and Adamowski, J. (2012). Standard precipitation index drought forecasting using neural networks, wavelet neural networks and support vector regression, *Journal of applied computational intelligence and soft computing*, 2012: 1-13.

[6] Belayneh, A. and Adamowski, J. (2013). Drought forecasting using new machine learning methods, *Journal of Water and Land Development*, 18 (I-IV): 3-12.

[7] Bonacci, O. (1993). Hydrological identification of drought, *Journal of Hydrological processes*, 7: 249-262.

[8] Bordi, I. Sutera, A. (2007). Drought monitoring and forecasting at large scale in Rossi *et al*., (editors), methods and tools for drought analysis management, Springer.

[9] Bulu, A. and Aksoy, H. (1998). Low flow and drought studies in turkey, proceedings low flows expert meeting, 10-12 June 1998, University of Belgrade.

[10] Cacciamani, C. Morgillo, A., Marchesi, S. and Pavan, V. (2007). Monitoring and forecasting drought on a regional scale: Emilia Romagna region, *J. Water science and technology*, l, 62(1): 29-48.

[11] Dracup, J. A., Lee, K. S. and Paulson, E. G. (1980a). On the statistical characteristics of droughts, *Journal of water resources research*, 16(2): 289-292.

[12] International Fund for Agricultural Development, IFAD. (2012). Upper Tana catchment natural resource management project report, east and southern Africa division, project management department.

[13] Jacobs, J. Angerer, J., Vitale, J., Srinivasan, R., Kaitho, J. and Stuth, J. (2004). Exploring the Potential Impact of Restoration on Hydrology of the Upper Tana River Catchment and Masinga Dam, Kenya, a Draft Report, Texas A & M University.

[14] Kendall, M. G. (1962). Rank correlation methods, Hafner publishing Co. ltd,New York.

[15] Kim, T. W. and Valdes, J. B. (2002). Frequency and spatial characteristics of droughts in the Conchos River Basin, Mexico, *International water resources association journal*, 27(3):420-430.

[16] Manikandan, M. and Tamilmani, D. (2013). Development of drought vulnerability maps in the Parambikulam-Alyar Basin, India, *Academic Journals*, 8(20): 778-790.

[17] Markovic, R. D. (1965). Probability functions of the best fit to distributions of annual precipitation and runoff hydrology paper No. 8, Colorado State University.

[18] Mckee, T. B. and Edwards, D. C. (1997). Characteristics of 20th century droughts in the United States at multiple time scales, *Journal of atmospheric science*, 634: 97-92.

[19] Mckee, T. B., Doesken, N. J. and Kleist, J. (1993). The relationship of drought frequency and duration to time scales in proceedings of 8th conference on applied climatology, Anaheim, California, U.S.A: 179-184.

[20] Mulla, D. (2013). Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps, *Journal of Biosystems Engineering*, 114 (4): 358-371.

[21] Mutua, B. M. and Klik, A. (2007). Predicting daily stream flow in un-gauged rural catchments; the case of upper Tana River basin, Kenya, *Journal of spatial hydrology*, 5(2): 64-80.

[22] Oludhe, C. (2012). Impacts of climate variability on power generation within the 7-forks dams in Tana River basin, *Journal of meteorological and related sciences*, KMS 10th conference, 13-20.

[23] Otieno, F. A. O. and Maingi, S. M. (2000). Sedimentation problems of Masinga reservoir. In land and water management in Kenya. Eds. Gichuki F. N., Mungai, D. N., Gachere, C. K.

[24] Robinson, T. P. and Matheernnicht, G. (2006). Testing the performance of spatial interpolation techniques for mapping of soil properties, *Journal of computers and electronics in agriculture*, 50(2006): 97-108.

[25] Saenyi, W. W. (2002). Sediment management in Masinga reservoir, Kenya, PhD thesis (Published), University of Agricultural Sciences (BOKU), Vienna Austria.

[26] Sayanjali, M. and Nabdel, O. (2013). Remote sensing satellite design using model based systems Engineering, *Journal of Science and Engineering*, 1(1): 43-54.

[27] Shi, P., Wu, M., Qu, S., Jiang, P., Qiao, X., Chen, X., Zhou, M. and Zhang, Z. (2015). Spatial distribution and temporal trends in precipitation concentration indices for the southwest China, *Int. J. Water Resour Manage*, 29: 3941-3955.

[28] Sneyers, R. (1990). On the statistical analysis of series of observations World Meteorological Organization (WMO), Technical note No. 143, Geneva: 192.

[29] Sombroek, W. C., Braun, H. M. H. and Van-der pour, B. J. A. (1982). Explanatory soil map and agro-climatic zone map of Kenya report E1, National agriculture laboratories, soil survey unit, Nairobi Kenya: 56.

[30] Wilschut, L. I. (2010). Land use in the upper Tana: Technical report of a remote sensing based land use map. In green water credits report 9 edited by Mcmillan B., Kauffmann, S. and De Jon, R. Wageningen, ISRIC-world soil information.

[31] Wang, L., Chen, W. and Zhou, W. (2014). Assessment of future drought in south east china based on CMIP5 Multimodel projections, *advances in atmospheric Science*, 31: 1035-1050.

[32] Water Resources and Management Authority, WRMA. (2010). Physiological survey in the upper Tana catchment, a natural resources management project report, Nairobi.

[33] Zoljoodi, M. and Didevarasl, A. (2013). Evaluation of Spatio-temporal variability of droughts in Iran using Palmer Drought Severity Index and its precipitation factors through (1951-2005), *Atmosphere and Climate Sciences Journal*, 3: 193-207.