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Temporal Variability and Trends of Rainfall and Streamflow in Tana River Basin, Kenya

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Abstract: This study investigated temporal variabilities and trends of rainfall and discharges in Tana River Basin in Kenya using Mann–Kendall non-parametric test. Monthly rainfall data from ten stations spanning from 1967 to 2016 and daily streamflow data time series of observations from 1941 to 2016 (75 years) were analyzed with the aim of capturing and detecting multiannual and seasonal variabilities and monotonic trends. The results for the datasets suggested that the streamflow is largely dependent on increasing rainfall at the highlands. The rainfall trends seemed to have been influenced by altitudinal factors. The coefficient of variation of the ten rainfall stations ranged from 12% to 17% but 70% of rainfall stations showed negative monotonic trends and 30% show significant trends. The streamflow showed statistically significant upward monotonic trend and seasonal variability indicating a substantial change in the streamflow regime. Although the increasing trend of the streamflow during this period may not pose future risks and vulnerability of energy and irrigated agricultural production systems across the basin, variability observed indicates the need for enhanced alternative water management strategies during the low flow seasons. The trends and time series data indicate the potential evidence of climate and land use change and their impacts on the availability of water and sustainability of ecology and energy and agricultural production systems across the basin. Variability and trends of rainfall and streamflow are useful for planning studies, hydrological modeling and climate change impacts assessment within Tana River Basin.

Keywords: climate change; time series; Mann–Kendall test; river basin; sustainability; water yield

1. Introduction

Impacts of climate variability and change are increasingly becoming a challenge in tackling food and water security problems worldwide. There is immense public concern on unpredictable or extreme weather and climate induced events and keen interest is on the coming decades' dynamic behavior of such events. Understanding climatic historical changes is necessary for optimization of water resources and food production. Historical datasets are important means of obtaining information on the temporal patterns of rainfall and streamflow time series for climatological and hydrological applications such as hydrological modeling, climate variability, water resources planning and management for various uses including agricultural production, environmental flows and engineering designs [1–4]. Changes in seasonal and annual rainfall patterns and hydrological regimes impact on water resources for agriculture, domestic and energy use especially in semi-arid and arid regions of the world [5]. Hydrologic time series is weather-period dependent and usually exhibits seasonality in a region. A trend is a significant change over time exhibited by a random variable commonly detected by means of statistical parametric and non-parametric methods.

Water resources availability, management and utilization within a basin is primarily impacted by spatiotemporal variability of rainfall and water yield which in turn affects agricultural production, food and water security, and ecosystems and ecosystem services. The temporal variability analysis of rainfall and river discharge at timescales help in determining the likelihood of extreme (drought or flood) event occurrences and management of water resources particularly for major consuming sectors; namely agriculture, hydropower and domestic water supply within basins. Climatic variable trends and change detection have, in the recent years, become a research focus for many investigators across the globe. These studies include trend analysis of climatic variables such as temperature, precipitation and water yield in various parts of the world. Da Silva et al. [6] investigated spatial and temporal variability of rainfall and river flow in the Cobres River Basin in southern Portugal and found decreasing trends of rainfall and river flow in the area. In India, Jain and Kumar [7] reported declining rainfall in major river basins and Machiwal et al. [8] observed non-normality in rainfall in Gurarat area of India. Ghanem [9] reported changes in seasonal and annual rainfall in Jordan while Muchuru et al. [10] found non-significant positive and negative rainfall trends with coherent oscillatory modes in Zimbabwe. Longobardi and Villani [11] studied annual and monthly precipitation time series at Campania region and the Lazio region, southern Italy using 81 years datasets from 382 sites and detected overall significant changes in the area. Therefore, in-depth knowledge and analysis of rainfall and river flow regimes on different time scales are increasingly becoming necessary for enhancing the management of water resources, planning and designing of hydraulic structures, agriculture production and to mitigate the negative effects of floods and droughts.

In East and Southern African regions, seasonal variations in rainfall as well as the rate of evapotranspiration describe the periodic weather patterns. Aberrant rainfall variability affects major water resources and reservoirs, wetlands, agriculture and socio-economics of rural farmers whose livelihoods are significantly derived from rain-fed systems of production [12]. The region heavily depends on rain-fed agriculture which is driven by intra-seasonal and inter-annual variability in climate including El Niño induced events and often resulting in frequent occurrence of extreme droughts and floods that negatively impact on agricultural outputs [13]. Irrigated agriculture is carried out on less than 10% out of the 17% of the land considered to have potential for irrigation [14]. The Government of Kenya, under Vision 2030 (Kenya's development blueprint from 2008–2030), has planned a number of water and food security projects including the mega High Grand Falls multi-purpose reservoir and about 292,000 ha in addition to existing dams and irrigation schemes in Tana River Basin. Rainfall and streamflow time series within the basin is crucial in understanding the impacts of climate change and long-term sustainability of the present and planned irrigation schemes within water, energy and food security nexus. However, to the best knowledge of the authors, preliminary analysis of hydrological time series data for the planning of water resources projects pertaining to energy, wetland ecology and conservation and agricultural systems has not been carried out in detail for a typical water resources study involving the use of hydrological data. The use of hydrological data for water resources planning, development, and management is often assumed to be consistent, free of trend and constituting a stochastic random component described by some probability distribution hypothesis. There is limited information on general trends of rainfall within the basin and no study has investigated variability and trends of rainfall and streamflow in the Tana River Basin.

The objective of this investigation was to use historical rainfall and streamflow datasets to study long period trend characteristics and time series of streamflow and rainfall in Tana River Basin. Non-parametric statistical technique was used to study river discharge and rainfall temporal monotonic trends with aim of investigating potential evidence of climate change and its impact on the water yield, which could eventually impact on the availability of water and sustainability of energy and agricultural production systems across the basin. Rainfall and streamflow variability and trends can be used for hydrological-based decision making and further hydrological and climatic modeling.

2. Data and Methods

2.1. Description of the Study Area

The Tana River Basin is the largest in Kenya and flows over 1000 km starting from Mount Kenya and the Aberdare Mountains and ending at the Indian Ocean (Figure 1). Its flow pattern is bi-modal, reaching its peak flows during the long rainy season and low flows during short rainy seasons. Long-term daily discharge data based on gauge height and rating curves are available from 1941 to present at Garissa Gauging Station (4G01) located at 0°27′49.19″ S, 39°38′11.77″ E and managed by the Water Resources Management Authority (WARMA). The Tana River Basin covers an area of 100,000 km^2 and can be divided into upper, middle and lower Tana sub-basins (Figure 1). The Tana River winds through a densely forested ecosystem at the headwaters (the mountainous areas of the Aberdare ranges, Mt. Kenya and Nyambene hills in the central parts of Kenya) before giving way to agricultural areas and rangelands downstream where the river flows for 700 km through semi-arid flood plains and terminating in a large delta at Ungwana Bay in the Indian Ocean. Among perennial rivers in eastern Kenya, only the Tana and the Athi–Galana–Sabaki river systems reach the Indian Ocean throughout the year [15]. The lower Tana has seasonal tributaries which only flow in short pulses during the rainy season [16]. The upper and middle Tana sub-watersheds have five hydro-electric dams and two more are planned for construction while the lower region of the basin boasts of large irrigation schemes namely Holla, Tana delta and Bura schemes. In total, 64,425 ha in the basin is under irrigation and an estimated 292,100 ha is planned at the lower Tana to be implemented by the year 2030 by the government of Kenya. The average annual precipitation varies from 2200 mm for the highlands to 370 mm for the lower Tana at the delta. Tana River Basin is Kenya's 2030 Vision significant development target for hydropower, domestic water provision, and irrigation despite the fact that hydropower production and irrigation expansion have been plagued by controversy with historical efforts leading to relocations and increased conflict [17].

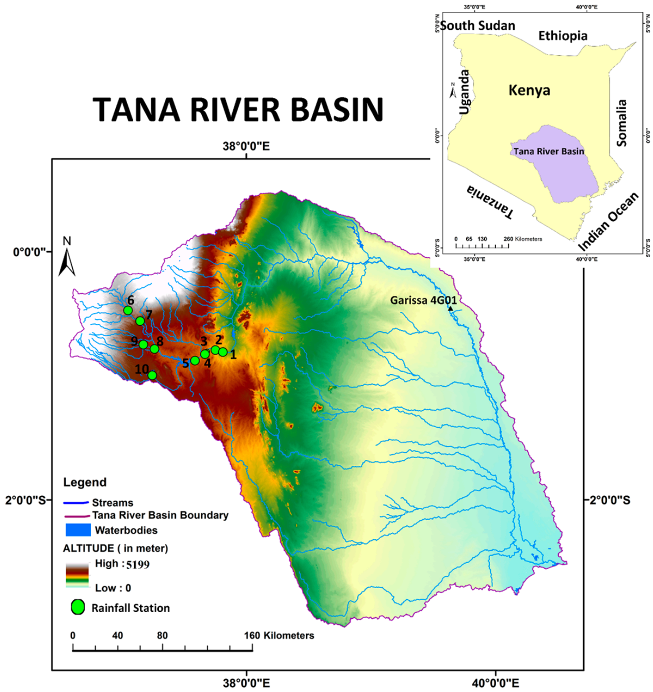

Figure 1. Location map of the study area showing Tana River Basin, elevations, rivers and streams, water bodies, Garissa Gauging Station (4G01) on Tana River, and rainfall stations numbered as: 1 (Gitaru), 2 (Kamburu), 3 (Kiambere), 4 (Kindaruma), 5 (Masinga), 6 (Sagana), 7 (Mesco), 8 (Tana), 9 (Wanjii) and 10 (Ndulla).

2.2. Datasets

Daily discharge data of Tana River recorded from 1941 to the year 2016 at Garissa Gauging Station and monthly total rainfall observations from a network of 10 stations within the Tana River Basin were considered in the present study because of completeness of data. Meteorological data in Kenya relate to different ministries and departments and each one collects data differently, thus making the data highly inefficient for analysis and sometimes part of the data are unavailable [18]. The rainfall datasets available for this study were from stations located at the upper and middle sub-basins within the basin. Table 1 gives a list of rainfall datasets obtained from the Kenya Meteorology Department for the ten rainfall stations. It can be seen that the longest observation records' span is 49 years and shortest span is 28 years. The year 1970 did not have any observation records of rainfall. It is also evident from Table 1 that Kindaruma and Kiambere rainfall stations had the majority of missing data. Daily river flow discharge dataset for Garissa Gauging Station was obtained from the WARMA.

Table 1. List of rainfall datasets.

Station	Elevation (m)	Commencement Date	End Date	Number of Years Spanned	Missing Data
Gitaru	932	July-78	October-16	38	December-82
Kamburu	990	June-76	October-16	40	No missing data
Kiambere	680	January-88	November-16	28	April 1991, May–June 1992, August 1992, July 1993, January 1994
Kindaruma	766	November-68	November-16	48	January–December 1970, January–December 1991, January–December 1992, January–September 1993, January–August 1994, May 1995, July–September 1995
Masinga	927	January-82	October-16	34	No missing data
Mesco	1060	January-84	October-16	32	No missing data
Ndula	1414	January-85	October-16	31	No missing data
Sagana	1609	January-67	October-16	49	January–December 1970
Tana	1089	January-67	October-16	49	January–December 1970
Wanjii	1146	January-67	October-16	49	January–December 1970

2.3. Method

In this investigation, the variables analyzed were river discharge rainfall and streamflow. River discharge primarily provides information on an integrated response of the entire river basin whereas rainfall contributes immensely to the runoff processes. First, the raw rainfall monthly records and daily river flow discharge data were examined and checked for missing values. Since there were no large missing records, the datasets were considered appropriate for analysis and R programming language for data analysis [19] was used in preprocessing (cleaning) the data, analysis and visualization. Secondly, the daily stream discharge and the monthly precipitation time series were aggregated annually and also in monthly trimesters as December–January–February (DJF), March–April–May (MAM), June–July–August (JJA) and September–October–November (SON) seasons which correspond to winter, spring, summer and autumn respectively, with the aim of observing potential changes at the seasonal scale and identifying outstanding monotonic trends. Finally, the trend analysis was performed using time series plots and Mann–Kendall test [20]. The method of analysis was RStudio (2014 version) which is an integrated development environment (IDE) for the R programming language. The hydroTSM [21] package in Rstudio was used for analysis of river discharges and rainfall because of its capability functions in the management, analysis, and interpolation and plotting of time series (monthly, annual and seasonal) from daily and monthly data [22].

Mann–Kendall test [20] is a non-parametric test for randomness against time for correlation and has, in the last half decade, become useful in water resources research for examining significance in trends within river basins [6,23–25]. The Non-Parametric Mann–Kendall (MK) test [20] and rank correlation method [26] were used to study the trend analysis because of their powerful nature over other methods in hydrological analysis [27]. The MK test is commonly applied to detect significant trends in hydro-meteorological time series and is highly recommended by the World Meteorological Organization (WMO) [7,10,28,29]. Before applying the MK test to the time series of annual stream flow and precipitation levels, they were checked for serial correlation and where existed, Mann–Kendall test in conjunction with block bootstrapping [30,31] was used in order to account for the serial correlation present in the streamflow and precipitation levels and to obtain an improved significance test for monotonic trend. The Mann–Kendall mathematical concept calculates the Mann–Kendall Statistics S, Var (S), and standardized test statistics Z as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(X_j - X_i) \tag{1}$$

where n represents the number of data points, X_i and X_j being data values in in the time series i and j respectively with $j > i$ and the sign function sgn ($X_i - X_j$) given as:

$$Sgn(\theta) = \begin{cases} +1 & \theta < 0 \\ 0 & \theta = 0 \\ -1 & \theta = 0 \end{cases} \tag{2}$$

Under the null hypothesis that X and Y are independent and randomly ordered, the statistic S tends to normality for large n, with mean and variance given by:

$$\partial^2 = \frac{n(n-1)(2n+5)}{18} \tag{3}$$

Subsequently the standardized Z statistics is then calculated as a normal standardized distribution:

$$Z = \begin{cases} \frac{S-1}{\partial} & if\ S = 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{\partial} & if\ s = 0 \end{cases} \tag{4}$$

The null hypothesis is rejected when the Z value computed by Equation (4) is greater in absolute value than the critical value $Z\alpha$, at a chosen level of significance α. A positive Z indicates increasing trend and a negative Z denotes decreasing trend [32,33]. For further details on the Mann–Kendall statistical parameters, readers are referred to relevant numerous literature [34].

3. Results and Discussions

3.1. Rainfall Characteristics

In this section, we present rainfall time series and trend analysis results at both annual and monthly scales. Salient basic statistical properties of the rainfall time series of ten rainfall gauging stations in Tana River Basin are given in Table 2. Figure 2 shows graphical visualization of the monthly time series for the ten stations. The highest mean annual rainfall was recorded in Mesco station (133.5 mm) and the lowest was registered in Kindaruma station (52.82 mm) according to the analysis of the present datasets. These two rainfall stations also recorded the maximum (228.01 mm) and minimum (79.40 mm) standard deviations respectively. However, maximum rainfall (2260 mm) is seen for Wanjii station while minimum (428.60 mm) is indicated for Kiambere station. Generally, the annual rainfall series are positively skewed for all the ten stations and the coefficient of variation shows no significant differences among the stations. Mean annual rainfall at the stations varied from 134 mm year^{-1} to 52 mm year^{-1}.

Table 2. Annual rainfall time series basic statistical properties for ten stations in Tana River Basin.

Rainfall Station	Elevation (M)	Basic Statistical Property					
		Mean (mm)	Standard Deviation (mm)	Maximum (mm)	Coefficient of Variation (%)	Skewness	Kurtosis
Gitaru	932	60.87	86.22	432.00	14.2	1.70	2.52
Kamburu	990	62.82	105.2	1338.00	16.7	4.9	46.01
Kindaruma	680	52.82	79.40	482.30	15.0	2.04	4.77
Kiambere	766	66.19	93.96	428.60	14.2	1.60	1.83
Masinga	927	55.02	80.00	532.30	14.6	2.15	5.72
Mesco	1060	133.50	228.01	2084.00	17.1	3.94	22.53
Ndulla	1414	69.99	119.28	1290.00	17.0	4.38	35.09
Sagana	1609	82.82	101.30	680.00	12.2	2.08	5.36
Tana	1089	79.57	104.18	541.30	13.1	1.88	3.69
Wanjii	1146	123.00	205.62	2260.00	16.6	4.01	26.27

3.2. Annual Rainfall MK's Trend-Test Analysis of Each Station

Table 3 shows the annual rainfall time series MK statistical properties results obtained from the ten stations data. From the results, the rainfall datasets at Ndulla ($S = 53$, $p = 0.03$) and Wanjii ($S = 11594$, $p = 0.001$) showed significant ($p < 0.05$) positive trends and Tana ($S = -9859$, $p = 0.04$) gave significantly negative trend. For all other stations, trends were non-significant within p-value < 0.05 but negative trends were indicated for 70% of the stations. To further visualize the detected trends, the datasets monthly data were regressed against time scale and regression results are shown in Figure 2 where rainfall time series along with fitted linear model (shown by redline) and model equation are shown. It is obvious from the graph that trend in the annual average rainfall at stations exists in annual rainfall time series for all stations. Mesco, Wanjii and Ndulla exhibited increasing trend and seemed to register increased amounts of annual rainfall in last 10 years of the period under review whereas annual rainfall at Kamburu and Masinga regressed time series indicated flatter/horizontal fitted trend line and increasing trend contrary to the most powerful and widely used trend detection MK test. All other stations regressed trends showed decreasing trends and agreed with MK non-parametric test results. Generally, there was declining rainfall trends in seven out of the ten rainfall stations as indicated by negative Mann–Kendall score in Table 4.

Table 3. Annual rainfall time series Mann–Kendall test statistical properties for ten stations in the Tana River Basin.

Station	Elevation (M)	Mann–Kendall Test Statistical Property			
		p-Value	Mann–Kendall Tau	Mann–Kendall Score *S*	Var (Score)
Gitaru	932	0.9496 *	(−)0.00453	(−)435	9,999,084
Kamburu	990	0.53044 *	(−)0.0197	(−)2125	118,890,472
Kiambere	680	0.40877 *	(−)0.0266	(−)1396	4,024,238
Kindaruma	766	0.25818 *	(−)0.0343	(−)5760	14,411,660
Masinga	927	0.87395 *	(−)0.0054	(−)445	7,833,073
Mesco	1060	0.127 *	0.000209	9593	669,506
Ndulla	1414	0.029618 **	0.0851	5399	3,105,362
Sagana	1609	0.55988 *	(−)0.0163	(−)2711	21,606,354
Tana	1089	0.0366 **	(−)0.0582	(−)9859	22,260,774
Wanjii	1146	0.005695 **	0.077	11,594	21,900,136

* Since the computed p-value is greater than the significance level $\alpha = 0.05$, one cannot reject the null hypothesis H_0.
** the computed p-value is lower than the significance level $\alpha = 0.05$ the null hypothesis H_0 is rejected.

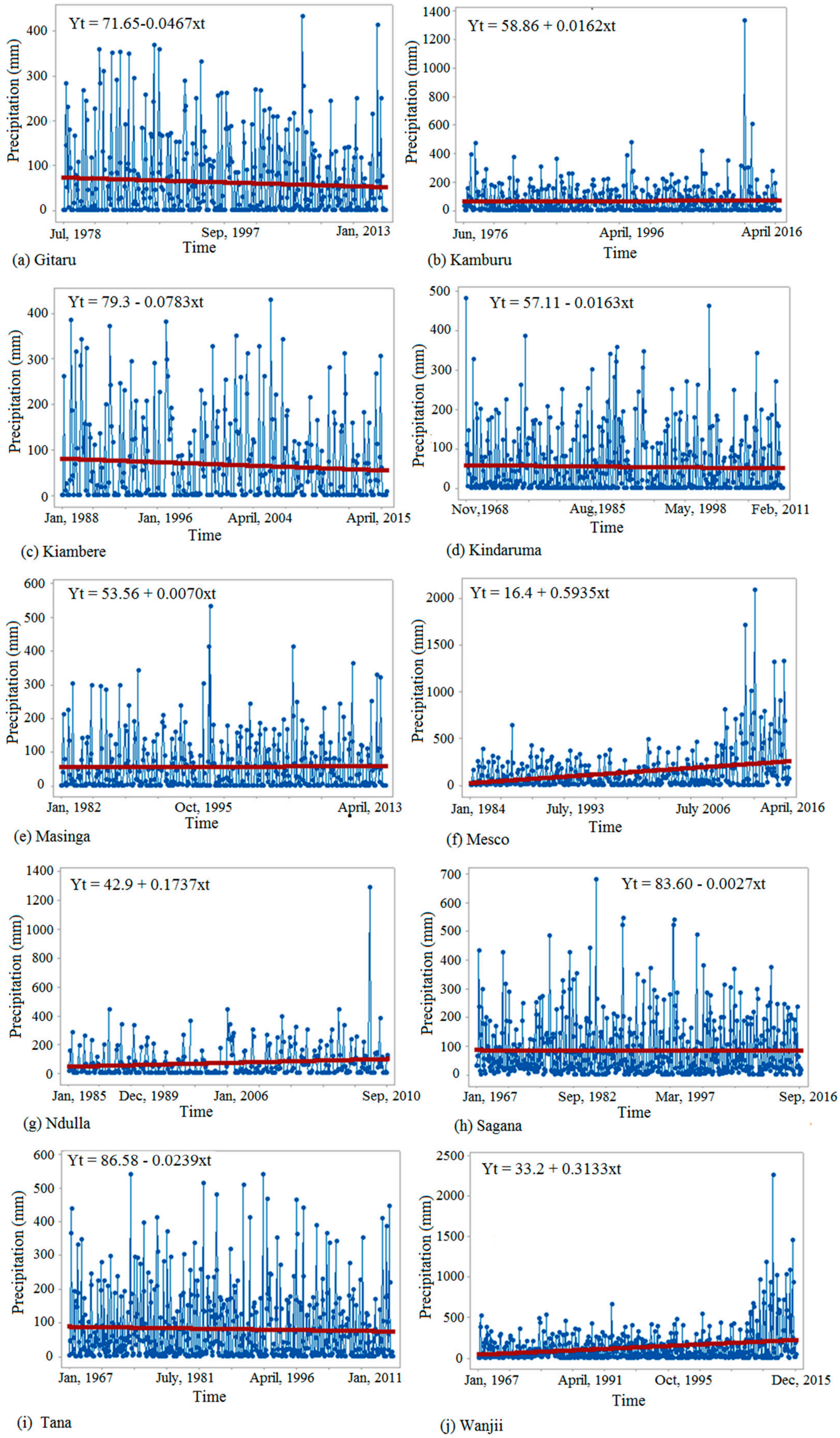

Figure 2. Monthly time series of two out of the ten gauging stations in Tana River Basin showing actual ( ) and fitted ( ) varables.

Table 4. 28 years annual rainfall time series Mann–Kendall test statistical properties for ten stations in Tana River Basin (January 1988–October 2016).

Station	Elevation (M)	Mann–Kendall Test Statistical Property			
		p-Value	Mann–Kendall Tau	Mann–Kendall Score *S*	Var (Score)
Gitaru	932	0.2329 *	(−)0.045	−2487	4,343,414
Kamburu	990	0.6932 *	(−)0.015	−816	4,267,526
Kiambere	680	0.4868 *	(−)0.0266	−1396	4,024,238
Kindaruma	766	0.2057 *	(−)0.0519	−2096	2,740,651
Masinga	927	0.5919 *	(−)0.0201	−1129	4,428,360
Mesco	1060	0.0004 **	0.128	7468	4,527,455
Ndulla	1414	0.0004 **	0.149	5148	2,134,379
Sagana	1609	0.7371 *	0.0122	716	4,537,381
Tana	1089	0.0504 **	(−)0.0712	−4200	4,606,167
Wanjii	1146	0.0021 **	0.113	6421	4,371,048

* Since the computed *p*-value is greater than the significance level $\alpha = 0.05$, one cannot reject the null hypothesis H_0.
** the computed *p*-value is lower than the significance level $\alpha = 0.05$ the null hypothesis H_0 is rejected.

These results suggest an increasing rainfall for higher ground areas, and more drying conditions for lower areas within the basin. However, in order to ensure that the uptrends and downtrends were not due to the use of different time periods of the rainfall records, the rainfall datasets for all stations were truncated to create same period datasets from January 1988 to October 2016 (28 years) based on minimum span shown in Table 1. The trend analysis was then done on data of the same period using MK test in conjunction with block bootstrapping to account for the serial correlation present in the annual precipitation levels and obtained improved significance test. The results of block bootstrapped MK test are given in Table 4. The results from the same period datasets analysis returned the same results as those of the station record period datasets (Table 2) with the exception of improved trend significance level for Mesco station record and Sagana station data sets signaling uptrend.

Further, a seasosonal trend analysis for all the stations was performed and the results are as shown in Table 5. With the exception of Kiambere and Mesco seasonal datasets, all the datasets exhibit insignificant trends at the 95% significance level for Winter (December, January and February) and for Spring (March, April and May). Similar results were obtained for all station datasets except for Mesco whose trend is strongly significant. The results suggest that the probability distribution of the geophysical process driving the variability of seasonal rainfall has not substantially changed over time for Winter and Spring, which are the dry and long rainy seasons respectively for the basin. In contrast to all datasets, Kiambere and Tana station datasets show significant trends for Summer (June, July and August) while Mesco dataset indicates significat trend for Autumn (September, October and November). The seasonal datasets' negative and positive trends for Winter, Spring and Summer exhibit varied trends that is a somewhat opposite compared to the annual rainfall dataset distribution pattern but the striking results of negative trends in Autumn (September, October and November) indicate drier conditions in low elevation areas.

Table 5. Seasonal rainfall time series Mann–Kendall test statistical properties for ten stations in the Tana River Basin.

Station	Elevation (M)	Mann–Kendall Seasonal Test Statistical Property							
		Winter		Spring		Summer		Autumn	
		p-Value	MK Tau	*p*-Value	MK Tau	*p*-Value	MK Tau	*p*-Value	MK Tau
Gitaru	932	* 0.109	(−)0.217	* 0.358	(−)0.123	* 0.823	(−)0.034	* 0.068	(−)0.241
Kamburu	990	* 0.527	(−)0.087	* 0.749	0.044	* 0.665	0.065	* 0.586	(−)0.073
Kiambere	680	** 0.035	0.286	* 0.445	0.103	** 0.00	1.00	* 0.081	(−)0.232
Kindaruma	766	* 0.591	0.08	* 0.559	(−)0.086	* 0.671	0.070	* 0.182	(−)0.185
Masinga	927	* 0.797	(−)0.037	* 0.079	0.5609	* 0.364	(−)0.124	* 0.358	(−)0.123
Mesco	1060	** 0.035	0.286	** 0.004	0.379	* 0.084	0.23	** 0.009	0.348
Ndulla	1414	* 0.290	0.062	* 0.225	0.139	* 0.323	0.046	* 0.202	0.187
Sagana	1609	* 0.828	0.0317	* 0.955	(−)0.01	* 0.749	(−)0.044	* 0.399	0.113
Tana	1089	* 0.295	(−)0.143	* 0.209	(−)0.167	** 0.026	(−)0.296	* 0.311	(−)0.136
Wanjii	1146	* 0.291	0.031	* 0.31	0.019	* 0.21	0.115	* 0.246	0.06

* Since the computed *p*-value is greater than the significance level $\alpha = 0.05$, one cannot reject the null hypothesis H_0.
** the computed *p*-value is lower than the significance level $\alpha = 0.05$ the null hypothesis H_0 is rejected.

3.3. Stream Flow Statistical Characteristics

This section presents time series and trend analysis of the river discharge. Few basic statistics commensurate with the objectives of the present study have been considered. Normally, hydrological flow data vary over a wide range of time scales and may not be stationary because of changes to management upstream and also because applications are often aspects-specific. Generally, the daily flow data were taken on an as-is-where-is basis and quality check was done. HydroTSM was used to obtain monthly, annual and seasonal time series from daily streamflow for analysis and plotting of time series to provide a graphical representation of river flow characteristics and a qualitative check on overall data integrity. Table 6 gives discharge time series basic statistical properties. The mean and maximum recorded streamflow were 168 and 1974 cubic meter per second (cumecs), respectively. Mean flow is a fundamental statistic of a flow record defined as the area under the hydrograph (the time series plot of varying river flow) divided by the length of the hydrograph and is usually expressed as flow in cumecs.

Table 6. Annual discharge time series basic statistical properties for Tana River showing minimum (min), 1st quartile (1st QU), mean, median standard deviation (SD) and Interquartile Range (IQR) in cumecs. Coefficient of variation (CV), skewness and kurtosis are also given.

Annual Discharge Time Series Basic Statistical Properties										
Min	1st QU	Mean	3rd Q	Median	Sd	Max	CV (%)	Skewness	Kurtosis	IQR
0.2158	75	168	191	112.7	168	1974	1.0045	3.1193	13.897	117

Figure 3 shows the seasonal streamflow time series and boxplots. The mean discharges varied from 50 cumecs to above 700 cumecs over the study period. Over the 75 years period, the mean annual normalized seasonal streamflow for summer period remained below 100 cumecs and the rest of the seasons recorded mean discharges above 100 cumecs. The highest annual mean flow for winter (>700 cumecs) was recorded in 1998 during 1997/1998 El Niño and similar amounts for spring was registered in 1968 indicating El Niño effect was also experienced at the basin in spring in that year [35]. Autumn had its highest mean flow (600 cumecs) in 1961 that happened once in the entire period of 75 years. Mean annual low flow (MALF) is the average of the lowest flow measured in each year of record. MALF for the spring were recorded in the years 1980 and 2001. The months of high river discharge coincide with the wet seasons (spring) and (autumn) clearly indicating that streamflow in this basin is largely rainfall dependent and confirms the correlation between streamflow and rainfall. In this basin, most of the rain falls between March and June with a peak event in May. Seasonal variability is the distribution of monthly mean flows. There was considerable monthly variability as indicated by the monthly average flows in Figure 4. The period between 1960 and 1970 presented instances of highest values of streamflow which were not seen in other years over the study period. The visualization of loess line in Figure 3 indicate steady but slight upward trend in streamflow. The average seasonal behavior of Tana River was bimodal with season maximum median flows being recorded in spring and autumn and lowest flows in summer. Annual streamflow distributions and moving averages are further illustrated in Figure 5. Preliminary analysis showed that the highest value of streamflow was concentrated around the period between 1960 and 1970, followed by relative low values of streamflow until 2002 and after that period a relative increase in streamflow was noted. The annual flows showed significant upward trends from 1950s reaching the peak in late 1960s before adapting oscillatory mode for the rest of the study period and registering extreme low flow in the year 2000 equivalent to that observed in 1950.

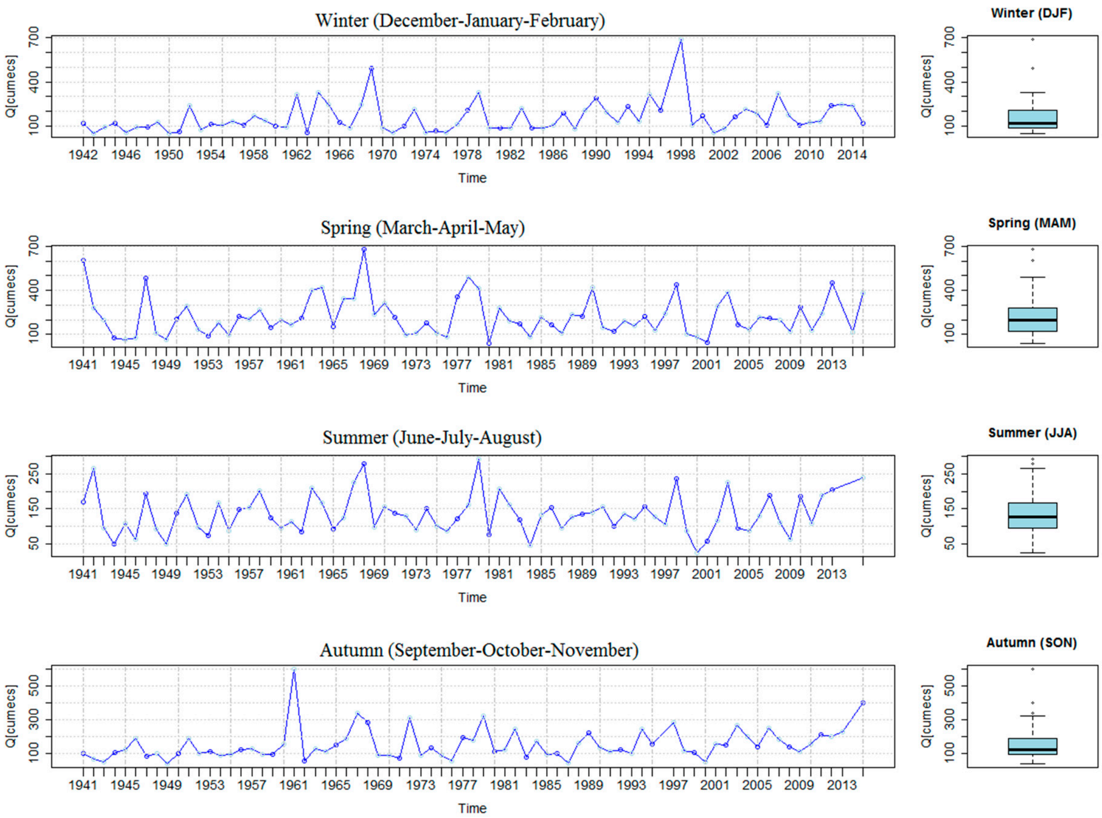

Figure 3. Time series and boxplot of seasonal stream streamflow.

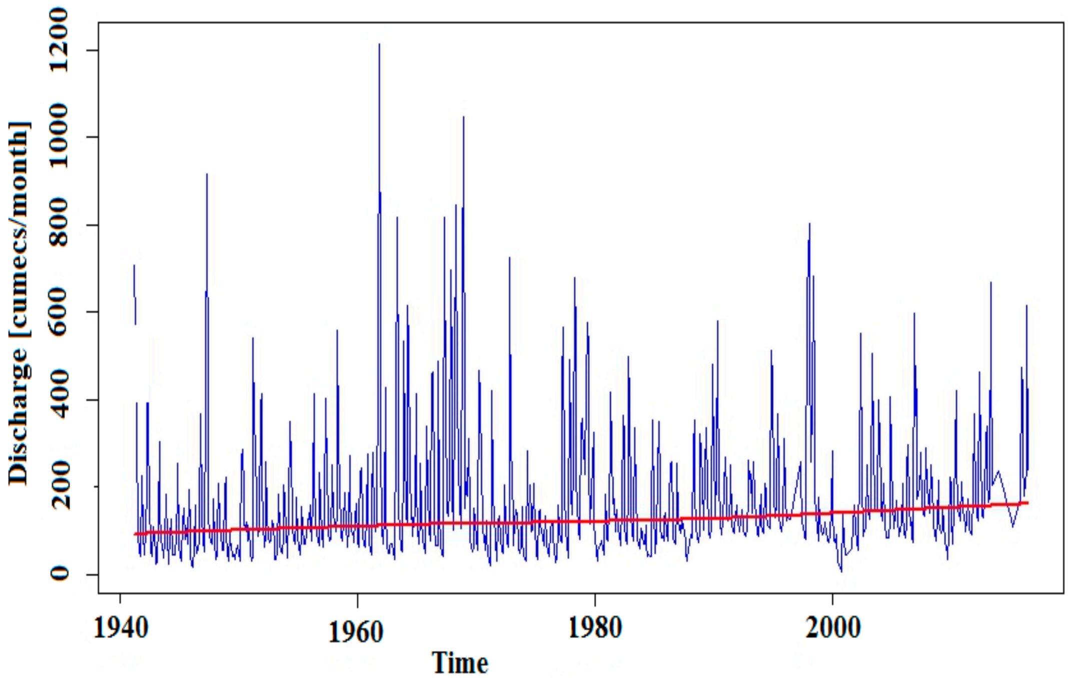

Figure 4. Monthly time series between 1941 and 2016. The red line is fitted loess trend line.

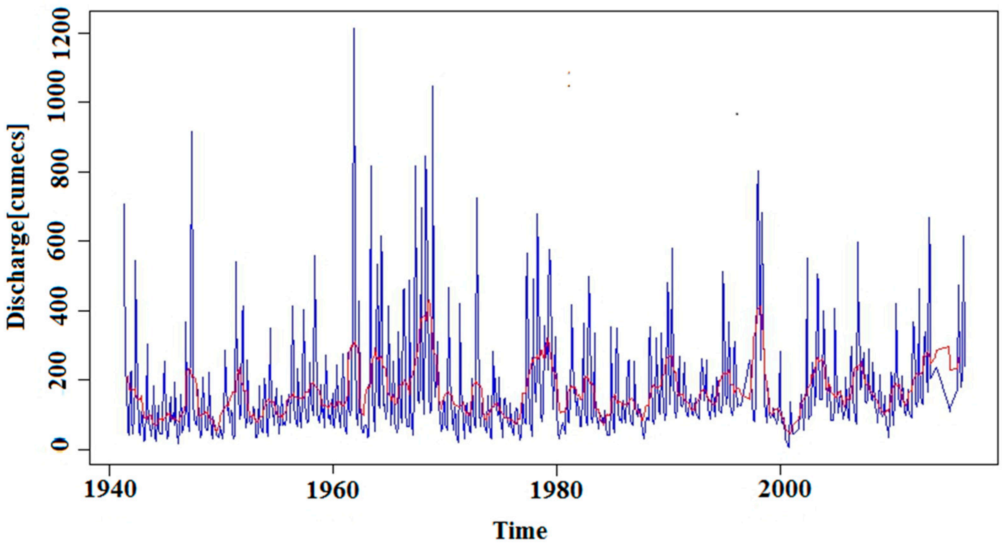

Figure 5. 75 years river flow monthly time series represented by blue line and annual moving averages by red line for Tana River.

Figure 6 shows the flow duration curve (FDC) representing the flow against the percentage of time that that flow is equaled or exceeded in the time period under study and further illustrates Tana River's distribution of flow. The spread of flows less affected by extremes of flood or drought indicated flows of 230 cumecs and 88 cumecs being exceeded 20% and 70% of the times respectively. The lower end of the flow duration curve is useful in describing water availability for abstractive uses such as irrigation and power generation. Generally, the minimum flow required to remain in the river is the mean annual low flow (MALF) or a fraction of it, or alternatively a high exceedance percentile, such as the flow equaled or exceeded 95% (or similar) of the time. The amount of water between the minimum flow or a flow requirement and the scheme capacity to divert could be very sensitive to both the choice of minimum flow and the shape of the curve. The curve exhibited mixed steep slope at the upper end and low flat slope at the lower end indicating that the river is largely fed by direct runoff upstream and sustained by the behavior of the perennial storage in the drainage basin.

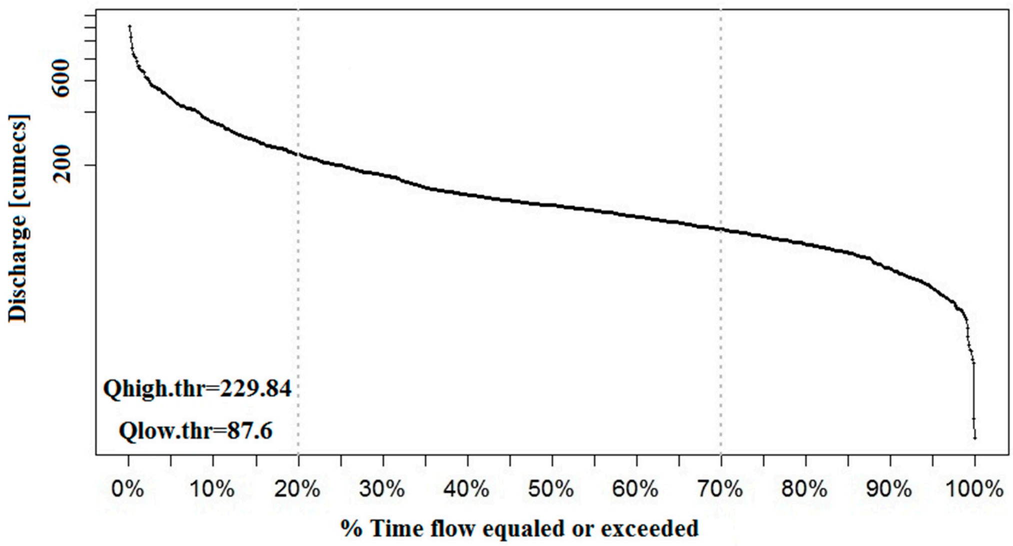

Figure 6. Tana River's flow duration curve.

3.4. Streamflow Trend Analysis

An investigation for the serial structural correlation of the streamflow time series data was conducted before proceeding with the trend analysis. The results of the auto correlation analysis for the period 1941–2016 exhibited statistically significant autocorrelation at 5% confidence level. The existence of significant serial correlations in the streamflow time series necessitated the removal of the effect of the serial correlations in the trend tests. MK statistics for the slope of the upward monotonic trend detected in the series of annual stream flow levels, derived by assuming non-negligible serial monotonic trend test, are shown in Table 7. The mean of the MKtaus from the R = 500 bootstrapped time series and the standard error of the standard deviation of the MKtaus from the 500 samples at 95% confidence interval are illustrated for the whole streamflow dataset used. MK test statistical properties tau was 0.151 and 2—sided p-value $\leq 2.22 \times 10^{-16}$ which meant that the null hypothesis concerning no trend could be rejected based on this 75 years observation data (1941–2016). The statistically significant p-value associated with the MK test suggests the presence of a statistically significant upward trend in the annual streamflow time series. A seasonal streamflow trend analysis did not show any deviation of trends from the annual distribution pattern (see Table 8). The streamflow dataset was further subjected to decadal trend as 1941–1971 (D1 dataset), 1972–2001 (D2 dataset) and 2002–2016 (D3 dataset). D1 and D2 represent three decades each and D3 represents the recent one and a half decades. MK test for D1 (0.144 and 2—sided p-value $\leq 2.22 \times 10^{-16}$), D2 (0.069), and 2—sided p-value $\leq 2.22 \times 10^{-16}$) and D3 (0.112 and 2—sided p-value $\leq 2.22 \times 10^{-16}$) showed significant uptrends at 95% significance level.

Table 7. Annual streamflow Mann–Kendall test properties and bootstrap statistics.

Streamflow Data Sets	Mann–Kendall Properties				Bootstrap Statistics		
	MK Tau Statistic	Two-Sided p-Value	Mann–Kendall Score S	Variance of Kendall Score	MK Tau Original	Bias	Std. Error
Whole dataset	0.151	$<2.22 \times 10^{-16}$	45,725,556	1.664506×10^{12}	t1* 0.1506114	−0.0150	0.0091
Pre-dam Dataset	0.0991	$<2.22 \times 10^{-16}$	9,010,393	272,615,424,000	t1* 0.2645801	−0.2708	0.0853
Post dam dataset	0.0523	$<2.22 \times 10^{-16}$	1,825,937	65,182,507,008	t1* 0.2645801	−0.2639	0.08496

Table 8. Seasonal streamflow Mann–Kendall test properties trend analysis.

Season	MK Tau	*p*-Value	MK Score	Variance of Kendall Score
Winter	0.29	0.0003	4,244,587	2.5902×10^{10}
Spring	0.195	0.0135	2,310,821	27,459,989,504
Summer	0.205	0.009	937,297	2,514,449,920
Autumn	0.316	7.8797×10^{-5}	3,346,066	24,818,937,856

The flow-duration curve in Figure 6 was used to further analyze the base flow (extreme values) trend characteristics by taking a stream discharge value at probability of exceedance p = 50% (Q_{50}) as base flow to separate high (>Q_{50}) and low flows (<Q_{50}) time series. The exceedance threshold from flow duration curve was considered helpful as opposed to selecting low and high extreme streamflow values which ignores much of the data [36]. The Non-parametric MK test was applied to the time series. The MKtaus and 2 sided *p*-values for this analysis were -0.457 and 1.8939×10^{-6} respectively for high flows and that of low flows were 0.189 and 2.22×10^{-16} respectively.

Owing to the fact that Tana River is regulated by a series of dams (Seven Forks Cascade) in the upper part of the basin (Figure 2), the influence of dam operation on streamflow variability was investigated since the streamflow gauging station records used in the analysis is below the dams. To do this, two sets of streamflow data series were extracted from the daily discharge data records of the Garissa gauging station, considering development of large reservoir Masinga and Kiambere dams between 1981 and 1988 respectively. The other earlier dams constructed between 1968 and 1974 (Kindaruma, Kamburu and Gitaru) are small reservoirs and may be insignificant in terms of regulating the river [37]. The first dataset (pre-dams period) therefore spanned from 1941 to 1980 and the second from 1989 to 2016 (post-dam period). The pre and post-dam period extracted datasets from the daily discharge record were subjected to MK test trend correlation analysis. The temporal coherence in streamflow trends for pre-dam and post-dam periods (Table 6) indicates little influence of flow regulation by the series of dams. Both periods signaled significant uptrends at same significance levels.

3.5. Discussion

Time periodic changes in streamflow characteristics can be attributed to the anthropogenic influences given that the flow measurement records used in the analysis were from a location downstream of major flow regulations (dams) which could impart non-stationarity (trend) into the data. Effect of climate related forces that drive snowmelting, streamflow timing changes, altered spring seasonal maximum flows, and intensified summer seasonal droughts may be unlikely at least for the present study as upstream regulations may be suitable for identification of long-term streamflow variabilities that might be caused by climatic and other environmental forces. Investigations carried in other regions of the world have reported variation in streamflow caused by climatic variables [38,39]. Novotny et al. [40] observed substantial impact of increased rainfall events on peak flow increases in Minnesota River watersheds whereas [41] reported 10 mm per year annual decrease in mean annual stream discharges in the middle reaches of the Yellow River in China. Changes in land cover and land use factors have been suggested to have had direct implications on flow trends in the Lake Naivasha Basin in Kenya [42]. Variations in climate, mainly the type, quantity, intensity and frequency of precipitation, have a pronounced effect on flow. However, application of the flow-duration characteristics to quantify hydrologic processes within Tana basin is limited by the unknown relations between precipitation quantity and storage in the present study. The temporal variations and trends on the stream flow in Tana River Basin may be attributed to climatic factors since streamflow records lacks the advantage of integrating variabilities into the basin watershed scale; real effects could be better observed in streamflow modeling in general circulation models.

The impact of the influence of dam construction on streamflow variability were somewhat insignificant. Although the present study did not have the advantage of hydro-electric dam operation releases data, it can be said that the hydro-electric dam development has had little impact on the hydrological flow regime variability in the Tana River. This can be attributed to the ability of the dams to store adequate runoff during the rainy seasons to sustain their operations and the run-of-river operations type for the Seven Fork Dam cascades. Much of the abstraction for irrigation happens downstream of the Garissa Gauging Station.

The results of this streamflow analysis, at annual scale, showed a tendency to increase for the long-term time series (1941–2016) and also at season time scale. The increasing of the streamflow during this period will not pose future risks and vulnerability on Seven Forks Dam cascade energy production and irrigated agriculture which are mainly fed by water coming from the upper Tana River basin. This is in agreement with [43] who recommended for the establishment of investment projects at the lower Tana Delta sub basin. The variability of seasonal streamflow observed may indicate that alternative management strategies may be enhanced mainly during the low flow seasons which is the most critical period for water management. The population growth coupled with the planned development of irrigated agriculture and High Grand Falls multipurpose dam in the Tana River Basin may exacerbate the difficulties to manage water if no comprehensive and effective efforts, in addition to existing legal framework, are made in order to manage the available water for agriculture, downstream wetland ecosystem and environmental services. Tana River floodplain ecosystem and communities are dependent on the pattern of river flows. Future work should use more sophisticated modeling in water resources planning and management that incorporate climate and anthropogenic change in order to provide non-stationarity in Tana River Basin hydrological analysis. In order to enable this work, there is need for further analysis of rainfall and river flow rates in the basin.

The results of this investigation agreed with some studies that have investigated the trend and magnitude of variations in rainfall on the sub-basin-scale. Ovuka, and Lindqvist [44] analyzed annual precipitation and rain periods and obtained no clear trends over the study period in Muranga District and Recha [45] reported persistence of below normal rainfall in Tharaka Nithi County. Both study areas are sub-basins of Tana River Basin. For the rainfall datasets analyzed, it can be said that most of the studied stations revealed a change in their annual rainfall patterns and varied patterns for seasonal datasets, but for the present study, there is insufficient information indicating any considerable change in the whole climate since the rainfall datasets stations are not well distributed within the basin. But the upward rainfall trends at the stations (Wanjii, Mesco and Ndulla) located towards highland areas (Mt. Kenya and Aberdares) and downward rainfall trends at the other stations (which are located in marginal lower regions of the basin) may indicate the effects of anthropogenic activities, although there is no clear evidence to attribute rainfall change directly to the anthropogenic climate change. The rainfall time series exhibited very small temporal variabilities in most areas in the basin and were insignificant in most of the stations. Sagana rainfall station trend variability may have been due to land use changes in this sub-catchment which might have affected changes in the station rainfall records and thus introduced random errors that tend to mask rather than enhance the time series trend patterns.

The seasonal rainfall dataset results suggest that the probability distribution of the geophysical process driving the variability of seasonal rainfall has remained unchanged over time for winter and spring which are the dry and long rainy seasons respectively for the basin. However, an unexpected condition is observed for autumn where negative trends, though insignificant at 95% significance level, exist in areas of altitude of less than 1000 m above sea level. This situation might impact negatively on the agricultural and livestock production activities in these areas. In addition, decisions related to agricultural water management will be impacted on due to the associated reduction of water levels. This declining autumn rainfall and high seasonal variability would often lead to underestimating the importance of climate signals (trends) that could be very catastrophic to Tana delta wetland ecosystem, pastoralists, farmers and hydropower production and the economy. Recent frequent droughts in the lower part of the basins could be a manifestation of the climate signals. The agricultural farming and livestock rearing, including pastoralism and the lower Tana delta wetlands production systems are shown to be at increasing risk of dependence on rainfall events from this trend analysis. These systems provide food security while maintaining the sustainable use of natural resources for communities in this arid and semi-arid areas of the basin whose rainfall pattern is bi-modal, with two rainy seasons extending from March to June (long rains) and from September to December (short rains). The fading autumn rains calls for more robust alternative strategies, such as irrigation and development of new water supply pans and dams, on the part of decision makers and communities on sustaining livelihoods and production systems in the mid and lower parts of the basin.

Similar findings have been reported in other regions in different countries [9,10]. Based on these results, it is of immense importance to raise concern on the future implications of decreasing rainfall trends, though non-significant at present, on the ecological, economic and social impacts at middle and lower altitude areas within the basin particularly for rural farmers who are vulnerable to drought, water stress and erratic nature of rainfall. This study observed statistically significant increasing trends in annual rainfall at higher elevations and negative but non-significant decreasing trends for the lower parts of the basin. Streamflow analysis also showed increasing trend and this may be attributed to the increasing rainfall trends at the highlands. Human activities and human induced climate change may be at play and impacting positively at upstream and negatively downstream. Use of the possible driving forces of the trend and/or variability to obtain an insight into the rainfall trend under data scarcity would provide more information; however, such an approach would give better results if the drivers of rainfall trends are known at station-based scale. For the present study, due limited historical data records and strong effects of natural climate variability, we could not conclude that attribute streamflow rainfall trends and differences to anthropogenic climate change. Therefore there is an increasing need for more rainfall stations downstream to have sufficient data for more concrete conclusions on trends and impact of climate change within this basin. This study presents preliminary temporal streamflow and rainfall variability trends in the basin over the study period using simple models and statistical analysis. Trends or non-stationarities in climatic data normally may be caused by human activities such as land-use changes or the human-induced climate change. Complicated modeling, for example ARIMA stochastic modeling, to make predictions and more detailed and comprehensive analysis of streamflow and rainfall response to all global warming variables such as snowfall from Mt Kenya, temperature, and evapotranspiration would add more to the understanding of the effects of climate on hydrological response and indicate whether new strategies for wetland ecology, sustainable management of water resources and agricultural production systems are needed. Continuous environmental monitoring, particularly in wetland areas and river ecosystem, to confirm the environmental ecological needs (aquatic flora and fauna), and adequacy of the environmental flow for the Tana River Basin is also recommended. Future work focusing on investigating the impact of global warming on rainfall and water yield at whole-basin scale and associated patterns with Intertropical Convergence Zone (ITCZ), El Niño and La Niña (ENSO), and Indian Ocean Dipole (IOD) is also recommended. The results presented in this research provides a useful baseline for additional work on climate change and potential impacts on wetlands, water and energy resources and agricultural production systems sustainability in the Tana River Basin.

4. Preliminary Findings and Conclusions

Temporal streamflow and rainfall variability were examined. Long term daily streamflow data spanning 75 years (1941–2016) were analyzed for monotonic trend detection. The paper also analyzed trends in monthly and annual precipitation in the basin over the 49-year study period (1976–2016) from different stations. Major preliminary findings and conclusions of this study are as follows:

(a) Annual rainfall trend analysis showed negative monotonic trend in seven rainfall stations and positive trends in three stations, indicating an increasing rainfall in high elevation areas, and more drying conditions for low areas within the basin.

(b) The annual rainfall time series exhibited very small temporal variabilities in most areas in the basin and were insignificant in most of the stations.

(c) The statistically significant trend were positive and consisted 30% of the annual and monthly rainfall datasets.
(d) The results from the trend analysis showed significant increasing annual streamflow trends and that there was a strong significant upward monotonic trend in streamflow suggesting increasing base flow in the basin with reduced high flows.
(e) The seasonal rainfall series in the basin have non-significant positive trend in areas of altitude of more than 1000 m and negative trends in areas of altitude of less than 1000 m above sea level.
(f) The construction of reservoirs have not adversely modified the Tana River's hydrological flow regime.

The negative and positive trends variabilities at various stations is a pointer to factors of human activities and human induced climate change and hence the need for more detailed research on the climate change and hydrological flows to enhance decision-support processes around water resources for various uses within the basin given the basin's importance in ecological biodiversity, agricultural and energy production systems. The results presented in this research provide a useful baseline for additional work on climate change and potential implications on wetlands, water and energy resources and agricultural production systems sustainability in the Tana River Basin.

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