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Impacts of Rainfall Variability on Streamflow in the Drylands of Northern Kenya: Assessing Water Availability under a Changing Climate

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ABSTRACT: Water availability is a function of climatic and land surface conditions, which determine the amount and distribution of atmospheric water as it reaches the surface. This largely depends on rainfall, whose variability affects water, food and livelihood security. This paper sought to quantify the effects of rainfall variability on water availability in an effort to support effective water resources management. Coefficient of Variation (CV), Standardized Anomaly Index (SAI) and Mann-Kendall trend test approaches were used to assess variability and trends, while correlation and regression analysis were employed to determine effects of rainfall variability on streamflow. A hydrological model, Soil and Water Assessment Tool (SWAT), was used to simulate streamflow with a view to assessing water availability under two climate change scenarios; Representative Concentration Pathways (RCP) 4.5 and 8.5. Results show that the area experiences moderate to extreme rainfall variability, as indicated by CV and SAI values that ranged from 20 to 99% and -2.5 to +3 respectively, resulting in moderate to extreme floods and droughts that often disrupt livelihoods. Current streamflow simulations (1981 - 2020) indicated increasing trends. Near and far future streamflow volumes will decrease by 15% during the April-May-June season while during October-November-December season they will increase by 13%, compared to the present. Increasing trends of rainfall and streamflow indicate that the area has opportunities for rainwater harvesting while the high variability indicates a need for early warning systems to cushion communities from climatic shocks evidenced by the impacts of climate extremes experienced in the area.

KEYWORDS: Climate change, Drylands, Rainfall variability, Streamflow, Water availability

1. INTRODUCTION

Climate is the main factor that drives the evolution of water resources via the hydrological cycle as well as land surface process. A change in either of the two will affect streamflow volumes and, as a result, water availability (1,2). Globally, under climate change, rainfall variability has been on the rise in recent decades and is projected to rise further into the future, leading to higher frequencies of rainfall extremes (3,4). Rainfall variability under climate change thus threatens water availability; an important resource that supports human survival and sustainable economic development, especially in the drylands across the globe (2,5,6).

Water availability encompasses biophysical, social and economic aspects (7). These aspects are inter-linked by the fact that the social and economic aspects, which deal with demand for and access to water respectively, depend on the biophysical aspect which focuses on the movement of water from the atmosphere to the earth's surface where it eventually becomes available as surface and groundwater (7,8). This paper looked at the biophysical aspect of water availability, which is mainly influenced by climate and land cover characteristics, both of which determine how rainfall, the ultimate source of water on land, becomes available as water in rivers, lakes and other water bodies (2,9).

Biophysical water availability factors that include climate, soil and vegetation cover, feed into the key water resources — wetlands, lakes, wells, rivers and streams — which ultimately get recharged from precipitation (8,10,11). Thus, any changes in the rainfall variability and in the characteristics of land surface cover are bound to affect the amount and distribution of the water available in these water resources and more so in the drylands (2,9,12). This aspect of water availability is the main factor controlling food and water security as it is a necessary component of growth for both crop and fodder especially in the dryland regions (3).

Drylands are areas characterized by water scarcity and sparse vegetation coverage where natural potential evapotranspiration greatly exceeds precipitation. They range from hyper-arid, arid, semi-arid to dry sub-humid parts depending on the level of aridity as determined by their highly variable precipitation and high rates of evaporation (13). (14) have reported that over 70% of the world's drylands are found in developing countries where inhabitants already face critical challenges related to poverty and food insecurity. In spite of their constraints by water scarcity and high sensitivity to climate change and variability brought about by their extreme ambient temperatures, and with extremes such as droughts and floods projected to intensify, drylands still play a major role globally as they occupy over 41% of the global terrestrial area and support nearly 40% of the world's population, 90% of who live in the developing countries (15,16). Drylands all over the world are known for forage production, making pastoralism a major livelihood activity in these areas. Other source-of-income activities to be found in drylands include cereal production such as wheat, barley and millet among others (17).

Water resources may be assessed for water availability through analysis of historical and projected watershed characteristics such as land use/land cover (LULC) and water supply from rainfall and streamflow trends as well as their variability (8,18). Key water resources in drylands include rivers, dams and wells. Availability of water in the drylands may, therefore, be assessed through monitoring of water levels in dams and wells as well as streamflow volumes in rivers (8,19). To understand the processes leading up to water availability in the drylands, information on rainfall, the ultimate source of water in terms of amount, variability and trends, is necessary. Changes in rainfall patterns often result in variations in the water available from preceding rainfall events, including streamflow volumes.

Streamflow volumes, the water physically available in streams and rivers, is a function of rainfall whose lag time depends on the physiographic characteristics of the river basin (20). This relationship is often used to assess and predict streamflow volumes, whose main source is the rainwater storage in the river basin, using rainfall trends and variability (Franzen et al, 2020; Li and Qian, 2018). Further, streamflow is often used to assess water availability from rainfall as it is the component of hydrologic cycle that directly links rainfall to water resources management (1,11). Rainfall extremes, a consequent of climate change, are globally becoming more frequent and thus intensifying the hydrological cycle ((2,23). These changes tend to compromise water availability through contamination and scarcity during positive and negative extremes respectively, which tends to adversely affect the community's means of livelihoods.

Most analyses of water availability rely on hydrological models used to quantify and predict presence and distribution of water in targeted water resources (24). Presence of water in a water resource serves as the starting point in any meaningful water availability study. Availability of water may be assessed using trends and variability of streamflow resulting from rainfall events (25). This requires collection and analysis of basic hydrologic data that include rainfall, temperature, LULC, Digital Elevation Map (DEM), and stream flow (26,27).

This paper used a hydrological modelling approach to quantify and predict biophysical water availability using SWAT hydrological model (28). SWAT is a popular public domain semi-distributed hydrological model operating on a daily time step that is capable of simulating impacts of climate and LULC changes under data scarcity scenarios. The model disaggregates the river basin into multiple sub-basins, which are further sub-divided into smaller hydrological response units (HRU) with unique soil and land use characteristics; this makes the model computationally efficient (29–31).

In Kenya, the number of counties turning to be drylands are increasing due, in part, to adverse effects of climate change and LULC changes driven by interacting cultural, socioeconomic and biophysical factors (32). Among those counties seriously affected are those in the Northern region that include Turkana, Kenya's second largest county by areal coverage. Like all other dryland counties in northern Kenya, Turkana County is characterized by biophysical water scarcity resulting from rainfall variability that often swings between the two extremes of droughts and floods (33–35).

Turkana County is drought-prone and has low access to essential services, including water supply. The low access to water, which is dependent on its biophysical availability, tends to compromise pastoralism and agropastoralism, the two main rainfall dependent livelihood activities in the county, thereby affecting the region's food security (32). Assessment of the status and trends of biophysical water availability for supply to various users in the county, therefore, becomes imperative for future water resources planning and documenting early warning indicators.

The main sources of water in Turkana County include hand-dug shallow wells, direct river access, and piped water from boreholes and river abstractions (35). Turkwel River is the main source of water to populations in the central parts of the county that serves multiple uses such as domestic consumption, watering of livestock, crop watering through flood-based farming and irrigation among others (32). A number of small-scale irrigation projects rely on the river's water or shallow boreholes that are inherently

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interconnected to it. It is estimated that the total irrigated area, mainly along the riverine areas of Turkwel and Kerio rivers in Turkana County, is about 3,700ha with a potential to increase it to over 16,000ha, subject to improved flood control (35). Although many studies have been carried out in Turkana, few of them have focused on linking streamflow to water availability from rainfall under climate change. Hence, a gap exists in the up-to-date and future information regarding effects of climate change and variability on streamflow volumes as an indicator of water availability. This information is critical for the present and future planning for water resources management.

This paper sought to understand the effects of rainfall variability on biophysical water availability in the drylands, with a focus on Turkana County in northern Kenya. The objective was to determine the effects of rainfall variability on streamflow as a proxy to biophysical water availability using a hydrological modelling approach and further give future predictions for water availability in the drylands of northern Kenya. The paper provides up-to-date data on the status and trends in the flow rates of Turkwel River as part of the assessment of the water available for use in different livelihood activities in the drylands. The paper used the streamflow volumes, which form part of the quantitative aspect of biophysical water availability, to assess the rain water availability for use in various livelihood activities in the county and other areas with similar characteristics.

2. MATERIALS AND METHODS

2.1 Study Area

The area of study (Figure 1) is located in the north-western part of Kenya between latitudes 1.00° N and 5.50°N and longitudes 34.00°E and 37.00°E. The area straddles two counties, Turkana and West Pokot, within which lies Turkwel River basin, the main focus of the study, covering a total area of about 83,000km^2. The altitude, which has a notable influence on the county's climate, ranges from 330m near Lake Turkana to about 3,530m above sea level on the western side near Mt Elgon.

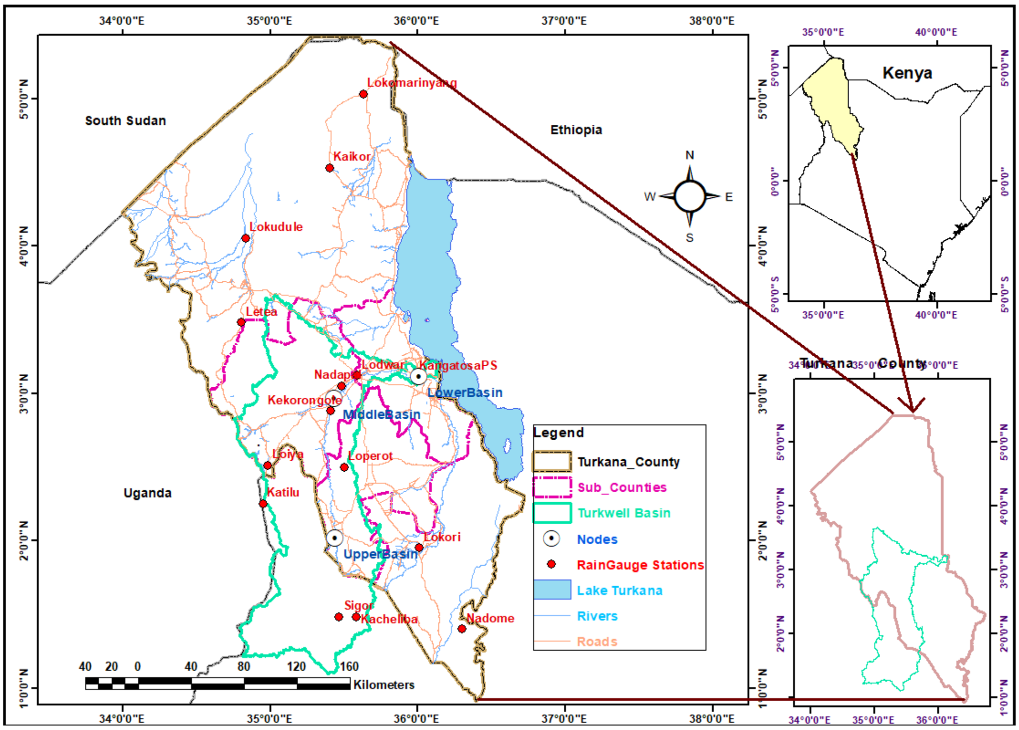

Figure 1: Location map of Turkana County and Turkwel River Basin, the area of study, showing rain and river gauging stations (Source, Author)

2.2 Data Types and Sources

This study is anchored on spatial and hydrometeorological datasets. Spatial datasets included land use and land cover (LULC) obtained from USGS website (https://earthexplorer.usgs.gov/), soil type obtained from the Soil and Terrain (SOTTER) database programme (https://www.isric.org/projects/soil-and-terrain-soter-database-programme), and 30m Digital Elevation Model (DEM)

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obtained from the Shuttle Rada Topography Mission (SRTM) website (https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-1)

Hydrometeorological datasets included time series of daily and monthly rainfall, maximum and minimum temperatures, and streamflow volumes. Data scarcity in the area of study renders it difficulty to get adequate station-observed datasets to analyze hydrometeorological data for trends and variability. Accordingly, satellite derived Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (https://data.chc.ucsb.edu/products/CHIRPS-2.0/) and Climate Hazards Group InfraRed Temperature with Stations (CHIRTS) (https://data.chc.ucsb.edu/products/CHIRTSdaily/) data, at 0.05º by 0.05º resolution, were used to represent the past and current climate data. Future climate data were derived from the Coordinated Regional Climate Downscaling Experiment (CORDEX) at the Deutsches KlimaRechenZentrum-DKRZ data portal (https://esgf-data.dkrz.de/search/cordex-dkrz/) at 0.5º by 0.5º resolution for two Representative Concentration Pathways (RCPs); the intermediate climate change scenario (RCP4.5) and the worst-case climate change scenario (RCP8.5) (36).

CHIRPS, CHIRTS and CORDEX data have been validated for use globally and for the Eastern Africa ((37,38)(39), 40) and found to have a good description of insitu data. On the other hand, SWAT 2012 model, obtained from the SWAT website (https://swat.tamu.edu/software/), was used to simulate streamflow (28).

2.3 SWAT Model Setup

SWAT was set up (41) using climate data that included daily rainfall, maximum temperatures and minimum temperatures; and spatial data that comprised Digital Elevation Model (DEM), processed SWAT land use and land cover classes, and Soil type. Water availability was modelled based on the water balance equation given by (42).

$$SW_t = SW + \sum_{t=1}^{t} \left(R_i - Q_i - ET - P_i - QR_i \right)$$

Where SW_t is the final soil water content, SW is the initial soil water content, t is the time in days, and R, Q, ET, P, and QR are the daily amounts of precipitation, discharge, evapotranspiration, percolation and return flow; all measured in mm.

The model was calibrated and validated at the sub-basin level based on average observed monthly discharge values and following a three-step procedure — model sensitivity analysis, calibration and validation (41,43,44). The model performance after calibration was assessed using four quantitative statistics: coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), Percentage Bias (PBIAS) and the ratio of root-mean-square error to the standard deviation of the observation data (RSR) as recommended (45).

Impacts of climate change and variability on streamflow, and hence biophysical water availability, were assessed by simulating streamflow at four different 30-year climate periods: baseline (1981 – 2010), present (2006 – 2035), near future (2036 – 2065) and the far future (2066 – 2095) periods which, for purposes of this study, were coded as 1990s, 2020s, 2050s and 2080s respectively as described by (41). Time series of simulated monthly streamflow were then analyzed for the effects of climate change.

2.4 Characterizing Rainfall and Streamflow

Rainfall and streamflow characteristics were examined in terms of annual and seasonal variations, trends and interannual variability. Seasonal variations were investigated using graphical methods by plotting mean monthly data for the period of study to reveal variations within the year. Trends of seasonal and annual data were studied using graphical and Mann-Kendall tests while their variability were explored using Coefficient of Variation (CV) and SAI.

Trend analysis of monthly rainfall data was carried out using both parametric and non-parametric methods. Parametric method involved plotting a time series and fitting a trend line while non-parametric method entailed use of the Mann-Kendall (MK) trend test with Sen's slope estimator (46); (47). The MK test was used to detect the presence and significance of trends on seasonal rainfall and streamflow for the baseline period and the present, near future, and the far future periods under RCP4.5 and RCP8.5 climate change scenarios as described in (46).

Interannual variability of annual and seasonal rainfall and streamflow were computed using SAI as the ratio of the difference between the individual variable of a particular year and the long term mean value of the available record to the standard deviation of the long term data available as described in (46). Negative deviations from the annual and seasonal mean values indicated dry while positive deviations indicated wet years and seasons respectively. The SAI values (Table 1) were categorized according to their indicative levels of dryness/wetness ranging from extremely dry to extremely wet as recommended by (47)

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Table 1: Statistics of categories of SAI level of wetness/dryness of a particular year or season of the year used in this study (47)

SAI Values	Level of wetness/dryness
Z > 2.0	Extremely wet
1.5 < Z < 1.99	Very wet
1.0 < Z < 1.49	Moderately wet
-0.99 < Z < 0.99	Near normal
-1.0 < Z < -1.49	Moderately dry
-1.5 < Z < -1.99	Very dry
Z < -2.0	Extremely dry

Spatial variability of rainfall was analyzed using the CV to measure variability of rainfall at different points in the area of study. Different values of CV at seasonal and annual time scales were mapped and extrapolated to display spatial variability. Levels of spatial variability were categorized as: low (CV < 20%), moderate (20% < CV < 30%), or high (CV > 30%) as recommended by (46). High values of CV indicated high risk while low values indicated low risk areas in the planning of rainfall and streamflow related investments.

Correlation analysis was used to determine the relationship between rainfall and streamflow while regression analysis was used to establish the effect of rainfall variability on streamflow as described in (48). Regression analysis was used to ascertain the extent to which rainfall variability affects streamflow as measured by the coefficient of determination (49).

3. RESULTS AND DISCUSSION

3.1 Rainfall and Discharge Climatology

Figure 2 shows the mean monthly variations of rainfall and streamflow averaged over the entire basin and at the outlet of Turkwel River, respectively using processed CHIRPS rainfall and model-simulated streamflow. These results show that peak rainfall months in the basin are April, July and October while peak streamflow months are May, August and October. It was noted from the figure that monthly streamflow lagged behind monthly rainfall by one month between January and September while in the last quarter, both rainfall and streamflow peaked together in October. Therefore, for purposes of comparison of seasonal rainfall and streamflow, March-April-May (MAM) rainfall was compared with April-May-June (AMJ) streamflow while September-October-November (SON) rainfall was compared with September-October-November (SON) streamflow.

The one-month lag of streamflow in the first three quarters and the match in the last quarter could be explained by the fact that the long rains season (MAM) follows a relatively dry period between December and February. As a consequence, most of the rainwater goes towards meeting the soil moisture deficit before any water finds its way to the river system. The coincidence between streamflow and rainfall in the last quarter could be explained by the fact that between the second and the third quarter, the basin is relatively wet and, therefore, most of the rain water during the SON short rains season finds its way to the river channels.

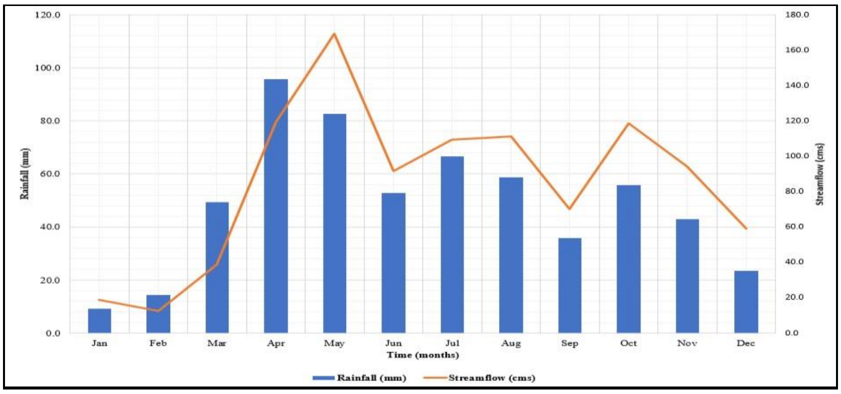

Figure 2: Mean monthly variations of rainfall and streamflow of the Turkwel River Basin. Both rainfall and streamflow follow a trimodal pattern with streamflow lagging rainfall by one month during MAM and JJA seasons

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Figure 3 shows the mean monthly rainfall variations at decadal time steps between 1981 and 2020 coded as 1980s (1981 - 1990), 1990s (1991 - 2000), 2000s (2001 - 2010), and 2010s (2011 - 2020). The figure shows that the peak rainfall in MAM decreased from about 98 mm in the 1980s to about 76 mm in the 1990s and thereafter consistently increased to about 92 mm and to about 116 mm in 2000s and 2010s respectively, showing a generally increasing trend in the MAM rainfall between 1981 and 2020. During the same periods, June-July-August (JJA) and SON rainfall followed the same pattern with SON showing higher changes than JJA. The result of these changes in seasonal rainfall is that the area received more rainfall in all the seasons in the recent decades than was the case in the past, which is in line with other studies carried out in the Horn of Africa (52). This means that more rainwater has become available in the area in recent decades in all the seasons.
The implication of this increased rainfall to the dryland communities is that with better water resources management, it is possible to make more water available from rainfall by enhancing rainwater harvesting. This would go a long way in cushioning the community's livelihoods from the shocks of extreme rainfall and, consequently, making the dryland communities water resilient.

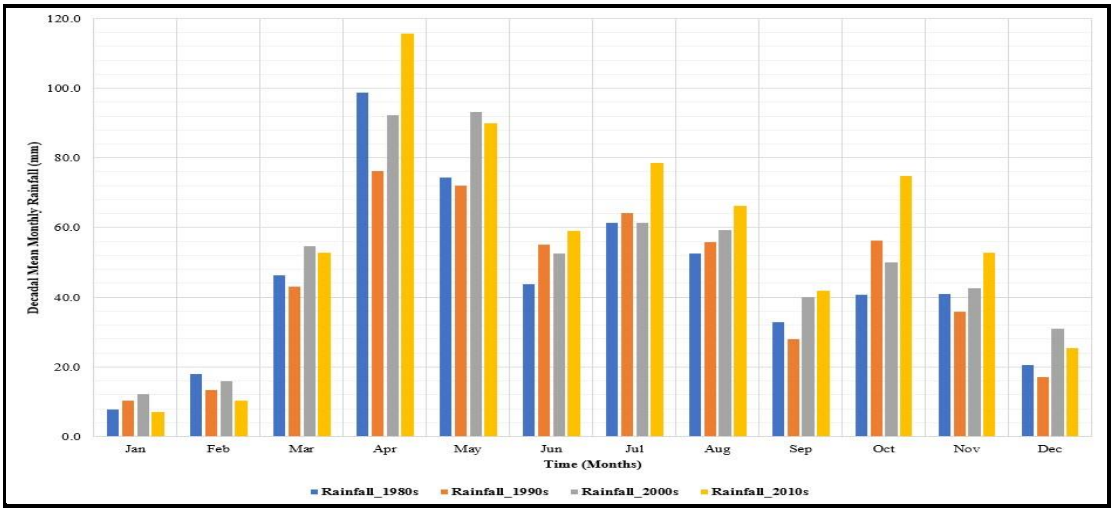

Figure 3: Decadal mean monthly rainfall variations over the area of study between 1981 and 2020. Generally, decadal mean rainfall has been increasing in the area with the 2010s decade recording the highest rainfall in all the three rainfall seasons

3.2 Rainfall and Streamflow Trends

Figure 4 shows rainfall time series for MAM and SON, the two main rainfall seasons in the area, for the period 1986 to 2016 together with their respective trends and seasonal decadal means. These results show that seasonal rainfall has been on an upward trend in both seasons with SON (Figure 4a) having a higher trend (1.7mm/year) than MAM (Figure 4a) (0.95mm/year), which matches the results in Figure 3. Notable changes in the mean seasonal rainfall from 216 to 237mm (a 10% increase) during MAM and from 109 to 156mm (a 46% increase) during SON, are indicative of a changing climate with more rainwater becoming available in the area particularly during the short rains season in line with previous studies (52). The higher rate of increase in the SON season rainfall compared to that of the MAM season indicated a probable change in the future seasonal rainfall distribution in the area. The SON season is apparently gaining more prominence in rainfall volumes just as much as MAM, thereby calling for a revision of water resources management policies in the area to accommodate this imminent change in seasonal rainfall distribution.
Figure 5 shows time series of AMJ and SON streamflow for the period 1986 to 2016, together with their respective trends and seasonal decadal means. It is clear from the figure that seasonal streamflow has been on an upward trend in both seasons with AMJ (Figure 5a) having a higher trend (3.6cms/year) than SON (Figure 5b) (3.3cms/year). Notable changes in mean streamflow from 238 to 343cms (a 44% increase) during AMJ and from 111 to 207cms (an 86% increase) during SON, are indicative of increasing volumes of water in the rivers that could be attributed to, *inter alia*, the increase in seasonal rainfall observed in the area over the same period (Figure 4).

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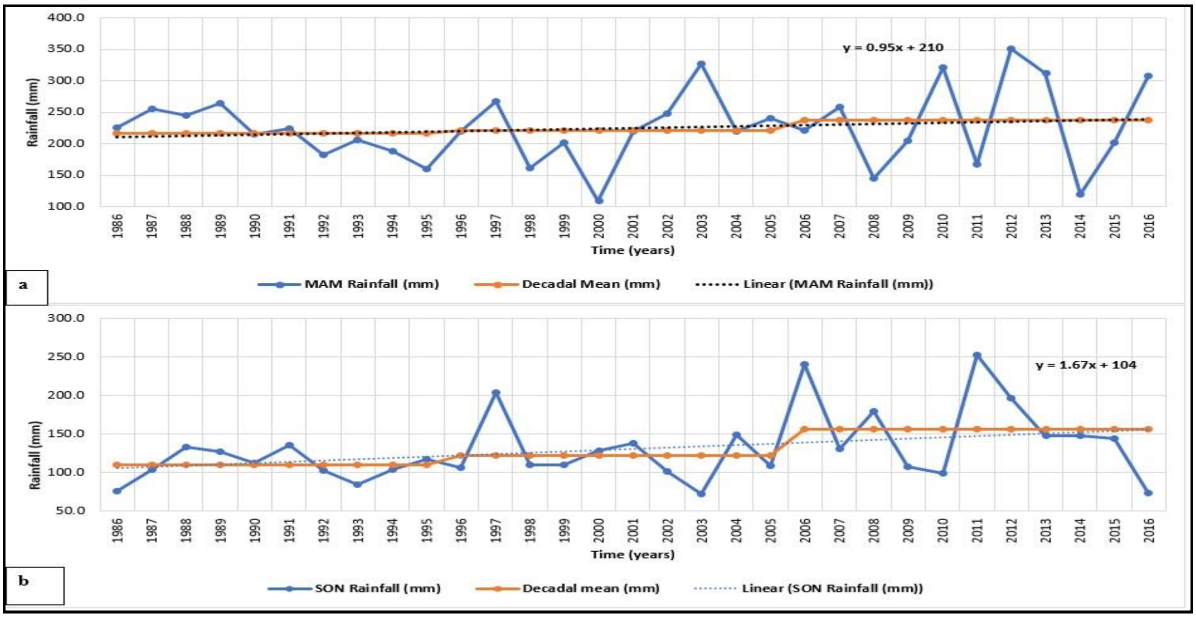

Figure 4: Time series of MAM (a) and SON (b) rainfall at the Lodwar Meteorological Station showing the trend and decadal means. There is a general increase in rainfall for both seasons with higher rainfall in subsequent the decade

These increased volumes in streamflow are indicative of enhanced water availability from rainfall, which points to a need for the water resources mangers to consider harnessing the increased streamflow to improve water availability in this area and other areas with similar characteristics.

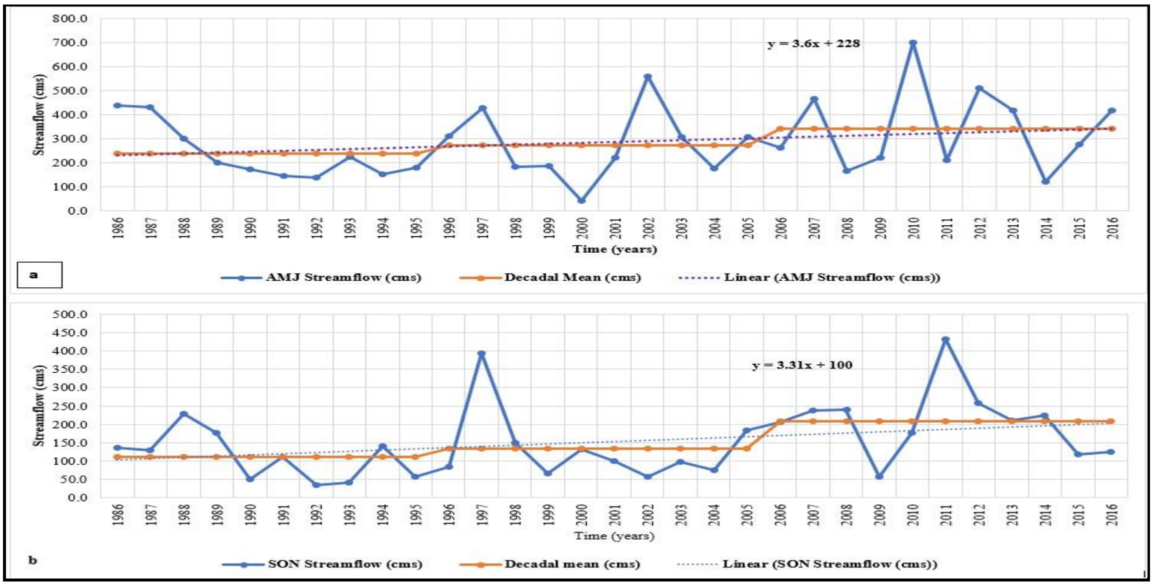

Figure 5: Time series of AMJ (a) and SON (b) streamflow showing the trend and decadal means at the outlet of Turkwel River. Streamflow in both seasons is on an increasing trend over the last four decades following the same patterns as those of the seasonal rainfall

Table 2 shows Mann-Kendall trend analysis statistics at different locations for rainfall trends. These results show that all the Kendall's Tau values were greater than 0 while all the p-values were less than 0.05, an indication that significant positive trends in rainfall at $\alpha = 0.05$ indeed exist in this area. These results confirm those of Figures 4, 5 and 6 that the area is becoming wetter with

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time and, hence, more water is becoming available. These results may thus be used by the County and National governments in reviewing policy and regulation to make future arrangements on how effectively to use the available water.

Table 2: Mann-Kendall trend statistics of monthly rainfall time series (1981-2020) at different locations at p-value = 0.05 and α = 0.05. Statistics show significantly increasing trends of rainfall in all the nine stations

S/No.	Station	Kendall's' Tau	p-value (Two-tailed)	Sen's Slope
1	Kaikor	0.147	<0.0001	0.288
2	Kangatosa	0.243	<0.0001	0.155
3	Kikorongole	0.288	<0.0001	0.311
4	Latea	0.099	0.002	0.151
5	Lodwar	0.106	0.003	0.037
6	Loiya	0.106	0.003	0.037
7	Lokomarinyang	0.245	<0.0001	0.657
8	Lokori	0.205	<0.0001	0.444
9	Nadome	0.141	0.000	0.302

Figure 6 shows time series of projected MAM and SON rainfall together with their trends and 30-year means for the period 2022 to 2095 under RCP4.5 climate change scenario using processed CORDEX data. MAM and SON rainfall show decreasing and increasing trends respectively. Under this scenario, MAM rainfall (Figure 6a) is projected to decrease from a 30-year mean of 112 mm to 96 mm, a 14% decrease, at the close of the century. It is worth noting that under this scenario, the mid-century 30-year period mean will be lower (94 mm) than that at the close of the century (96 mm) an indication that the current upward trend (Figure 5) will reach its peak in 2040s and thereafter decrease up to 2070 before starting to rise again up to the close of the century. On the other hand, SON rainfall (Figure 6b) is projected to increase from a 30-year mean of 105 mm to 122 mm, a 16% increase, by the close of the century. It is also worth noting that just like in the case of MAM under this scenario, the rise in the 30-year mean rainfall is not consistent. The current upward trend (Figure 5) is expected to reach its peak in the 2050s decade and thereafter start declining to the end of the century (Figure 6b).

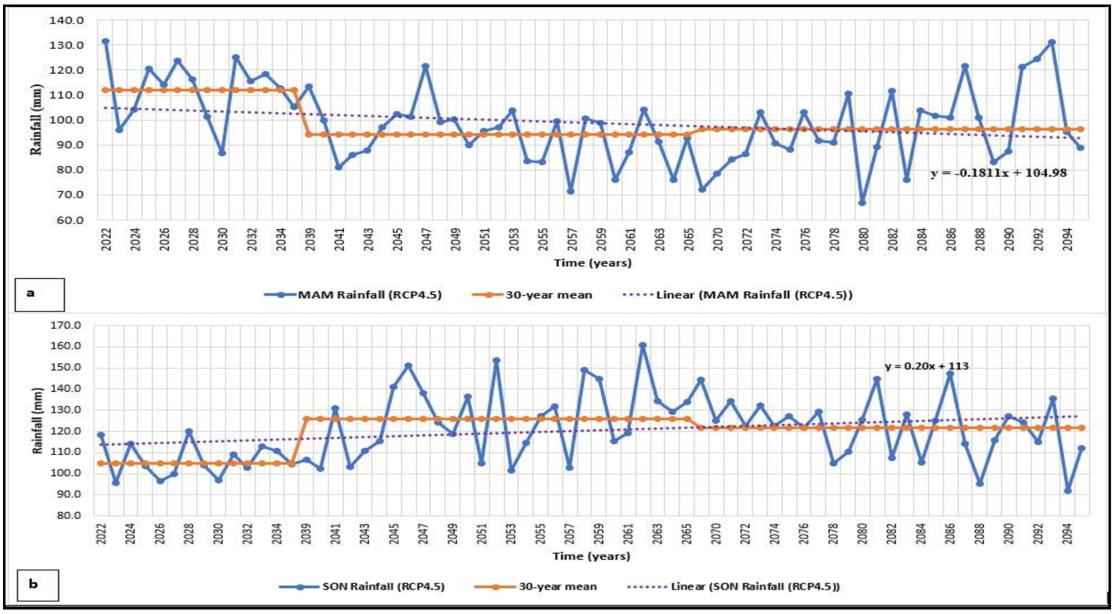

Figure 6: Time series of projected MAM (a) and SON (b) rainfall under RCP4.5 showing the trend and 30-year period means. Under this scenario, MAM rainfall is currently on a decreasing trend up to late 2060s when trends reverse and increase up to the end of the century while SON rainfall is currently on an increasing trend up to late 2060s when trends reverse and decrease up to the end of the century

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Figure 7 shows time series of projected MAM and SON rainfall together with their trends and 30-year means for the period 2022 to 2095 under RCP8.5 climate change scenario. Just like under the RCP4.5 scenario, MAM and SON rainfall show two different trends where rainfall is increasing during SON but decreasing during MAM. However, under this scenario the 30-year mean MAM rainfall decreases while SON rainfall increases consistently from the present into the far future period. MAM rainfall (Figure 7a) is projected to decrease from a 30-year mean of 103 mm to 98 mm, a 5% decrease, under this scenario at the close of the century. On the other hand, under this scenario SON rainfall (Figure 7b) is projected to increase from a 30-year mean of 108 mm to 132 mm, a 22% increase, by the close of the century.

From the foregoing, it is expected that under the moderate climate change scenario (RCP4.5), we are moving into a period of lower MAM and higher SON rainfall volumes towards the middle of the century. MAM rainfall is then expected to take on an upward trend while SON rainfall is expected to take on a downward trend towards the close of the century. On the other hand, under the business-as-usual climate change scenario (RCP8.5), MAM rainfall is expected to continuously drop as we move from 2020s decade through 2050s decade to the end of the century while SON rainfall is expected to continuously rise up to the close of the century (Figure 7).

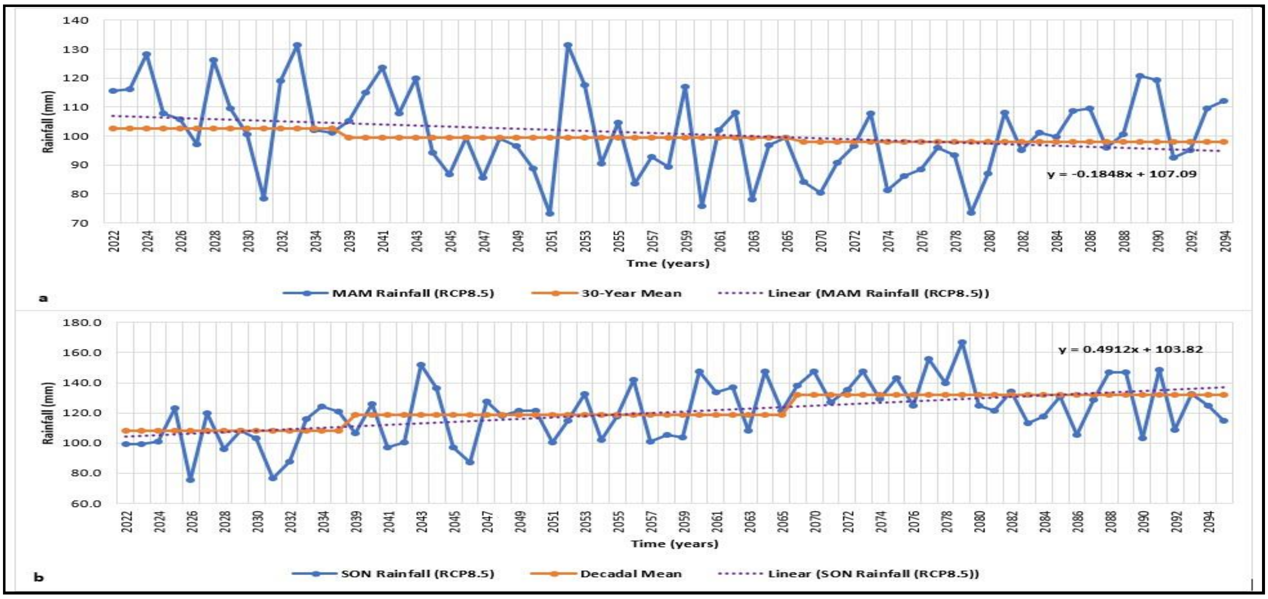

Figure 7: Time series of projected MAM (a) and SON (b) rainfall under RCP8.5 showing the trend and 30-year means. Just like in the case of RCP4.5, MAM rainfall under this scenario is also on a decreasing trend up to late 2070s when it is expected to reverse and increase up to the close of the century while SON rainfall is currently on an increasing trend up to late 2070s when it will reverse and decrease up to the end of the century show significantly increasing trends of rainfall in all the nine stations

These projected changes in MAM and SON rainfall under the two climate change scenarios are in line with similar studies conducted over the Horn of Africa [e.g. (39)and (53)]. It is clear from these results that future MAM rainfall will be less while SON rainfall will be more than present as indicated by the trends in both scenarios. There is need, therefore, to sensitize the community on possible implications of these changes to their livelihood activities. Floods may now become more frequent in SON than in MAM as is the case currently. This may call for the revision of policy in the water resources planning and governance to account for these expected changes. This would include, *inter alia*, incorporation of the early warning systems, especially in the period 2023 to 2043 and 2067 to 2072 where transitions in rainfall trends are expected in both seasons.

Figure 8 shows the percentage contribution by season to the total annual rainfall at different climate periods under RCP4.5 and RCP8.5. As seen from these figures, MAM season currently accounts for over 50% of the total annual rainfall while SON season accounts for just under 20%. As we move into the future, MAM season's contribution to the annual rainfall is expected to fall to about 28% under RCP4.5 (Figure 8a) and to about 29% under RCP8.5 (Figure 8b) while SON season's contribution is expected to

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rise to about 36% under RCP4.5 (Figure 8a) and 39% under RCP8.5 (Figure 8b) respectively at the close of the century. This is a clear indication that SON is expected to become the main rainfall season in this area as we move into the future.

The out-of-phase pattern of change in the projected MAM and SON seasonal rainfall behaviour is indicative of a shift in the seasonal distribution of rainfall in the area. This projected change in seasonal rainfall distribution has the potential to affect livelihood activities of the affected communities whose means of support (pastoralism and agropastoralism) are heavily dependent on rainfall. In view of this, there is need to revise policy on rainwater harvesting, taking into account that in future, no single season is expected to account for over 50% of the annual rainfall as is the case currently. There is also need to sensitize the community on the need to diversify livelihood sources.

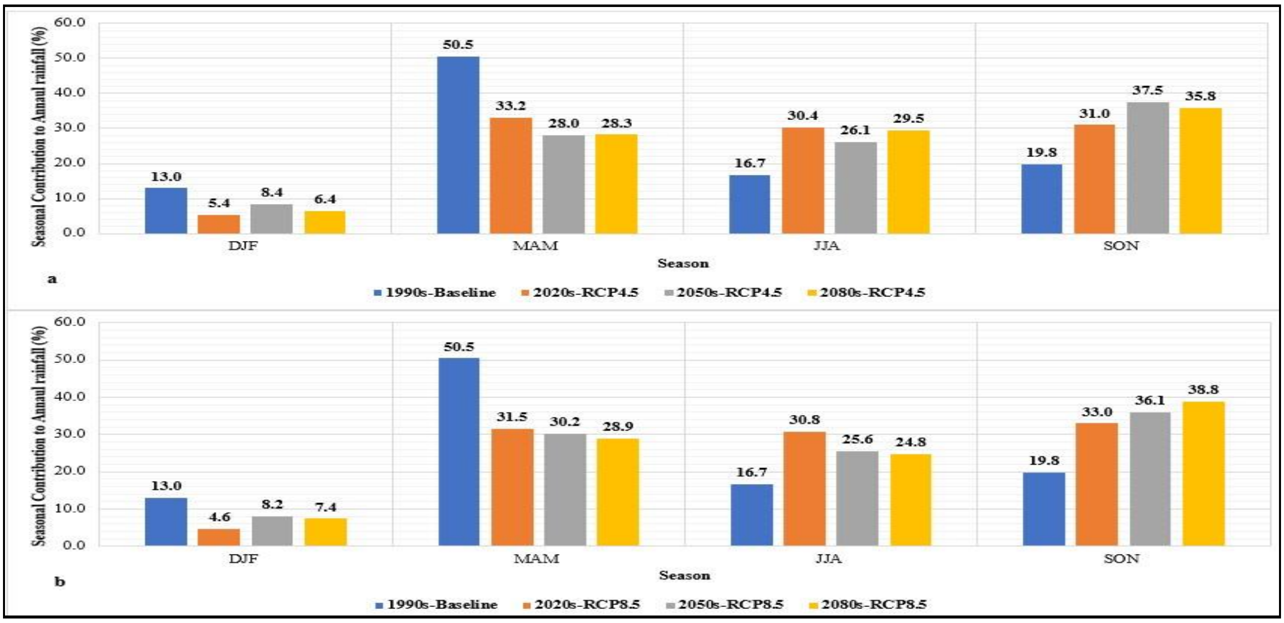

Figure 8: Projected changes in seasonal contribution to annual rainfall from the baseline period to the close of the century under RCP4.5 (a) and RCP8.5 (b) in Turkana County. Under RCP4.5 scenario, percentage contribution of MAM rainfall to annual rainfall is projected to decrease from over 50% to just over 28% while that of SON is projected to increase from just under 20% to 36%. Under the business-as-usual scenario (RCP8.5), percentage contribution of MAM rainfall to annual rainfall is projected to decrease from over 50% to just under 29% while that of SON is projected to increase from just under 20% to 38%.

Figure 9 shows time series of projected AMJ and SON streamflow volumes under RCP4.5 climate change scenario for the period 2022 to 2095 together with their respective long-term trends and the 30-year means for the present, near and far future periods using model-simulated streamflow data. Figure 9a shows that currently under RCP4.5 climate change scenario, AMJ season has higher streamflow volumes compared to the near future. This is in contrast to the SON season (Figure 9b) where streamflow volumes are currently lower and are projected to be much higher than those of AMJ season as we move into the near future. Moving from the present into the near future, AMJ streamflow volumes will drop by 17% (Figure 9a) while those of SON will rise by 17% (Figure 9b). As we approach the far future, AMJ streamflow volumes will increase by 4% while those of SON will drop by 2%. It was noted that under RCP4.5, the two seasons are expected to experience diametrically opposite changes as we move from the present into the near and far futures, an indication of a possible change in the distribution of seasonal water availability from rainfall.

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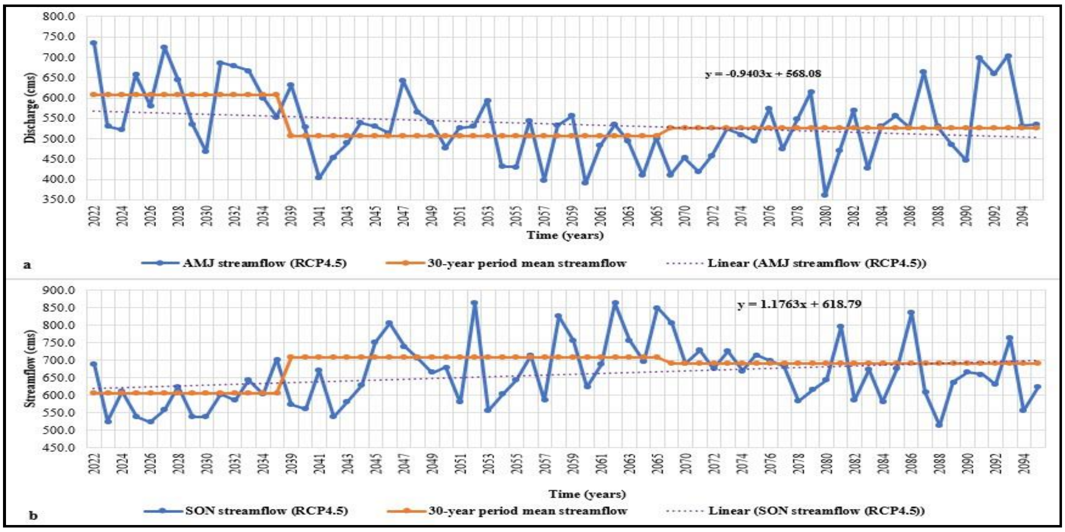

Figure 9: Time series of projected AMJ and SON streamflow under RCP4.5 showing the long-trend and 30-year means for the present, near, and far future periods. AMJ streamflow is on a decreasing trend projected to continue up to late 2060s when it is expected to reverse and increase up to the end of the century. SON streamflow, on the other hand, is on an increasing trend projected to continue up to the middle of 2060s when it is expected to reverse and decrease up to the end of the century

Just like under RCP4.5, Figure 10 shows that currently, under RCP8.5 climate change scenario, AMJ season (Figures 10a) has higher while SON (Figures 10b) has lower streamflow volumes compared to the near and the far future periods. However, as we move into the near and far future under RCP8.5, AMJ streamflow volumes consistently decreased by 3% and 2% respectively. On the other hand, SON streamflow volumes consistently increased by 7% and 10% respectively over the same period. The projected increase and decrease in streamflow volumes for the AMJ and SON seasons respectively as we move into the future are indicative of a shift in the seasonal distribution of water availability where SON is becoming the main streamflow season.

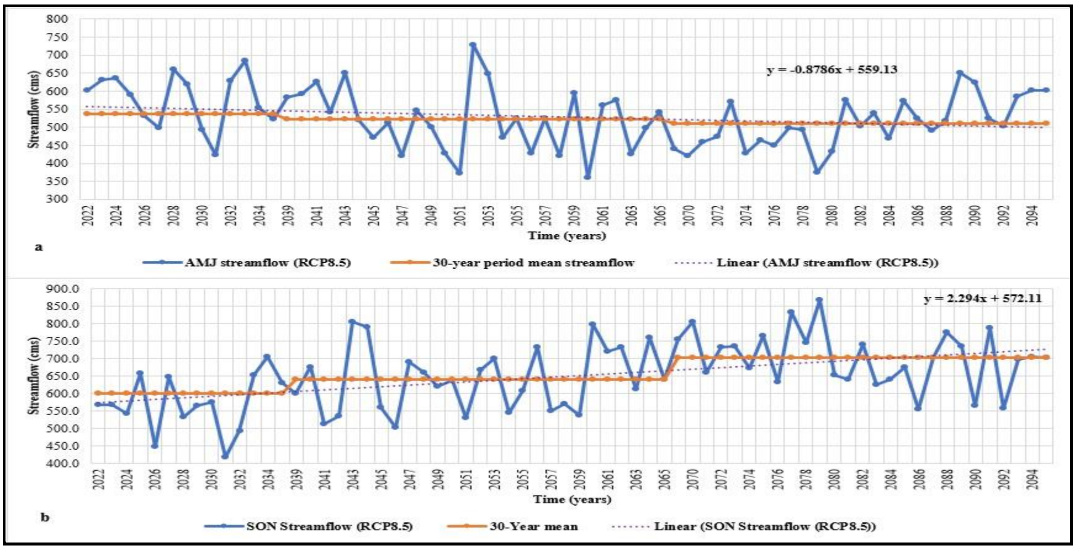

Figure 10: Time series of projected AMJ and SON streamflow under RCP8.5 showing the long-trend and 30-year means for the present, near and far future periods. Under the business-as-usual scenario, AMJ streamflow is on a decreasing trend that is expected to continue up to the end of the 2070s decade when the trend will reverse to increase up to the end of the century. On the other hand, SON streamflow is on an increasing trend that is expected to continue up to the end of the 2070s decade when the trend will reverse to decrease up to the end of the century

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3.3 Rainfall and Discharge Variability

3.3.1 Historical Variability

Figure 11 shows spatial annual (Figure 11a) and MAM (Figure 11b) rainfall variability in Turkana County as depicted by the coefficient of variation. It was noted from the figure that rainfall in this area is highly variable with the coefficient of variation ranging from moderately (20% < CV < 30%) to extremely (CV > 50%) high variability. Annual rainfall variability ranges between 25% and 55% while that of MAM, the main rainfall season in the area, ranges between 37% and 91%. These results show that the central parts of the county experience higher variability than the northern and southern parts. These high variabilities make it difficult to plan for livelihood activities that are dependent on rainfall such as pastoralism and agropastoralism, the main livelihood activities in the central parts of the county.

This high to extreme variability in rainfall is likely to lead to greater scarcity and variability of the water available for household food production in the county. This is a real threat to the livelihoods of the local communities who depend on pastoralism and agriculture, especially in the central parts of the county. It affects their income from agriculture and livestock production and therefore food security.

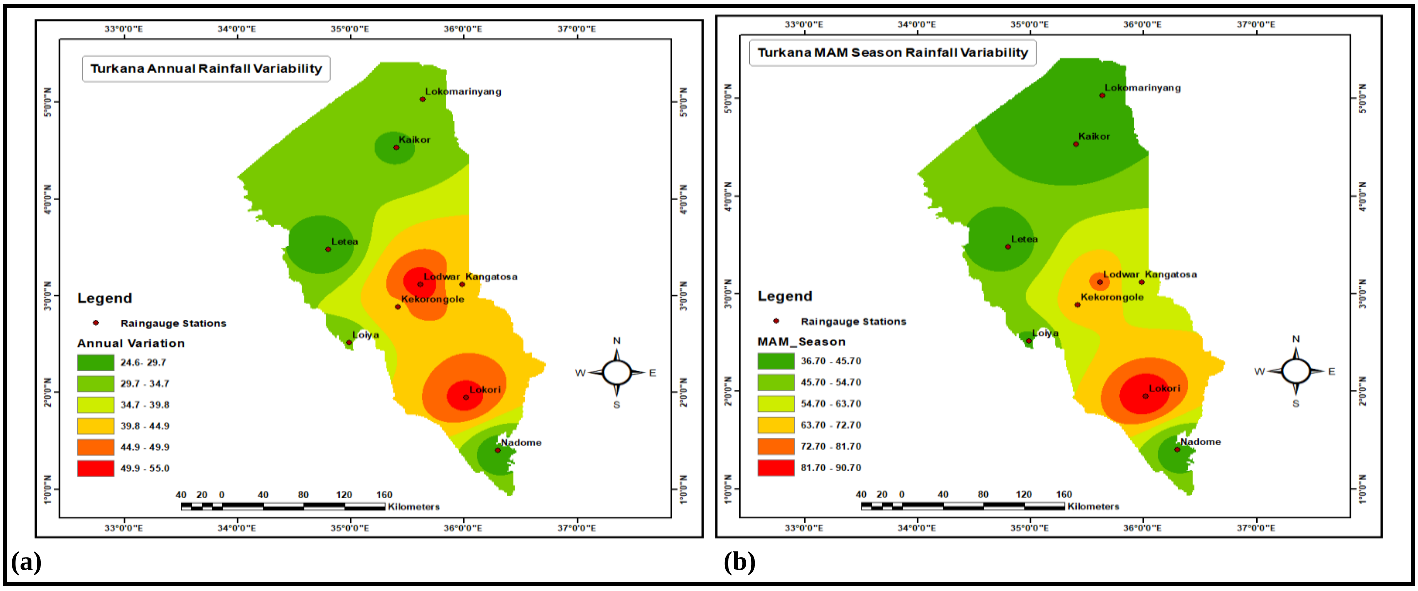

Figure 11: Coefficient variation for (a) Annual rainfall and (b) MAM rainfall showing spatial variability of rainfall in Turkana County. There is higher rainfall variability in the central compared to the northern and southern parts of the county.

Figure 12 shows temporal variability and the three-year moving average for both rainfall and streamflow during the two rainfall seasons (MAM and SON). These results show that both rainfall and streamflow in the area are highly variable with variability ranging between moderately dry (-1.0<Z<-1.49) to extremely wet (Z>2) conditions. From the three-year moving average, it was noted that there are cycles of dry and wet periods in both seasons. During the long rains season (Figure 12a) there was generally depressed rainfall and streamflow varying from below to near normal between the years 1989 and 2001, except 1997 which was an El Niño year. It was during this period that the area experienced the worst drought in this season (2000), in the entire baseline period of study. Thereafter, the season has been experiencing more frequent near normal to above normal wet conditions with notable extremes in discharge variability following near normal rainfall (2002 and 2007). This could be explained by the fact that climate change is influencing rainfall intensity and duration where it is increasingly falling in short but intense episodes that lead to more severe floods. Further, the frequency of extreme above normal streamflow has increased to about two years on average between 2002 and 2016, leading to higher volumes of rain water lost as runoff that sometimes reaches flood levels (years 2002, 2007, 2010, and 2012). This increased amount of water by way of runoff and floods provides an opportunity for rainwater harvesting to cushion the communities from the shocks visited upon their livelihoods by these extreme variabilities in the water available in the area.

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During the short rains season (Figure 12b), a similar pattern to that of the long rains season was noted, with the exception that extreme variability in this season was more frequent and higher (1997, 2006 and 2011). The period after 2005 generally experienced normal to above normal wet conditions, except in 2009 and 2010. This is an indication that the season has become wetter in the recent past. The 1997 and 2011 moderate to extreme rainfall accompanied by the extreme flooding, are due to the El Niño rainfall. Since only about 20% of the annual rainfall is experienced during this season, the extremely wet years have a risk of flash floods causing more damage unless early warning systems are put in place.

It was also noted that during the baseline period of study, there was no time that the two seasons had extreme variability in the same year. When one season experienced extreme variability, the other one experienced near normal rainfall and streamflow. Further, the three-year moving averages show that the wet and dry seasonal variations are cyclic where, on average, rainfall and streamflow in these two seasons were mostly below to near normal between 1981 and 2001. Thereafter, they have tended to be normal to above normal in both seasons. This means that in the recent past, there is more water coming to the basin from rainfall than before, pointing to a need to device ways of harvesting this water in an effort to improve the community's resilience to water scarcity.

This is a clear indication that the degree of rainfall variability and discharge are increasing but tending towards more flood situations than droughts. An indication that the area is increasingly receiving more but unpredictable rainfall. This was confirmed by some of the perceptions from the community that rainfall in the area had become more unpredictable with more intense floods than before, which had negatively affected their livelihoods. This enhanced water from rainfall may need to be harnessed as a means of enhancing community resilience to climate change and variability. Further, the high rainfall and discharge variabilities call for the establishment of an early warning system in the area to improve rainfall predictability for better planning of livelihood activities.

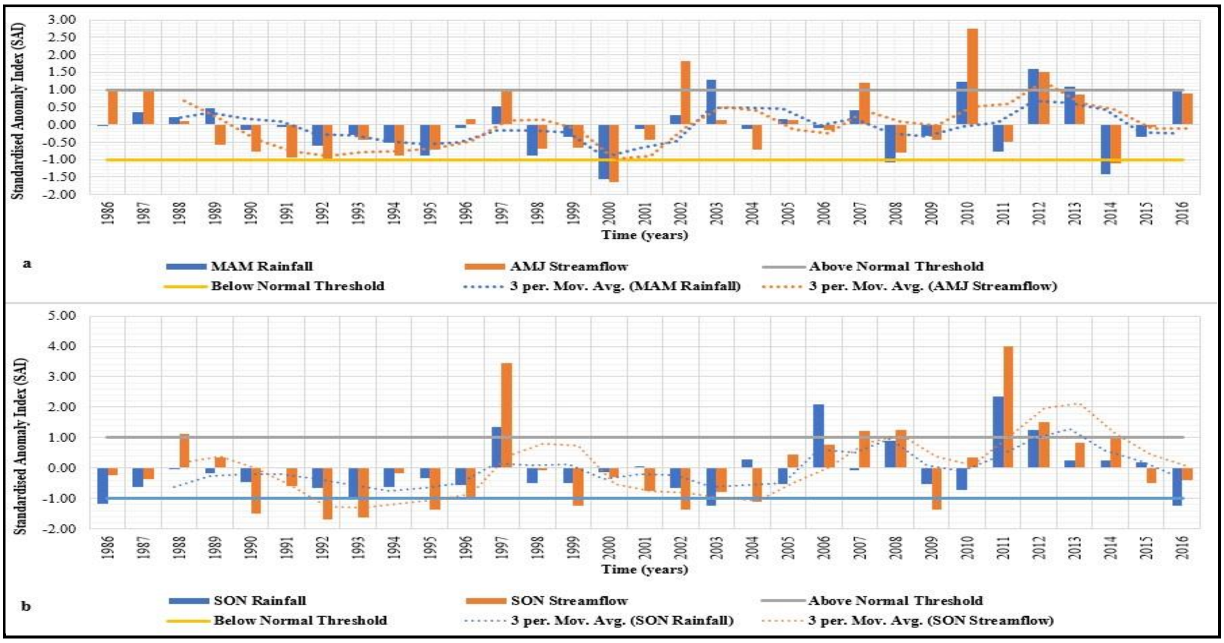

Figure12: Time series and the three-year moving averages of historical rainfall and streamflow for the long and short rainfall seasons, MAM (a) and SON (b) respectively. During MAM, flood frequency episodes have increased since year 2000 while drought frequency episodes have remained relatively unchanged. During SON, flood frequency episodes have increased since year 2005 while drought frequency episodes have decreased in line with the increasing rainfall trends

3.3.2 Projected Variability

Figure 13 shows projected rainfall and streamflow temporal variabilities during the two rainfall seasons (MAM and SON) in the area of study under RCP4.5 climate change scenario between 2022 and 2095 where it was noted that going into the future, both rainfall and streamflow are highly variable with more severe floods during SON (Figure 13b) and more severe droughts during MAM (Figure 13a). Of particular interest are periods between 2022 and 2050, 2051 and 2080, and beyond 2080. Within the period between 2022 and 2050, which is the transition from present to the near future, two phenomena stand out in the two seasons. During the MAM season (Figure 13a), there is a period of near normal to above normal rainfall and streamflow with occasional extremes between 2022 and 2039 followed by a period of continuous below normal rainfall and discharge between 2040 and 2050 except year 2047 when a flood is expected. This period of plenty followed by a period of scarcity of water is of interest to the county and national administrations as it would form a basis for planning for the storage of the excess water for use during the time of scarcity. This is more so given that this is the main rainfall season in the area and whatever happens in this season controls the livelihoods in the area for the rest of the year.

Thereafter the period between 2051 and 2080, which is the near future, will be characterized by normal to below normal rainfall and discharge with a higher frequency of moderate to severe droughts. This is, therefore, more likely to be a period of water scarcity in this season. However, this will be more than compensated during the SON season when rainfall during the period 2047 to 2078 is projected to be above the current normal and tending towards extreme wet conditions (Figure 13b). The period beyond 2081, the far future, will experience increasing trends in rainfall and discharge variability tending to above current normal with moderate to extreme floods, making this a period of plenty of water from rainfall during the MAM season.

Figure 13b shows projected rainfall and streamflow temporal variability between 2022 and 2095. Just like the MAM season, projected SON rainfall and streamflow highly variable. However, this season, from 2022 to 2050, is projected to experience more frequent droughts than is currently the case. Unlike during the long rains season, this will be a period of water scarcity. Likewise, the periods between 2051 and 2080, and beyond 2081 are projected to experience wetter than the current normal conditions unlike in the case of the long rains season. Overall, the near future period in this season is projected to be wetter unlike during the long rains season thereby making this a season of plenty during this period. For the far future period, variability alternates between moderately dry to moderately wet conditions.

From the foregoing, MAM rainfall is expected to be lower than present while it is anticipated that SON rainfall will be much higher than is the case currently. SON season is expected to become the main rainfall season in the future. These results would form a basis for informing disaster management planning in the county.

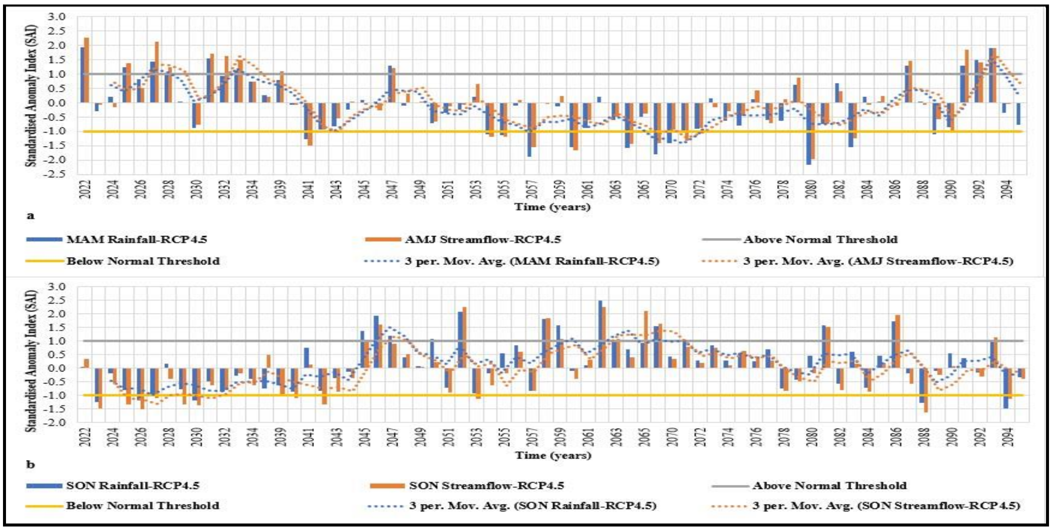

Figure 13: Time series of projected MAM rainfall and AMJ streamflow variabilities under RCP4.5 together with their respective three-year moving averages. Currently experiencing higher flood frequency episodes up to 2040 followed by higher drought episodes up to 2080s decade

3.4 Effects of Rainfall Variability on Streamflow

Figure 14 shows regression of seasonal rainfall on seasonal streamflow for the long rains (Figure 14a) and short rains (Figure 14b) seasons at the outlet of Turkwel River. These results show that rainfall variability is a good predictor of streamflow variability and hence water availability in this area. From the results, it was noted that a change in one mm of rainfall is likely to change the streamflow by 2.0 and 1.6 cms during the long rains and the short rains seasons respectively. The variation in streamflow that is explained by the variation in rainfall is reasonably acceptable at about 60% and 54% during the long and short rains seasons

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respectively given that this area is data scarce. The part of the streamflow variation that is not explained by the variation in rainfall could be attributed to other factors such as land use and land cover as well as the soil type characteristics in the basin.

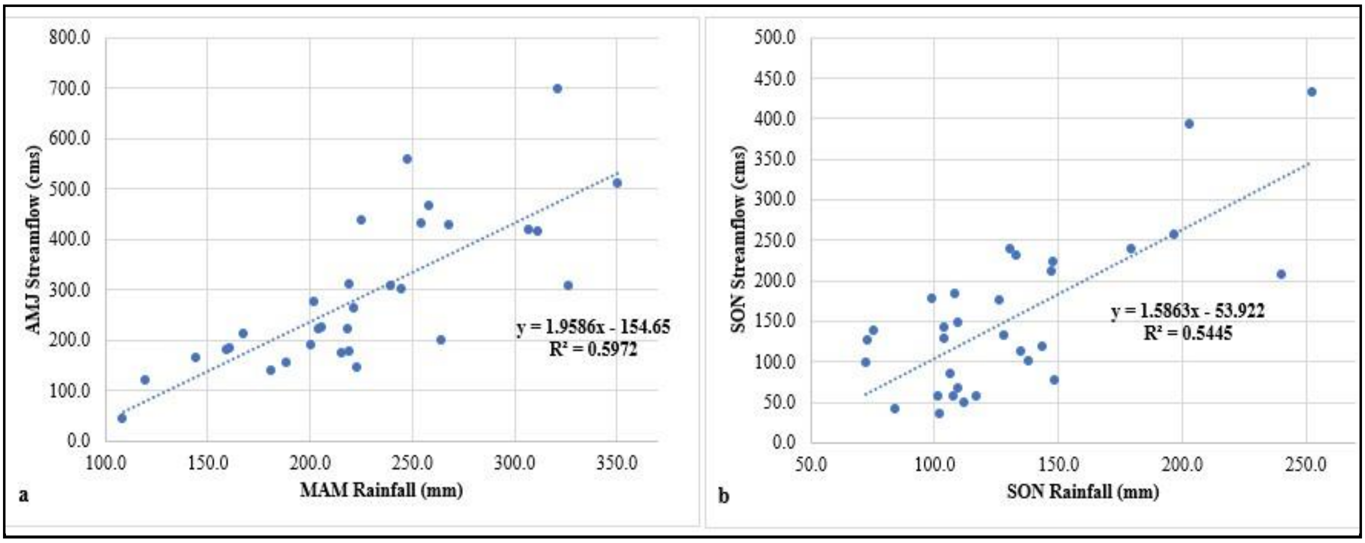

Figure 14: Linear regression of total MAM rainfall on the mean AMJ streamflow at the outlet of Turkwel River. Streamflow is highly dependent on rainfall as 60% of streamflow variability is influenced by rainfall variability

Given that over 50% of the variation in streamflow is explained by variation in rainfall, it may, therefore, be concluded that rainfall variability is indeed the main factor that affects water availability in this area. Water resources managers could, therefore, use rainfall variability as a predictor of water availability in the basin and other basins with similar characteristics to enhance resilience in climate extremes in dryland regions.

4. CONCLUSION

Rainfall and streamflow in Turkana County and Turkwel River Basin are highly variable and are currently on an upward trend in both MAM and SON rainfall seasons. However, projected rainfall and streamflow results indicated a likely shift in the seasonal rainfall distribution where MAM rainfall is expected to decrease while SON rainfall is projected to increase, thereby suggesting that SON is likely to become the main rainfall and streamflow season in the future.

Rainfall variability has a significant impact on water availability in drylands and use of hydrological modelling plays a pivotal role in illustrating its effects on streamflow and, consequently, water availability. Over 50% of variations in streamflow can be explained by rainfall variability and, therefore, rainfall may be used as an indicator of water availability in the area of study and any other area with similar characteristics.

Under the two climate change scenarios considered in this study, namely RCP4.5 and RCP8.5, MAM rainfall is generally on a decreasing trend while SON rainfall is on an increasing trend. This is an indication of a changing climate in the area, which suggests that more water is expected in the county during SON and less during MAM compared to the present as we move into the future. How this change in the distribution of seasonal water will be managed is likely to determine its impacts on the community's livelihoods.

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Conflict of Interest Statement

The authors declare no conflict of interest in as far as this study is concerned.

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