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Impacts of climate change on peak streamflow in Kakia-Esamburmbur Sub-catchment of Enkare Narok River catchment, Kenya

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Abstract Climate change has shown significant effects on catchment water balance mainly linked to hydrological extremes. Hence, the objective of this study was to predict the impacts of climate change on peak streamflow in flood prone Kakia-Esamburmbur sub-catchment of Narok County, Kenya. Soil and Water Assessment Tool (SWAT) was used to simulate the impacts of climate change on peak streamflow, whereas Gumbel distribution was used to project the peak flows (for base simulation and two climate change periods). Three climate change scenarios were simulated based on International Panel on Climate Change (IPCC) projected for the East Africa region. These scenarios were Representative Concentration Pathway 2.6 (RCP2.6), RCP4.5 and RCP8.5. Gumbel distribution method was used to determine the peaks of the simulated streamflow corresponding to 2, 5, 10, 50, and 100-year return periods (T). Model performance values obtained for calibration and validation were Nash-Sutcliffe efficiency (NSE): 0.57 and 0.52, coefficient of determination (R^2): 0.61 and 0.66, and percent bias (PBIAS): 5.8% and 24%. The simulation showed that the change in peak flood will respectively increase by 6.7% to 8.2% for Period 1 and between 18.5% and 24.3% for Period 2 for floods of return periods between 2 and 100 years. The findings of this study provide useful insights for developing flood risk management strategies for Narok town.

Keywords Climate change, SWAT, Gumbel's distribution, flood magnitude.

1. Introduction

Flood is one of the most catastrophic disasters in the world [1]. It is recognized as one of the main causes of property damage and loss of lives. Flood is therefore one of the most destructive natural hazards [2]-[3]. The Centre for Research on the Epidemiology of Disasters (CRED) in Brussels and the United States Office for Foreign Disaster Assistance (OFDA) estimated that flood affected more than 1.4 billion people and killed around 100,000 people all over the world in the later part of the 20th century [4]. It is further estimated that flood damaged property worth about $180 billion between 1991 and 1995 around the world [5]. In 2002, floods killed about 112 people in East Africa, out of which 46 were from Kenya [6]. Beside the loss of lives and the destruction of properties, floods also causes displacement of populace during flood events. For example, in 2002 more than 1,500 homes were destroyed by floods in East Africa [6]. In Kenya, 17 major floods were experienced between 1964 and 2004 with associated loss of lives and property [7]. the cost of infrastructures and property damage related to the 1997 and 1998 El Niño floods in Kenya was estimated at around $1.8 billion [8].

Many studies have been done to determine the causes of floods [2],[5],[9]-[11]. Some of the natural causes include heavy rainfall, climate changes, snowmelt, cyclones, dam breaches and tsunamis [10]-[11]. Increased urbanization related with population growth, improper land use practices, poor maintenance of drainage channels, and wanton deforestation are the main anthropogenic causes of floods [2],[12]-[13]. These causes act individually or in combination to intensify the impacts on floods. As stated earlier, heavy rainfall have great impacts on flood especially when climate change is taken into account. That is why during the summit of the African parliamentarians on climate change held on 13 October, 2009 at the United Nations Environment Programme (UNEP) offices in Nairobi, the Kenya's president stated that the impacts of climate change will mostly affect the environment, agriculture, health, water, infrastructure and energy sectors [8].

Temperature and precipitation are likely to vary in response to climate changes [14]. This implies that some of the areas prone to flooding will experience more frequent and higher magnitude of flood events. Increase in flood magnitudes will lead to higher flows that might exceed the design capacity of drainage channels and other hydraulic structures. Even if these structures were effectively designed, their capacity may turn out to be inadequate in such events [6]. Reliable information about present and future flood frequencies and magnitudes are therefore required for decision making and design of effective flood management structures.

The impacts of floods, due to climate change, in developing countries are likely to be more, when compared to developed countries, due to their limited capacity to manage floods [15]. Inadequate planning, poor monitoring and lack of adequate policies on flood risk management has a direct negative effect on mitigating the impacts of floods. In Europe for example, the European floods directive (2007/60/EC; EC 2007) guides European Union (EU) member countries on management of floods before, during and after a flood event. However, even with these measures in place, catastrophic floods still occurs, (such as 2013 flood in Rhine River), and this shows the importance of flood risk management strategy that should be reviewed and updated regularly [16]. Good planning for flood risks management calls for predicting future floods events. This includes estimating the magnitudes and frequency of such floods. Such predictions should take into account factors that might aggravate the floods such as climate change. In Kakia-Esamburmbur sub-catchment, a flood prone catchment in Narok County located in Kenya where this study was conducted, information on the impacts of climate change on future flood risks is lacking.

Kakia-Esamburmbur sub-catchment face extreme events and natural hazards, (i.e. floods during the rainy season and droughts during the dry season). In the past the catchment has experienced destructive floods leading to loss of lives and properties[17]. Since 1992, Narok town which Kakia and Esamburbur streams flow through has experienced scourges of flash floods [18]. The floods have affected agricultural activities, energy transmission, road infrastructures, livestock production, education, health, tourism, wildlife and loss of human lives [19]-[20]. In 2010, around three people lost their lives in Narok and in 2013, 15 people died in Narok county and about 350 people were displaced due to flood [21]-[22]. In 2012, Ewaso Ngiro South Development Authority (ENSDA) assessed the impacts of floods in Narok town and recorded the following statistics: two loss of lives, 101 loss of business properties, 87 damage to properties, 60 destruction of business premises and the cost of average daily income loss from business was estimated at $48,000 [23]. In April-May 2015, floods caused serious damages to people and properties in Narok including loss of 15 lives [24]. A previous study have shown that Narok County is sensitive to climate change characterized by droughts during dry seasons and floods during rainy seasons [25]. It is therefore evident that with climate change, occurrences of floods are likely to increase in terms of magnitude and frequency. However, there is no streamflow data available for Kakia-Esamburmbur sub-catchment and also no past studies that relate the climate change to flood magnitude within that sub-catchment. Simulation of past and future streamflow is useful to determine the magnitude of flood in Kakia-Esamburmbur sub-catchment. Hence, this study was carried out to predict the impacts of climate change on peak streamflow in the flood prone Kakia-Esamburmbur sub-catchment.

2. Materials and Methods

2.1. Study Area

Kakia-Esamburmbur sub-catchment falls within Enkare-Narok catchment and comprises Kakia (30.48 km^2) and Esamburmbur (15.72 km^2) sub-catchments (Figure 1). The confluence of Kakia and Esamburmbur streams is within Narok town, before draining into Enkare-Narok River. In spite of the small size of Kakia-Esamburmbur sub-catchment, compared to the larger Enkare Narok River catchment (971.08 Km^2), the two catchments are mainly attributed to flooding in Narok town. The altitude of the study area varies between 1828 m and 2147 m above the mean sea level. The catchment generally experiences two rainy seasons (bi-modal) in a year. The long-rain season is usually between March and May while the short one falls between October and December. The average annual rainfall is about 750 mm and average temperature varying from 8 ◦C to 28 ◦C [23]. The main land uses in the catchment are forestry, shrublands, pastures, agriculture, and urban. Agriculture, the main land use, is dominated by crops such as maize and wheat [26].

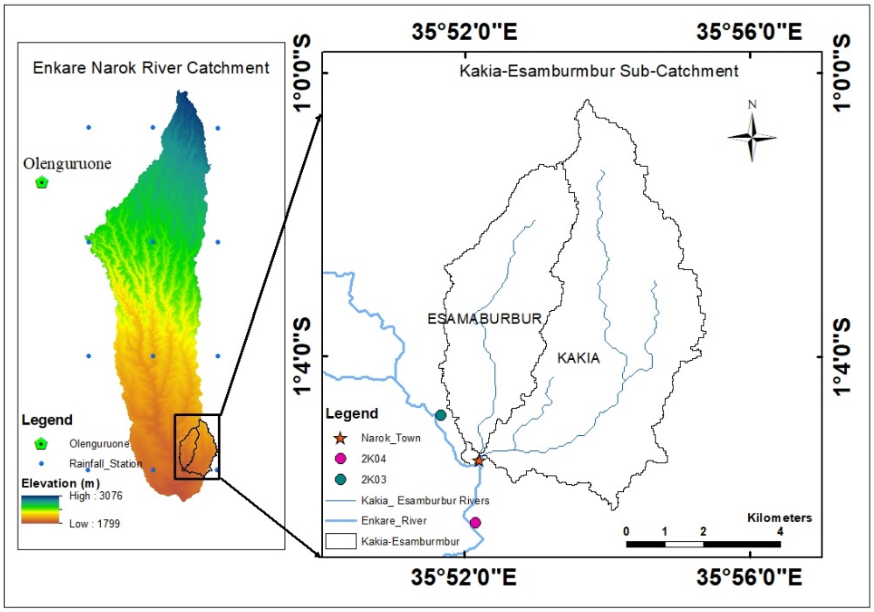

Fig. 1. Location and elevation characteristics of Kakia-Esamburmbur sub-catchment in Enkare Narok River catchment, Kenya.

2.2. Data acquisition and preparation

Soil, Water and Assessment Tool (SWAT) model was used to simulate streamflow under plausible impacts of climate change scenarios. The input data required for running SWAT include Digital Elevation Model (DEM), land use, soils and weather data (rainfall, temperature, solar radiation, relative humidity and wind speed). In addition, streamflow data is required for calibration and validation of SWAT. A 30 m resolution DEM of Enkare Narok River catchment was obtained from United States Geological Survey (USGS) at www.earthexplorer.usgs.gov. Land use map of the catchment was obtained from Kenya Sentinel2 LULC 2016 website (http://opendata.rcmrd.org/datasets/kenya-sentinel2-lulc-2016) prepared by the Regional Centre for Mapping of Resources for Development (RCMRD). Soil data was obtained from the harmonized continental KenSOTER derived database (SOTWIS) (https://www.isric.org/projects/harmonized-continental-soter-derived-database-sotwis) of the International Soil Reference and Information Centre (ISRIC). Daily wind speed, relative humidity and solar radiation data were obtained from global weather dataset (https://globalweather.tamu.edu) based on the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR). Daily minimum and maximum temperature data were collected from the National Aeronautics and Space Administration (NASA) for Prediction of Worldwide Energy Resource (POWER) website (https://power.larc.nasa.gov). Observed wind speed (1995-2010), and other climate data (relative humidity, solar radiation, temperature) of Narok were collected from Kenya Meteorological Department (KMD) on a daily basis from 1992 to 2010. Daily rainfall data were obtained from Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) (http://chg.geog.ucsb.edu/data/chirps) and Daily Observed rainfall data of Olenguruone (1970-1992) were obtained from KMD. The Kakia and Esamburmbur streams are not gauged. However, there are two River Gauging Stations (RGS) in Enkare Narok River, 2K03 and 2K04, which could provide streamflow data for this study. 2K03 is located at the old water supply station upstream of Narok town and 2K04 is located further downstream in Narok town (Figure 1). The daily discharge data of Enkare Narok River at 2K03 and 2K04 were obtained from the Kenya's Water Resources Authority (WRA). The quality of streamflow data from 2K04 was found to be poor and in comparison with data from 2K03, which is upstream, it was found to be inaccurate and hence not used for this study. Therefore, despite the many gaps in streamflow data for 2K03, it was the only option for calibration and validation of SWAT model in Enkare Narok River catchment, thus used for this study.

Projected changes in temperature and rainfall data under climate change for Representative Concentration Pathways 4.5, 2.6 and 8.5 was obtained from International Panel on Climate Change (IPCC) [14], [27]-[28]. Among various climate parameters, only projected rainfall and temperature were used as input data to simulate projected streamflow in Kakia-Esamburmbur sub-catchment. This is because they are the only climate parameters whose projected values are available from the IPCC [14].

2.3. SWAT Model set-up

SWAT is a physically based and computationally efficient model which was developed to predict the long term impact of sediment, land use, agricultural chemical yields, and land management practices on water in complex watersheds with varying soils, and management conditions over long periods of time [29]. SWAT 2012 was used to simulate streamflow in Kakia-Esamburmbur sub-catchment. Enkare Narok River catchment was delineated and subdivided into 33 sub-catchments and 33 hydrological response units (HRU's). The outlet of Kakia-Esamburmbur sub-catchment was set at the confluence of Kakia and Esamburmbur streams and Enkare Narok River. The Soil Conservation Service (SCS) Curve Number (CN2) method was used to calculate the surface runoff.

The SWAT model provides three methods for calculating evapotranspiration: Hargreaves, Priestley-Taylor, and Penman-Monteith methods. The FAO-56 Penman-Monteith is the most widely used method and has been recommended as standard for reference evapotranspiration [30]. However, Penman-Monteith method requires solar radiation, air temperature, wind speed, and relative humidity on daily basis as input while the Hargreaves method require daily temperature only, which can be measured with less errors than the three other parameters [31]-[32]. Additionally to that, Hargreaves is more applicable in arid and semiarid areas [32], which is the case for Kakia-Esamburmbur sub-catchment hence potential evapotranspiration (PET) was estimated using Hargreaves method.

2.4. Calibration and Validation of SWAT to predict streamflow in Kakia-Ensamburmbur sub-catchment

The SWAT model was setup with the main outlet at the confluence of Kakia and Esamburmbur streams and Enkare River (which includes Kakia-Esamburmbur sub-catchment), and calibrated at 2K03. This was because of the proximity and the similarities between the main catchment (Enkare Narok) and the Kakia-Esamburmbur sub-catchment. From knowledge of the catchment the Kakia-Esamburmbur is topographically similar to the main Enkare Narok River catchment. Additionally, there is a lot of similarity between Kakia-Esamburmbur sub-catchment and other sub-catchments of Enkare Narok River catchment in terms of soil types and land uses. Therefore, same change in parameters values attained during calibration were applied in the entire catchment (including Kakia-Esamburmbur sub-catchment). This is in line with a similar work done in a neighbouring catchment located in Narok and Bomet County, Kenya, where spatial proximity of two neighbouring sub-catchments (Nyangores and Amala) was considered during application of SWAT model in the Mara River basin [33]. In the study, SWAT model parameters for calibrated Nyangores sub-catchment were transferred to Amala sub-catchment. In Upper Tana watershed, spatial proximity also performed better than the global average and regression method in a study where model parameters had to be transferred from gauged sub-watersheds for streamflow simulation in ungauged sub-watersheds [34]. Many other studies have shown that simulating streamflow on ungauged catchments based on spatial proximity is the most reliable method followed by physical similarity [35]-[37].

The streamflow data from 2K03 was divided into two periods and one period was used for model calibration while the other period was used for validation. Calibration was done with streamflow data of the period between January 1985 to April 1990 and validation was done with data for the period ranging from August 1995 to March 1998. Four years prior to 1985 were used as warm up period. Data consistency was considered during the selection of calibration and validation periods. The selected period for calibration and validation was chosen because it had less gaps in observed streamflow data. Table 1 present the parameters that were manually adjusted to fit observed and simulated flows guided by available literature on SWAT model [38]-[40]. The values of CN were changed depending on the type of land use whereas the values of the soil available water capacity (SOL_AWC) were changed depending on soil type and different layers of each soil. The calibrated parameters values are also presented in Table 1. For validation, the calibrated parameter values were used without any further changes to validate the model with a separate streamflow dataset.

Table 1. SWAT parameters adjusted during the calibration process and their final calibrated values

Parameter Name	Description	Range	Calibrated Value
ESCO	Soil evaporation compensation factor	0.01 - 1.00	0.9
ALPHA_BF	Base flow alpha factor (days)	0 - 1	0.048
GW_REVAP	Groundwater ‘revap’ coefficient	0.02 - 0.2	0.2
SOL_AWC	Available water capacity of the soil layer (mm/mm soil)	0 - 1	Varying
CN2	SCS runoff curve number for moisture condition II	0 - 100	Varying
SHALLST	Initial depth of water in the shallow aquifer (mm)	0 - 5000	1000
DEEPST	Initial depth of water in the deep aquifer (mm)	0 - 10000	2000

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SWAT performance in Enkare Narok River catchment was evaluated using three statistical performance indices as recommended by [41]. Those indices are coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE) and percent bias (PBIAS) given in (1), (2) and (3) respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}}\right]^2 \quad (1)$$

$$NSE = \frac{\sum_{i=1}^{n}(O_i-\bar{O})^2-\sum_{i=1}^{n}(P_i-O_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2} \quad (2)$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(O_i-P_i)*100}{\sum_{i=1}^{n}(O_i)}\right] \quad (3)$$

where O_i is the ith observed value, P_i is the ith simulated value, $\bar{O}$ is the mean of observed data, $\bar{P}$ is the mean of simulated data and n is the total number of observations. The R^2 expresses a linear relationship that exist between the observed and simulated flow and is also considered as a reference in performance evaluation because it is widely used [42]. However, it only takes into account the dispersion between observation and prediction since it only evaluates the linear relationship between the two variables [43]. Another disadvantage of R^2 is that it is oversensitive to extreme values (outliers) and insensitive to additive and proportional differences between model predictions and observations [44]. On the other hand, the NSE is highly sensitive to outliers, extreme values, sample size, and bias in magnitude and time-offset [45]. However, one of the disadvantages of NSE is that it is also not very sensitive to systematic model over or under prediction especially during low flow periods since the differences between observed and predicted values are calculated as squared values [43]-[46]. As a result, larger values in a time series are strongly overestimated whereas lower values are neglected [43]-[47]. To overcome those weaknesses, PBIAS was also used since it helps to identify average model simulation bias (overprediction versus underprediction) [42]. PBIAS measures the average tendency of simulated flow being smaller or larger than the observed streamflow[48].

2.5. Prediction of impact of climate change on streamflow

The predicted monthly changes in temperature and rainfall for the study area (East Africa region) projected by the IPCC [14] under RCP4.5 over the near term (2016 - 2035) and the mid-term (2046–2065) periods are given in Tables 2 and 3. These projections were based on the distribution of an ensemble of 42 models used in CMIP5 since the aim of our study was to estimate the sensitivity of streamflow in Kakia-Esamburbur sub-catchment based on general future projections. In this study no outputs from any of the 42 GCMs was selected and none of them were downscaled, but the values presented in Tables 2 and 3 have been estimated at 50th percentile of the CMIP5 distribution. A study conducted by [49] investigated whether using a subset of GCM can reduce uncertainties in modelled future change in runoff in south Asia. They found little difference in the projections from using only the 'better' performing GCMs versus using all 42 GCMs. The study recommends use of projections from all the available GCMs to provide an indication of the full range of uncertainty. Therefore we adopted and used the seasonal projected values of rainfall and temperature for the region (Tables 2 and 3) based on all the 42 GCMs. These values, however, compare well with those of other studies that have used specific GCMs of the CMIP5 for the same region [50]-[52]. The finding of these studies are that in the 21st century, temperature and rainfall will increase at a rate of 0.2^{0}C and 0.5^{0}C per decade and 10% and 20%, respectively under the RCP4.5 and RCP8.5 scenarios. Based on the reported changes in temperature and precipitation, SWAT model was run to simulate the predicted streamflow under climate change as Periods 1 and 2 (Tables 1 and 2). No other data were added or changed apart the precipitation and temperature data for streamflow simulation in periods 1 and 2. The calibrated and validated model with the current (observed) weather data was used as the reference simulation base period (1985-2013) to assess the change in peak discharge.

Table 2. Projected monthly temperature changes (^{0}C) under RCP 2.6, 4.5 and 8.5 for the East Africa region.

Month	RCP	2016-2035 (Period 1)	2046-2065 (Period 2)
Dec – Feb	2.6	1	1
	4.5	1	1.5
	8.5	1	2
March-May	2.6	1	1
	4.5	1	1.5
	8.5	1	3
June-August	2.6	1	1.5
	4.5	1	2
	8.5	1	3
September-November	2.6	1	1
	4.5	1	1.5
	8.5	1	3

Table 3. Projected monthly precipitation changes (%) under RCP 2.6, 4.5 and 8.5 for the East Africa region.

Month	RCP	2016-2035. (Period 1)	2046-2065 (Period 2)
October - March	2.6	10	10
	4.5	10	10
	8.5	10	20
April - September	2.6	0	10
	4.5	0	0
	8.5	0	0

2.6. Estimation of peak streamflow in Kakia-Esamburmbur sub-catchment

Gumbel distribution, also known as Extreme Value type I (EVI) method (Equations 4-6) [53] was used to estimate the magnitude of floods of selected Return Periods (T). The flood magnitudes were estimated for 2, 5, 10, 50 and 100 years return period (T). Across the three simulation periods, the simulated yearly maximum annual flood peaks were used to predict expected flow for a given return period using flood frequency analysis (4-6).

$$X_T = \bar{X} + K.\sigma \tag{4}$$

$$K = \frac{Y_T - \bar{\bar{Y}}n}{\sigma_n} \tag{5}$$

$$Y_T = -\ln\left[\ln\left(\frac{T}{T-1}\right)\right] \tag{6}$$

where X_T is the magnitude of the flood; $\bar{X}$ is mean of the maximum instantaneous flow; K is a frequency factor; σ is standard deviation; Y_T is a reduced variate; $\bar{\bar{Y}}_n$ is reduced mean; σ_n is reduced standard deviation; T is the return period. Gumbel distribution was adopted in this study because of its simplicity as well as its wide application in modelling extreme events in previous studies [54]-[55].

3. Results and Discussion

3.1. SWAT model calibration and validation

The monthly calibration and validation hydrographs (Figures 2) show a good fit between the observed and simulated streamflow. The calibration hydrograph (Figure 2a) has a better fit than the validation hydrograph (Figure 2b). Nevertheless, it can be noticed from Figure 2b that the quality of data during the validation period was low i.e. the data had many long gaps varying from days to months e.g. 33% was missing between August 1996 and February 1997. Despite the low quality of data, the fit was considered satisfactory as it would be difficult to fit the hydrograph where there is no observed data and filling missing long continuous data was not feasible. The results could also have been affected by the quality of the input data, particularly climatic data which was largely satellite based. It can however be seen that there was a better fit of low flows than high flows.

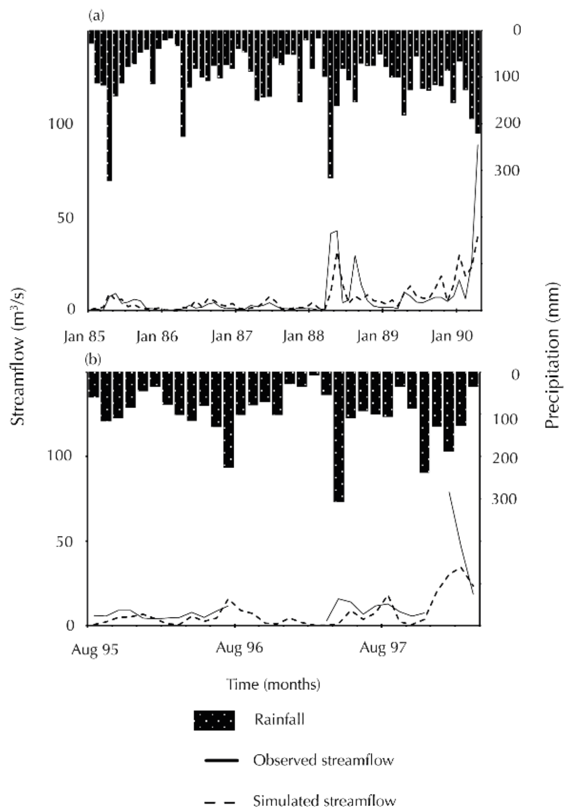

Fig. 2. Observed and simulated monthly flows for (a) calibration period and (b) validation period.

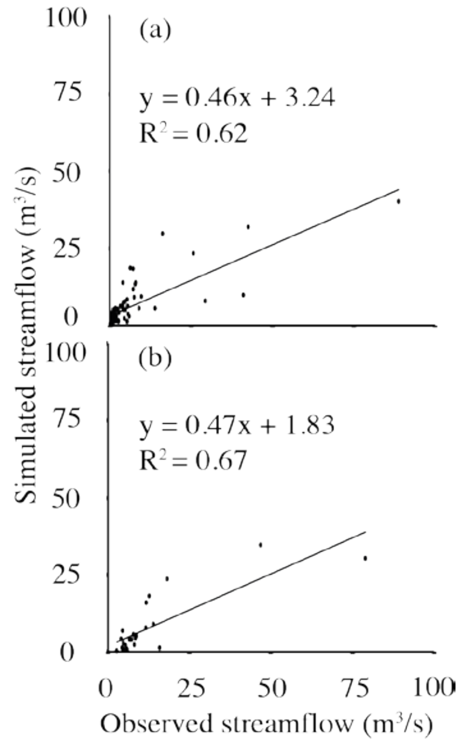

Fig. 3. Scatter plot of monthly streamflow for (a) calibration from January 1985 to April 1990 and (b) validation from August 1994 to March 1998.

The fit between observed and simulated flows is also reflected in the statistical measures of model performance (R^2, NSE, and PBIAS) presented in Table 4. The statistical results for calibration (January1985–April 1990) and validation (July 1994–March 2010) periods (Table 4, Figure 2a,b and Figures 3a,b) indicate that the model produced satisfactory results for both calibration and validation periods based on criteria given by [40] and [42]. R^2 values during calibration and validation periods were 0.61 and 0.66, respectively. NSE values of 0.57 and 0.52 were obtained for calibration and validation period, respectively. According to [41], the monthly NSE values for streamflow between 0.50 and 0.65 are considered satisfactory while values of efficiency between 0.75 and 0.36 were considered satisfactory for [48]. The PBIAS values obtained for calibration and validation were 5.8% and 24%, respectively. According to [41], the PBIAS of ±15 < PBIAS < ±25 was considered satisfactory and PBIAS < ±10 to be very good. For Van Liew et al [48], values of PBIAS between ±20% and ±40% were considered satisfactory for streamflow. Hence in this study the results of calibration and validation were considered satisfactory.

Table 4. Monthly Streamflow calibration and validation statistics

Statistic	Calibration	Validation
R^2	0.61	0.66
NSE	0.57	0.52
PBIAS	5.8%	24%

The model performance statistics values obtained in this study shows that the model performed better during calibration than validation period (Table 4). However, the values obtained for both calibration and validation exercise are still within acceptable range [40]-[41]. The positive values of 5.8% and 24% for PBIAS indicate that the flow was slightly underestimated during both calibration and validation periods [56]. This may be attributed to the underestimation of high flows. As it can be seen in Figure 2a and 2b, the model underpredicted the high peaks e.g. March-May 1988. This may have been caused by error in data collection (gauge height) during high flows or errors in extrapolation in a rating curve when converting gauge height to discharge for high flows [57].

3.2. Impact of climate change on magnitude of flood peaks in Narok

The projected change in climate data (Table 2 and 3) was used to simulate the plausible future streamflow due to climate change. From that the maximum monthly stream flow in Kakia-Esamburmbur sub-catchment was simulated and presented in Figure 4.

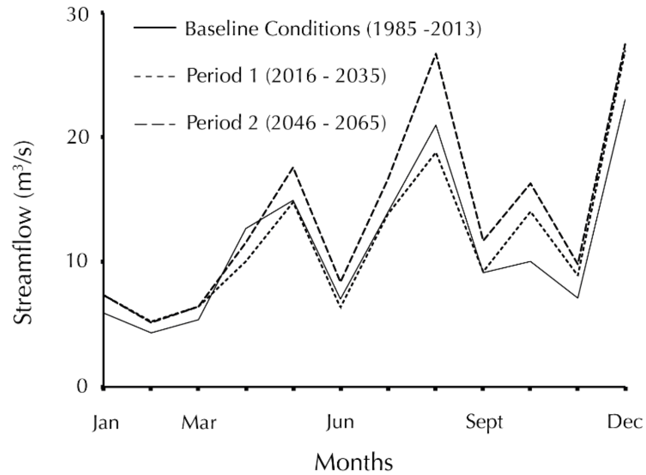

Fig. 4. Baseline and future maximum monthly streamflow in Kakia-Esamburmbur sub-catchment.

It can be observed that streamflow varies with climate change and that future monthly peak streamflow is generally higher than the baseline conditions. This is in line with a study done by [58] which found that climate change in western Kenya will lead to a significant increase of stremflow in 2050s than in 2020s. Between the months of April and September the peak flow for Period 1 is less than the baseline flow. This is due to the fact that from the projected changes in climate for the catchment (Table 3), there will be no change in rainfall but there is an increase of temperature by 1^0C. This is likely to cause an increase in evapotranspiration [33] and hence more water is lost from the catchment (through evapotranspiration) leaving less water for streamflow and hence the observed decrease in monthly peak flow. Another observation which can be made is that the increase of streamflow is caused by a small change in climate parameters. In fact, the increase in temperature is 1^0C and 10% (October-March) for precipitation during period 1 while for period 2, the increase in temperature will be between 1.5^0C and 2^0C with a monthly increase of 10% rainfall.

Simulated impact of climate change on the magnitude of peak floods for the two climate change periods show an increasing trend (Table 5). The results were calculated by frequency analysis using Gumbel distribution of simulated stream flow under climate change.

Table 5. Projected peak flows (floods) of Kakia-Esamburmbur sub-catchment under climate change*.

Return periods	Flood magnitude (m^3/s)			Change in Peak flow (%)	
	Baseline conditions (1985 -2013)	Period 1 (2016-2035)	Period 2 (2046-2065)	Period 1 (2016-2035)	Period 2 (2046-2065)
2	13.6	14.7	16.9	8.2	24.3
5	17.1	18.4	20.9	7.6	22.1
10	24.7	26.5	29.6	7	19.5
50	28	29.9	33.3	6.8	18.9
100	29.9	31.9	35.4	6.7	18.5

**Based on 50% percentile of all GCM in CMIP5 for RCP4.5 scenario*

Gumbel distribution predicts that for the baseline conditions, the most probable flood (return period of 2 years) has a value of 13.6 m^3/s while the most extreme (return period of 100 years) is about 30 m^3/s (Table 5). Thus, even without climate change, if an extreme flood occurs (e.g. 100 year flood), the hazard will be more than double the common (most probable) flood experience in the catchment. This 100-year flood can be very disastrous for Narok town (in terms of loss of lives and property) which has low capacity to handle such floods. Although this is a rare flood to occur it can occur any time and the flood risk may be quite high for Narok town which is largely located on a flood plain. This is an indicator that even without climate change Narok town needs to prepare adequately for such a flood.

The percent change in flood magnitude due to climate change were calculated in comparison to the base conditions (1985-2013). Results shows that for Period 1 (2016-2035 period) there will be an increase of 8.2% in peak flow of return period (T) of 2 years. The change in peak flow for this period varies between 6.7% and 8.2% for T between 2 years and 100 years with more frequent floods having a higher percent increase (Table 5). However, this may still cause substantial damage to lives and properties considering the fact that the town does not currently have the adequate capacity to handle the existing (past) flood events, even without considering climate change. The rise in peak floods will increase further during 2046-2065 period. The increase will be between 18.5% and 24.3% when compared to baseline flood flows (Table 5). As indicated in Period 1 (2016-2035), the percentage change in peak flood is higher for more probable floods. This is a substantial change in flood hazard that would pose a high flood risk if proper flood risk management plans/strategies are not put in place. The flood risk may even be higher due to possible expansion of Narok town and increase in investments that would be more vulnerable to floods. It can also be noted that for Period 2, the 10-year flood is equivalent to the 100-year flood under baseline conditions. This implies that the frequency of what we currently consider as rare flood events in the area will increase under climate change [58]. It is therefore paramount that the County Government of Narok and the Kenya's national government agencies responsible for flood management in Narok develop flood management plans for Kakia-Esamburmbur sub-catchment, as the floods will become more catastrophic and more frequent. Similar findings have also been observed elsewhere. For example, a study done by [9] found that return periods of historical 100 year floods in the northernmost regions of Canada and South-western Ontario were projected to become 10–60 year return period events in the future.

Four RCPs scenarios namely RCP2.6, RCP4.5, RCP6.0 and RCP8.5 are projected by the IPCC [14]. There is no preference assigned to one scenario compared with others [59] but their particularity is based on the potential emissions from human activities, natural causes or both. To consider the impact of uncertainties of future emissions on flooding, additional simulations to the one using RCP 4.5 were made based on two extreme IPCC projections i.e. RCP2.6 and RCP8.5. For 2016-2035 period, the predicted change in peak flood for RCP2.6 and RCP8.5 remain the same as the one of RCP4.5 (Table 5). This is because the projected changes in rainfall and temperature does not change for the 3 RCPs (RCP2.6, RCP4.5 and RCP8.5) as presented in Tables 2 and 4. While evaluating the contribution of climate change on discharge in upper Mara River, [33] also found out that there was no variation in streamflow for 2016-2035 period. Results of Table 6 shows that compared with RCP4.5, peak flood will decrease under RCP2.6 while it will increase under RCP8.5. The predicted potential increase in peak flood for all return periods in Kakia-Esamburmbur sub-catchment therefore varies according to the actual future emissions. Thus, the predicted potential increase in peak flood under RCP4.5 for 2046-2065 period could fall anywhere in the range between projected peak floods under RCPs 2.6 and 8.5.

Table 6. Predicted change in peak flows (floods) based on different IPCC emission projection scenarios.

Return periods	Flood magnitude (m^3/s) for the period 2046–2065		
	RCP2.6	RCP4.5	RCP8.5
2	16	16.9	17.3
5	20	20.9	21.5
10	28.9	29.6	30.9
50	32.6	33.3	34.8
100	34.8	35.4	37.1

This study gives relevant information about future flood magnitude that can be helpful to designers and planners for decision making about flood risk plans and strategies within the sub-catchment.

4. Conclusions

The objective of this study was to evaluate the impact of projected climate change on peak flood in Kakia-Esamburmbur sub-catchment. Projected changes in temperature and rainfall were used to simulate change in streamflow for the catchment using SWAT. Simulated stream flow for base simulation (1985-2013) and two climate change periods of Kakia-Esamburmbur sub-catchment were used for flood frequency analysis using Gumbel distribution. The two climate change periods were Period 1 (2016-2035) and Period 2 (2046-2065). The impact of climate change to peak floods were calculated based on variation in flood peak for each climate scenario with reference to base condition. Generally, climate change will increase the magnitude of floods in Kakia-Esamburmbur sub-catchment and thus the flood risk in Narok town will get higher. The magnitude of floods under climate change will have an increase between 6.7% and 8.2% for floods in 2016-2035 period and between 18.5% and 24.3% in 2046-2065 period under RCP4.5 scenario. Under climate change, floods that are currently considered rare in Kakia-Esamburmbur sub-catchment will become more frequent. For example, a 100-year return period flood is projected to become a 10 year return period flood in the future (2046-2065) under climate change. From the findings (of increase of magnitude and frequency of extreme floods in the future) we recommend Narok County Government to develop flood risk management strategies that should cover Narok town but also extend to the catchment where the flood water is generated. We also recommend further study to develop flood hazard and risk maps to show the extent of the flooding in Narok town that would be caused by the flood magnitudes reported in this study.

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