Tanzania Journal of Science 48(1): 99-108, 2022
ISSN 0856-1761, e-ISSN 2507-7961

Suitability of Flood Hazard Assessment Methods for Tanzania: A Case of Little Ruaha and Upper Ngerengere Catchment

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Received 28 Aug 2021, Revised 18 Mar 2022, Accepted 20 Mar 2022, Published Mar 2022
DOI: https://dx.doi.org/10.4314/tjs.v48i1.9

Abstract

Understanding the applicability of flood quantile estimation methods in flood hazard assessment is fundamental for planning, prevention, and management of flood risks. Therefore, this study evaluates and compares three hydrological methods, namely Hydrologiska Byråns Vattenbalansavdelning (HBV), Soil Conservation Service-Curve Number (SCS-CN), and regional regression equation (RRE), to estimate flood quantiles embedded in the existing flood damage assessment framework by applying them to two different river catchments, Little Ruaha (LR) and Upper Ngerengere (UN), Tanzania. The evaluation of method performance was carried out using three standard statistical measures for data from 1954 to 2010 and the 1971–1988 period in LR and UN catchments (LRC and UNC). The findings indicated that no single approach could fit all catchments and return periods for these case studies. Overall performance indicated that the RRE method provides more accurate and consistent quantile estimates than other approaches. These findings indicate that spatial scale, model structure, parameters, and hydro-climatic data condition are the most important elements influencing the suitability of the supplied methods for flood risk assessments, which serve as the foundation for developing an improved flood damage assessment framework.

Keywords: Flood Quantiles; Estimate Methods; Flood Risk Management; Little Ruaha; Ngerengere

Introduction

Riverine floods have posed persistent risks to people who live in low-lying areas and floodplains (Valimba and Mahé 2020). Floods of different magnitudes have repeatedly occurred in various flood prone areas as well as the usually none flooding areas. Typical overflows during flooding events have characterized the floodplains although instream (within the channel) flooding has been observed in highland and lowland rivers. Historical overflows and instream flooding have caused a number of fatalities, damages to properties and infrastructures where they had occurred, mainly in floodplains. Such occurrences in highland and lowland areas indicated imminent risks of humans and ecosystems to impacts of flooding in different landscapes. As such, the management of flood risks and associated damages is vital to protect people's lives and properties, and infrastructures.

Assessment of flood risks for managing flood damage has traditionally involved the use of flood risk assessment frameworks consisting of flood hazard and vulnerability assessments. Flood hazard assessment quantifies flood magnitudes (flood quantiles) and their spatial spreads (inundation mapping) with different return periods useful for planning, prevention, and management of flood risks (Winter et al. 2019). Linking flood magnitudes (Q) to their return periods (T) has used flood frequency analysis (FFA) methods on sequences of indices of flood flows (annual maximum, peaks over threshold) extracted from long historical observed streamflow records to produce flood quantiles (Q_T) (Kidson and Richards 2005). The challenge of the lack of long streamflow records has necessitated the reconstruction of long records by i) hydrological models relating river discharges to climatic (and land characteristics) inputs, or ii) estimation of flood quantiles from rainfall quantiles using long rainfall records.

Various flood quantile estimation methods are embedded in different flood risk assessment frameworks. Each framework, however, uses a specific flood quantile estimation method. The widely used methods in flood risk assessment frameworks are the rational method used in the SUFRI framework (Bueno et al. 2011), HBV rainfall-runoff model and FFA in Damage Scanner framework (Klijn 2009), regional regression equations in HAZUS-MH framework (FEMA 2009), curve number method in Fragility curves framework (de Risi et al. 2013) and integrated hydrological and hydraulic modelling approach in KKU-SJNK framework (Kobayashi et al. 2016). The performance of different flood quantile estimation methods depends on spatial-temporal variations of climate and catchment characteristics (i.e. rainfall, evapotranspiration, soils, land surface cover, geology, surface storages, etc) (Baroni et al. 2019, Iacobellis et al. 2013, Siderius et al. 2018).

The availability of long and reliable streamflow or climate data affects selection among existing flood quantile estimation methods in such a way that FFA is used when long, continuous streamflow records are available. FFA/hydrological modelling (for record extension) is applicable for short or long-gapped streamflow records, while rainfall quantiles extracted from intensity-duration-frequency (IDF) curves are used in cases with missing streamflow records. The use of specific flood quantile estimation methods embedded in the existing flood risk assessment framework for highly variable Tanzanian climate and physiography might result in under- or over-estimation of flood magnitudes leading to under- or over-estimates of flood damages. This study, therefore, aimed at testing the suitability of the embedded HBV model/FFA, Curve number (CN) method and Regional Regression Equation (RRE) for estimating flood quantiles in gauged medium-sized Little Ruaha catchment and small Upper Ngerengere catchment.

Materials and Methods

Description of study catchments

Since the need is to assess the suitability of the three methods (HBV model/FFA, curve number SCS-CN and Regional Regression Equation-RRE) against FFA on observed streamflow, the selection of study catchments considered the availability of long, continuous daily river discharges. Additionally, the selected catchments are small and moderate sizes, located in different physiographic conditions, and have different flow regimes.

Upper Ngerengere catchment

The small mountain upper Ngerengere sub-catchment (18.33 km^2) is part of the Ngerengere River catchment in the Wami/Ruvu Basin and is located between latitudes 6°54 and 6°58 South and longitudes 37°36′0 and 37°39′East (Figure 1). The sub-catchment has a rugged topography, with elevations ranging from 2,260 m at the Uluguru Mountains' summit to 600 m at Konga's outlet. The catchment is drained by River Ngerengere as a confluent river of its Kinungwe and Lumambwe tributaries with its headwaters in the north-western part of the Uluguru Mountains. Such an altitudinal drop corresponds to an average river slope of 0.4 m/m making it a steep sloping river. The climate within the catchment is characterised by a bimodal rainfall regime whereby the early short rains (vuli) occur in November-January and long rains (masika) are received in March-May. The average annual rainfall amounts range between 1,000 mm and 2,300 mm. The mean annual temperature is 25 °C, while the maximum daily temperature can reach 34–36 °C in December-February, and the minimum daily temperatures can drop to 11 °C. Acrisols soil types dominate the area with land use cover of forest, cropland and bushland. The rural landscape is dominant with small rural centres at Konga and Mondo.

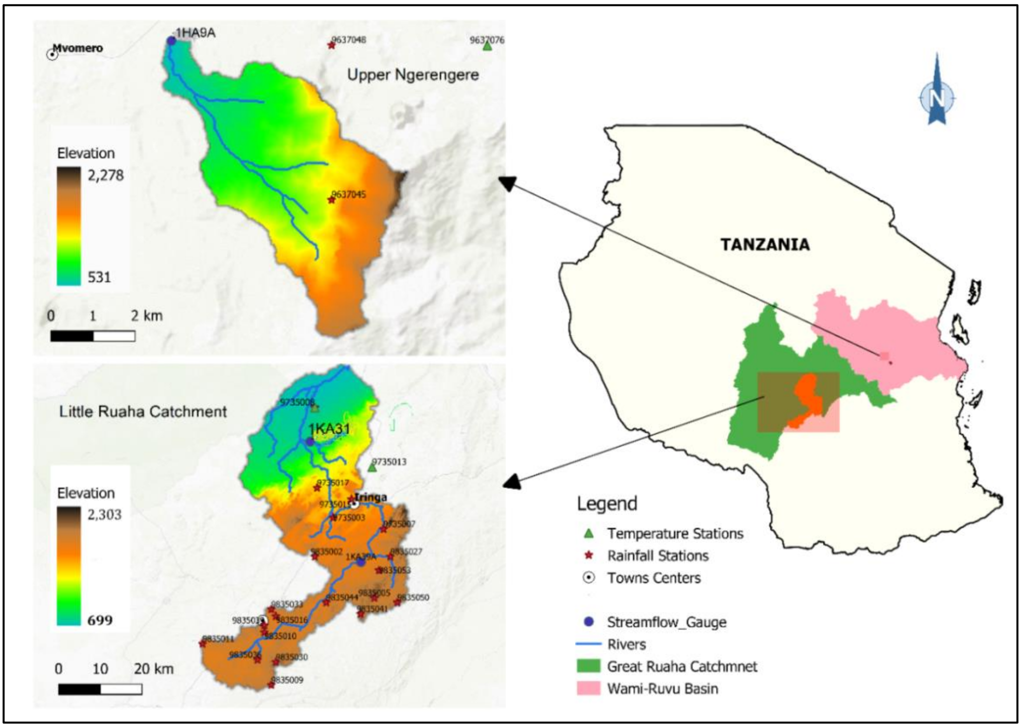

Figure 1: Overview map of Upper Ngerengere and Little Ruaha study catchments including available precipitation, temperature and discharge stations.

Little Ruaha catchment

The Little Ruaha catchment is a medium-sized (area: 5,193 km^2) upstream tributary of the Great Ruaha River (GRR) within the Rufiji River Basin. It lies within longitudes 35°2' and 35°36'East and latitudes 7°11' and 8°36'South (Figure 1). The large catchment is sub-divided into two study sub-catchments with outlets at Mawande (entire catchment area: 5,193 km^2). The area's topography varies from the flat area with an altitude of approximately 650 m to high mountainous ranges above 2,300 m. The river originates from Poroto and Kipengere Mountains in the southern highlands at an elevation of 3000 m. The catchment is drained by the little Ruaha River as a principal tributary with its headquarter on the western sides of southern highlands. As a result, the altitude decrease corresponds to an average river slope of 0.004 m/m. The river flows vary correspondingly with the rainy season. The rainfall regime is mainly unimodal with the rainy season that extends between late November/early December and late April/Early May. Mean annual rainfall varies from 500 mm in lowlands to 700 mm in the highlands, while mean annual temperature ranges from 18 °C at higher altitudes to 28 °C in the lowland. The dominant land cover in the sub-catchment is cultivated land (~60%), the built-up area is less than 1%, while the remaining area comprises savannah, forests, grasslands and shrubs. Cambisols, fluvisols, leptosols, acrisols, lixisols, nitisols, and solonetz are among the soil types found within the catchment.

Materials

Discharge data

Records of observed daily discharges at the outlet of the Little Ruaha catchment (1KA31) and for the Upper Ngerengere catchment (1HA9A) were selected for this study. FFA requires long, most continuous discharge data available for 32-42 years within the 1952-1994 period at the selected catchments (Table 1). Available discharge data indicates a preference occurrence of annual maximum daily discharges in March and April. Consequently, annual maximum flow series were extracted for all years with continuous data in March and May or otherwise, the value was considered missing.

Table 1 Available discharge, rainfall and temperature data in study catchments

Catchment	Discharge	Catchment rain	Temperature
1HA9A	25/3/1954–31/12/1988	1/1/1966–31/12/2009	1/1/1971–31/12/2016
1KA31	1/1/1957–31/3/2010	4/1/1950–31/10/2010	1/1/2009–28/2/2020

Rainfall and evapotranspiration data

HBV modelling requires concurrent availability of daily discharge, average temperature and evapotranspiration (also represented by long-term available monthly values). Rainfall data were available at 2 and 10 rain gauges in UNC and LRC, respectively. However, with different data availability periods and lengths within the 1950–2007 grand period, were used to construct catchment rainfall series in the 1950–2010 (LRC) and 1966–2009 (UNC) periods (Table 1) by the arithmetic mean method. Maximum daily rainfall quantiles were obtained by frequency analysis similar to FFA using EasyFit software. The rainfall quantiles were obtained for each record and for the catchment series. The low catchment rainfall quantiles were corrected by a factor computed as the ratio between interstation average quantiles and catchment quantiles.

Daily minimum and maximum temperature records collected span 1 January 2009–28 February 2020 period at Iringa Met station (LRC) and 1 January 1971–31 December 2016 at Morogoro Met (UNC) (Table 1). Since these records do not extend in the earlier periods, they were extended to 1 January 1957 (LRC) and 1 January 1966 (UNC) by the Fourier method (e.g. Iwok 2016). Daily evapotranspiration data were not available and were computed from daily temperatures by the Hargreave-Samani model (Samani 2000).

Land use/cover data

The land use/cover data for Little Ruaha and Upper Ngerengere catchments were derived from Africa Land Cover Characteristics Data Base Version 2 from 1992 with a resolution of 1000 m (Loveland et al. 2000) and Landsat 1-5 MSS C1 level 1 from 1975, respectively. The maps gave seven land use classes of barren (or sparsely vegetated), cultivated cropland, forest, grassland, savanna, shrubland and urban (built-up) land in LRC and UNC.

Catchment physiographic characteristics

Soils data

The soils data downloaded from Harmonized World soil database (FAO/IIASA/ISRIC/ISS-CAS/JRC 2009) FAO website (www.fao.org/AG/agl/agll/dsmw.htm) were used to determine soil types and hydrological soil group of the study catchments. The NRCS.TR-LookUp table (USDA-NRCS 1986) gave six soil types: cambisols, fluvisols, leptosols, lixisols, nitisols and solonetz in LRC and only acrisols and ferrasoilsin Ngerengere. LRC is dominated by acrisols (34%) and nitisols (33%).

Topographical data, catchment boundaries and hydrographic network

The digitally available georeferenced topographic 1:50,000 maps were obtained from the GI Lab database of the Institute of Resources Assessment (IRA) of the

University of Dar es Salaam and used to extract catchment boundary, locations (latitude, longitude, and altitude), river network, slope, catchment outlets and river flow lengths.

Methods

Flood frequency analysis

Flood frequency analysis (FFA) was carried out on annual maximum series by fitting probability density function (pdf) using EasyFit software, which included 61 pdf. The best fitting pdf were selected based on the three goodness of fit test (Kolmogorov-Smirnov (K-S), Anderson Darling (A-D) and Chi-Squared (χ^2)) (http://www.mathwave.com) and quantile-quantile (Q-Q) plots. The best four ranked pdf were initially selected using average ranks (the average of the ranks for each goodness-of-fit criterion). Thereafter, Q-Q plots were examined to identify the ranges where each pdf provided the best quantile estimates (plots close to the 45^o line). Flood quantiles were computed for return periods of 2, 5, 10, 25 and 100-yearsusing StatAssist of EasyFit software. FFA was used on observed and reconstructed (by HBV modelling) long discharge and rainfall series.

Hydrologiska Byråns Vattenbalansavdelning (HBV) modelling

The HBV modelling is usually used in record reconstruction (filling and/or extending) short and/or gapped discharge records using available long continuous climate records (Huang and Bardossy 2020). Its description is provided in Seibert (2005) and Seibert and Vis (2012). However, for the purpose of this study, available long continuous records at selected gauging stations were deliberately shortened (to extend in the 1 October 1955–30 September 1980) and gaps introduced within this period. Used periods in Little Ruaha and Ngerengere catchments for calibration were 1990–1999 and 1972–1981, respectively, with available continuous climate and discharge records, which were considered sufficient (Li et al. 2010, Razavi and Tolson 2013). HBV models were validated for 2003–2007 and used to fill and extend discharge records to 30 September 2010. Calibration of HBV involves automatic calibration using the embedded Genetic Algorithm and Powell (GAP) optimisation procedure and manual calibration of parameters to reflect catchment characteristics. Model performance was evaluated visually by observing hydrograph plots for the efficacy of reproducing flow peaks and statistically by the Nash-Sutcliffe coefficient of efficiency (NSE). The reconstructed (filled and extended) discharge series were then used in FFA.

Soil Conservation Service- Curve Number (SCS-CN) method

The SCS- CN method is a physically-based and spatial distributed method in which the discharge is estimated by rainfall and water catchment coefficient represented by the curve number. The curve number coefficient is a function of land use/cover and hydrological soil group of the catchment. ArcGIS HEC-GEO HMS was used to extract land use/cover and hydrologic soil groups data within the study catchments, and the look-up table was defined based on the standard SCS curve number table. The area-weighted CN was determined for each grid cell considering the three classes of antecedent moisture conditions (AMC). The antecedent moisture conditions are AMC I for practically dry (wilting point) catchment conditions, AMC II for average conditions, and AMC III for practically saturated (wet) catchment conditions. The potential maximum retentions (S) from each CN were computed from

$$S = \frac{25400}{CN} - 254 \qquad (mm) \qquad (1)$$

Consequently, CN II was computed as the curve number CN from the above equation as

$$CN = \frac{25400}{S+254} \qquad (2)$$

CN values for AMC I and AMC III were calculated from (Chow et al. 1988)

$$CN(I) = \frac{4.2CN(II)}{10-0.0588\times CN(II)} \qquad (3)$$

$$CN(III) = \frac{23CN(II)}{0.13\times CN(II)} \qquad (4)$$

Runoff (Q) and peak discharges (q_p) estimates were determined from each grid cell using the following equation:

$$Q = \frac{(P_T - 0.2S)^2}{(P_T + 0.8S)} \qquad (5)$$

$$q_p = 0.208\,\frac{AQ}{T_p} \qquad (6)$$

where Q is and design daily rainfall quantile (P_T) are in mm, q_p in m^3/s, catchment area in km^2) and Tp is time to peak obtained as 0.7 of time of concentration (t_c), which was computed from Kirpich method.

Regional regression equation (RRE) method

The regional regression equations developed by Mkhandi et al. (2000) were adopted. The equations are based on flood discharge and catchment characteristics such as maximum annual flow (MAF). The equations are of the form

$$Q_T = T_T \times MAF \qquad (7)$$

where Q_T is the estimated flood quantile (m^3/s), T_T is the regional statistical growth factor for T years and MAF is the mean annual flood (m^3/s).

The homogenous region map for Tanzania by Mkhandi et al. (2000) was used to determine the case study region. Little Ruaha and Upper Ngerengere catchment boundaries were superimposed on Tanzania's homogenous flood region map to identify the regions falling within the study catchment regions: Tan 12 and Tan 5. Maximum annual floods (MAF) were computed from annual maxima for the periods 1954–2010 (Little Ruaha) and 1971–1981 (Ngerengere). The T_T value was approximately extracted from the regional frequency curves (Mkhandi et al. 2000).

Suitability assessment of flood quantile methods

The suitability of performance of each quantile estimation method was evaluated against the FFA quantiles estimated from the observed series. This study employed percentage bias (PBIAS), Nash–Sutcliffe coefficient of efficiency (NSE) and the ratio between root mean square error and root squared deviation of observed data (RSR) statistical criteria. The three criteria were calculated as

$$PBIAS = \frac{\sum(Q_{sim} - Q_{obs})}{\sum Q_{obs}} \times 100 \qquad (8)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}\left(Q_{obs,i} - Q_{sim,i}\right)^2}{\sum_{i=1}^{n}\left(Q_{obs,i} - \overline{Q_{obs}}\right)^2}\right] \qquad (9)$$

$$RSR = \left[\frac{\sqrt{\sum_{i=1}^{n}\left(Q_{obs,i} - Q_{sim,i}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_{obs,i} - \overline{Q_{obs}}\right)^2}}\right] \qquad (10)$$

where $Q_{obs,I}$ is i^{th} flood quantile from observed discharges, Q_{sim} is i^{th} flood quantile from estimation method, while $\overline{Q_{obs}}$ is the mean of observed data being evaluated and n is the total number of observed data used in the analysis.

According to Nonki et al. (2021), PBIAS is related to soil and evaporation components of the water balance, while NSE is important for high flows part of the hydrograph representing fast runoff. RSR on the other hand is important for low and high flows and affects all hydrological components. The selection of the three criteria was based on their ability to represent high flow part of the hydrograph and roles of soils in generating high flows. The magnitudes of these criteria were described by Moriasi et al. (2007) (Table 2).

Table 2: Criteria for describing classes of differences (Moriasi et al. 2007)

Performance rating	PBIAS	NSE	RSR
Very good	< ±10%	0.75–1.00	0–0.5
Good	±10%–±15%	0.65–0.75	0.5–0.6
Satisfactory	±15%–±25%	0.50–0.65	0.6–0.7
Unsatisfactory	> ±25%	< 0.50	≥ 0.7

Results and Discussion

Results of FFA on observed flows

Observed annual maximum flows were 27–230 m^3/s in LRC and 2–26.45 m^3/s in UNC. Based on KS, AD and Chi-squared statistical goodness-of-fit criteria, the best four pdfs were Rice, Nakagami, Weibull and Gamma distributions (LRC) and Log-logistic, General Extreme Value (GEV), General Logistic and Dagum (UNC). However, the Q-Q plots of the 4 distributions for LRC indicated the Rice pdf as the best for estimating flood quantiles up to 180 m^3/s and Gamma for quantiles exceeding 180 m^3/s. Similarly, Log-logistic distribution was the best pdf for estimating flood quantiles up to 17.3 m^3/s in UNC. However, there is only a single flow magnitude above 17.3 m^3/s (which was 26.45 m^3/s) in the entire 49 years of record, making it difficult for all pdf examined to capture this value. Consequently, quantiles exceeding 17.3 m^3/s were not considered for UNC. Quantiles estimates for LRC and UNC are given in (Table 3).

Table 3: Flood quantile (m^3/s) from FFA

Catchment	Return period (years)					
	2	5	10	25	50	100
LRC	83.3	125.77	152.69	185.16	195.88	230.53
UNC	7.02	10.74	13.88	19.04	**24.04**	**30.30**

HBV modelling and FFA

The NSE were 0.61 (0.63) and 0.57 (0.66) for calibration and validation in LRC (UNC), respectively. Then the 2, 5, 10, 25, 50 and 100-year floods were estimated by fitting the distribution to the synthetic annual maximum flow series of HBV simulated data. The fitting results indicate Pearson 5(3P) as the best distribution for estimating flood quantiles in LRC. Similarly, the Log-Logistic distribution was the best pdf in UNC for calculating the quantiles. The estimated flood quantiles for both catchments are listed in Table 4.

Table 4: Flood quantiles using FFA on HBV modelled flows

Catchment	Return period (years)					
	2	5	10	25	50	100
LRC	86.13	116.22	137.7	166.79	186.21	214.52
UNC	20.75	22.71	23.997	25.701	27.055	28.49

Results of SCS-CN method

The best pdf for annual rainfall were GEV and Frechet 3P in UNC and LRC, respectively. Rainfall quantiles range between 107 mm/d (T = 2 years) and 240.8 mm/d (T = 100 years) in LRC and between 89.9 mm/d (T = 2 years) and 288.9 mm/d (T = 100 years) in UNC. The estimated CN for AMC-I (dry), AMC-II (normal) and AMC-II (wet) conditions CN in LRC (UNC) were 74.8 (29.6), 87 (82) and 93.8 (199), respectively. These rainfall quantiles were used to estimate flood quantiles were estimated for 2, 5, 10, 25, 50 and 100-year return periods (Table 5).

Table 5: Flood quantile from SCS-CN method

Catchment	Return period (years)					
	2	5	10	25	50	100
LRC	82.07	125.19	152.170	175.210	195.33	435.240
UNC	15.14	23.77	29.72	37.41	43.52	48.999

Results of regional regression equations (RRE)

Based on the regional frequency curve of Tanzania by Mkhandi et al. (2000), the regional hydrostatic factor (T_T) values for LRC and UNC at different return periods were calculated and presented in (Table 6). The results show that the two catchments have similar hydrostatic factors for each return periods since they fall in TAN 5 region, which were used in computing flood quantiles (Table 6).

Table 6: Flood quantile from regional regression equations

Catchment	Return period (years)					
	2	5	10	25	50	100
Hydrostatic factor	0.9	1.5	1.8	2.3	2.6	2.9
LRC	82.8	138.03	165.64	211.65	229.66	266.86
UNC	11.62	12.45	14.11	17.43	21.68	26.56

Suitability of flood quantile estimation methods

Quantiles produced by FFA on observed annual maxima were closely reproduced by HBV/FFA and SCS CN methods in Little Ruaha Catchment (LRC) (Figure 2a) and by RRE method in Upper Ngerengere Catchment (UNC) (Figure 2b), the method which is also moderately better reproducing FFA flood quantiles in LRC (Figure 2a). However, the SCS CN and HBV/FFA methods could not reproduce the FFA flood quantiles in UNC (Figure 2b). PBIAS, NSE and RSR computed between FFA flood quantiles and those from HBV/FFA, SCS CN and RRE methods replicated the abilities of the three quantile estimation methods in reproducing flood quantiles computed using FFA on observed annual maxima. The values of the three criteria (PBIAS, NSE, and RSR) for flood quantiles from the RRE method were rated good to very good in both study catchments (Table 7). All three criteria were rated as consistently unsatisfactory for the SCS CN method in both study catchments (Table 7). However, except for the poorly estimated 100-year return flood in LRC by this method, all other quantiles are comparable to FFA quantiles (Figure 2a) and its exclusion resulted in very good rating. PBIAS, NSE and RSR for HBV/FFA method were rated very good in LRC and unsatisfactory in UNC (Table 7) where the method consistently overestimates flood quantiles for all return periods (Figure 2b).

The very good performance of RRE in the two study catchments could be caused by the fact that RRE for Tanzania were established based on purely measured data of stream flows (Mkhandi et al. 2000). The varying performance of SCS CN and HBV/FFA could be linked to the conceptual modelling nature of the methods involving the use of lumped (spatially reduced) observed data and model parameters describing conceptually the underlying hydrological processes (Seibert 2005). As well as the catchment response time parameters such as time of concentration (T_c) as presented in SCS-CN method (Gericke and Smithers 2014). This approach could be constraining the performance of these methods in generating extreme high flows when the involved hydrological processes are not well captured by model structure, model parameters, catchment-scale and inadequate input data (Iacobellis et al. 2013, Siderius et al. 2018, Baroni et al. 2019). As a result, NSE and RSR, which assess the high flow part of the hydrograph and hydrological processes linked to fast runoff (Nonki et al. 2021) are being affected. This could be the effect where fast flashy flood flows in steep sloping UNC are not captured well in the SCS-CN and HBV/FFA methods leading to unsatisfactory NSE and RSR (Table 7).

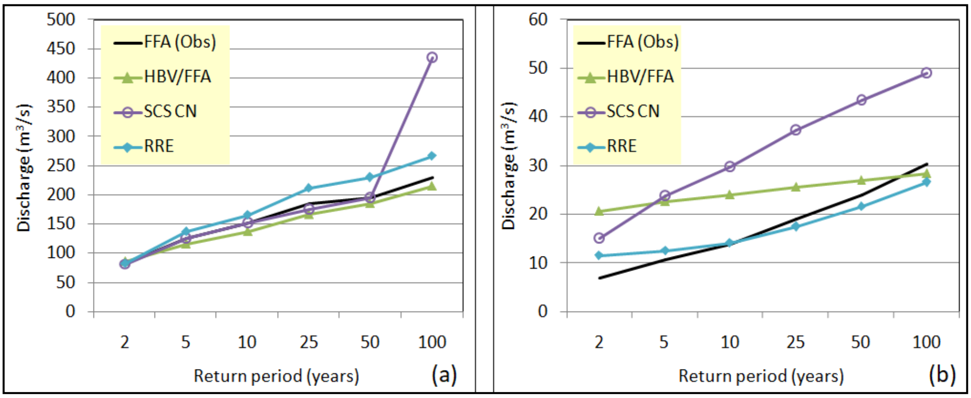

Figure 2: Flood quantiles estimates for different methods in (a) LRC and (b) UNC.

Table 7: Efficacy of flood quantile estimation methods against FFA on estimated quantiles

Catchment	Criterion	HBV/FFA		SCS CN		RRE	
		Value	Rating	Value	Rating	Value	Rating
LRC	PBIAS	6.8%	Very good	-19.7%	Satisfactory	-12.5%	Good
	NSE	0.928	Very good	-2.006	Unsatisfactory	0.751	Very good
	RSR	0.269	Very good	1.734	Unsatisfactory	0.499	Very good
UNC	PBIAS	-41.6%	Unsatisfactory	-89.1%	Unsatisfactory	1.1%	Very good
	NSE	-0.300	Unsatisfactory	-3.113	Unsatisfactory	0.877	Very good
	RSR	1.140	Unsatisfactory	2.028	Unsatisfactory	0.350	Very good

Conclusions

The main concerns found in estimating the flood quantile at these sites were the different patterns of flood quantile and the trend of quantile values from low-medium (2–25-years) to high (>50-years) return period. All the methods considered in this study were able to capture well the peak discharge; however the variations in estimating flood quantiles differed from one method to another as well as from one return period range to another within the approach. Based on the findings, we discovered that the RRE approach had the best overall performance. The suitability of RRE appears to be strongly influenced by watershed characteristics like size and rainfall pattern, which are both taken into account in the hydro statistic factor (T_T). The considerable difference in methods performance measures and between approaches indicated that these catchments of differences in size and hydro-climatic pattern can use any techniques. Similarly, the HBV model performed significantly better in LRC than in UNC, suggesting that the efficiency of the method is dependent on model parameters, catchment-scale and calibration data. Furthermore, the SCS-CN method performed poorly in all the study catchments, implying that model performance is dependent on catchment response, such as time parameters. Consequently, we conclude that selecting relevant approaches is heavily influenced by the goal they are employed, structure, parameters, hydro-climatic data conditions, and the required spatial and temporal scale.

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