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ORIGINAL ARTICLE

Modelling of river flow in ungauged catchment using remote sensing data: application of the empirical (SCS-CN), Artificial Neural Network (ANN) and Hydrological Model (HEC-HMS)

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Abstract

In the present study an attempt is made to provide empirical and deterministic modelling approach for deriving flood frequency curve in ungauged Keseke river catchment, South Nation Nationality and People (SNNP)-Ethiopia. The research work consists of (i) extracting of remote sensing data; (ii) evaluation and validation of remote sensing data; (iii) modelling of river flow using remote sensing data (climate and physiographic data) of the river catchment; (ii) three types of hydrological models validation and evaluation; (iv) developing of flood frequency model for each sub-catchment. The evaluation and validation of remote sensing data and river flow prediction is carried out on eight selected rivers in Keseke River catchment. The single gamma distribution quantile mapping is a good approximation to adjust satellite precipitation product data and the Pearson correlation function has shown a good correlation, mainly on heavy rain events. Results reveals that the SCS-CN and ANN approaches are suitable to predict river runoff in ungauged with reasonable accuracy in the investigated sub-catchments, and appears acceptable correlation between estimated and corrected satellite rainfall. A field campaign to obtain possible data was executed via interview and river cross section measures. The flood quantiles are compared with one time flow observation from field measured value (which is estimated from the river cross-section size) to identify the most representative hydrological model structure.

Keywords Ungauged catchment · SCS-CN · HEC-HMS · ANN · GIS · Remote sensing · Modelling · Keseke catchment.

Introduction

Daily river flow estimation in ungauged catchments and understating of the hydrological process has attracted interest to many hydrologists and water resource modellers, but many challenges still remain (Gunter and Anderson 2005; He et al. 2011). Hydrology and water resources are a science closely related to local meteorology, hydro-climate, land use, digital elevation model, soil type, geomorphology, and highly depends on observation data (Zhao et al. 2012; Zhand et al. 2015). Adequate water availability is vital for sustainable development. Establishing up to date and timely information on the adequacy of available water resources requires a comprehensive water resources assessment strategy (Beven 2001; Wale et al. 2009; Gibbs et al. 2012). So far, a limited number of catchments have sufficient hydrologic measurements required for comprehensive water resource assessments (Wale et al. 2009; Randrianasolo et al. 2011), while others do not have enough measurements. In addition, despite data scarcity in some catchments, the quality of this data, when available, remains questionable. Lack of sufficient data length, inadequate data, less quality or the use of questionable quality results in hydrologic units that are in this study referred to as ungauged (Sivapalan et al. 2003; Patil and Stieglitz 2012; Hrachowitz et al. 2013). The use of distributed physical models for water resources or hydrologic assessments in such ungauged catchments is therefore not possible due to lack of input data. Moreover, attempts at improving some traditional hydrologic tools (for example, the unit hydrograph and flow duration curves) for ungauged catchments has been led to unnecessary sophistication of these approaches (Sivapalan et al. 2003). The quest to predict surface runoff in such catchments therefore remains at the centre of hydro-informatics and water resources planning

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and management (Randrianasolo et al. 2011; Schaefli et al. 2011).

It has been reported by many researcher that hydrological models are mainly depending on the input data, hydroligcal parameter and structure of the model (Meresa et al. 2016; Meresa et al. 2017; Meresa and Gatachew 2018). Particularlly, studies on river modelling in ungauged catchment using the climate and physiographic characteristics are possible only if detailed information about topography, land use, soil, vegetation, and climate are depends on available data (Gunter Bloschl 2005; Wale et al. 2009; Adib et al. 2010; He et al. 2011). Runoff response estimation from ungauged river catchments is currently a topical issue in hydrology and water resources management (Gunter Bloschl 2005; Wale et al. 2009; Adib et al. 2010; He et al. 2011) and in developing coutries for hydraulic infrastuructre construction. However, spatial and temporal datasets of observed precipitation, temperature, soil moisture, runoff are unavailable for catchments, which is very commen in semi-arid and arid environments of the developing countries.

There are alot of methods that are solving the problems of ungauged catchment. Particularly, extrapolating response information from gauged to unagauged catchments, remote sensing data, global hydrological models, unit hydrographs, coupled meteorological and hydrologic models, regionalization of model parameters and multiple regression (Yadav et al. 2007; Moretti and Montanari 2008; Wale et al. 2009; Adib et al. 2010; Srinivasan et al. 2010). However, due to heterogeneity characteristics of catchments and nonstationarity of hydrological and meteorlogical charactersitcs, it is impossible to use regionalization, hydrological parameter transferring and multiple regression techniques for most of Ethiopian catchments (Meresa and Gatachew 2018). But, with the advances of remote sensing techniques, hydrological and climate relevant information in ungauged river catchments can be derived from various sensors and it would be important to understand the river runoff behaviour in specific watershed and the interactions among climate and physicographic behaviour (Yadav et al. 2007; Meresa et al. 2016; Meresa and Gatachew 2018). A major problem facing the user of these data (precipitation, temperature, soil moisture, and normalized difference vegetation index) is how to effectively incorporate and ready made remotely sensed data into hydrological models andstudies (Gumindoga et al. 2015).

Remote sensing datasets provides large spatio-temporal coverage of hydrological and meteorological variables (Hengl et al. 2007; Maathuis 2007). The availability of relatively high resolution climate (precipitation, temperature) and hydrological variables (soil moisture, NDVI) together with hydroligcal and Geographical Information System (GIS) makes it possible for gauged and ungauged catchments rainfall-runoff modelling in time and space (Sreenivasulu and Bhaskar 2010). Exploiting the capabilities and applicability of remote sensing datasets is the most suitable alternative option given the scarcity and/or ungauged of observed meteorological and hydrologic networks in Keseke river catchment. Remote sensing, hydrological modeland GIS techniques can therefore be useful in observing critical river catchment characteristics required for model parameters estimation that capture crucial atmospher-land dynamics (Gumindoga et al. 2011; Dube et al. 2014).

Nowadays, there are several studies performed the rainfall and runoff process simulation using empirical, data deriven, hydrological model and statistical models comparisons. Meresa and Gatachew (2018) compared three conceptual hydrological models for climate change impact study, and found that accuracy of the modelled flow is mainly depends on the model structure and number of model paramters. Yaghoubi and Massah (2014) compared three models of HBV, IHACRES and HEC-HMS in Azam Harat river catchment in Iran. Among these models HVB model performed better in proved resinable river flow in mean and variabilitywhereas HEC-HMS exhibited worst perfomence in root mean squere value. Asati and Rathore (2012) developed an autoregressive model, ANN and MLR for a complex catchment behaviour which is non-linear relationship between rainfall and runoff, which is compared without incorporating the nature of process. Dastorani et al. (2009) compared artificial neural network with various data driven models for rebuilding the observedflow data and they concluded the ANN were dominantin comparison to other models (the normal ratio and correlation methods). In general, it seems HEC-HMS, SCS-CN and ANN are the most widely applied to predict runoff in river catchments. That is why in this research work, the comparison was done using these three empirical and deterministic hydrological models. Due to the reason that there are no previous studies in Keseke river ungauged catchments that are focused on water balance, run-off prediction, water quality, pollution and urban drainage issues. This research work provides innovative research approach and robust solutions in runoff estimation in ungauged catchment. The reason is that hydrological (not available-ungauged) and meteorological observation networks in the Keseke river catchment are not dense and reliable. Furthermore, the few available meteorological data often present significant gaps. This makes the research work very innovative and original in terms of study area, methodology and framework approach.

Generally, river runoff models are designed to to gain a better understanding of the hydrologic characterstics of a catchment and to generatea synthetic hydrologic data for river flow facility design like flood protection, water resources planning, mitigation of contamination, or for flood earlywarning and forecasting. Specifically, the objective of this study is therefore to (i) evaluate and validate remote sensing data, (ii) estimate runoff in each sub-catchment through the integration of GIS and remote sensing techniques, (iii) compare empirical and deterministic hydrological models for runoff prediction (HEC-HMS, ANN and SCS-CN), (iv) spatial–temporal characterizing of hydro climate data, and (v) develop flood frequency curve model for each sub-catchments.

Description of study area and datasets

The Keseke catchment is located in Southern Nations Nationalities and Peoples (SNNP) regional state. The geographic coordinates for the river catchment are 597,223.4 mN/233,905.1 mE in UTM at head and 518,376.3mN and 214,956.1 mE in UTM at tail. The total area of the catchment is 1698 km^2. The elevation of the catchment varies from 543 m in the south part to 2147 m in the northern part of the study area (Fig. 1). The rainfall distribution pattern of the catchment is uneven with dual seasonal period and has duranial intense rainfall. Collecting of daily time series of precipitation and temperature from 1981 to 2017 from Ethiopian Meteorological Agency was carried out. Dimike meteorological station was used as the core station to correct remote sensing climate data in the Keseke catchment area.

The predominant soils in the study area have similar hydrologic properties as given by the Hydrological Soil Group in Fig. 2b. Over 70% of the soils are in groups A and B indicating soils that are of a clayey nature or sandy but shallow and therefore tend to promote runoff rather than infiltration (Fig. 2b). The dominate soil characteristics of Keseke catchment area are chromic cambisols (77.61%), Eutric cambisols (2.34%), Eutric Fluvisols (15.88%), and Lithic Leptosoils (13.17%). Keseke river catchment is dominantly covered by shrub land (58.16%) and Forest (21.11%), which shows that land cover significantly determines hydrological characteristics of the catchment (Fig. 2a).

Table 1 shows the lists of the selected sub-catchments inside the main Keseke catchment. Among 12 locations, seven sites are situated exclusively, without being dependent on other catchment flow. The other five selected locations are dependent to each other and located in the main stream of the river. Weremba, Durko and Pere sub-catchments are the smallest locations, 23.22, 42.84 and 48.20 km^2 respectively.

Research methodology

Figure 3 shows a conceptual methodological framework that uses to fellow the overall research work steps. Starting from the two main input data types include rainfall and DEM, and then the other input data such as soil, land cover, land use, meteorological data are identified depending on the model approach. The main output from this model is river runoff at the outlet of the catchment for flood frequency cuvre model development.

Generally, there are three lines of methodological approaches that are clearly described in Fig. 3, river runoff value was estimated for each sub-catchment in Keseke catchment based on soil type, land use, topographic, NDVI and climate data. The three research lines are: yellow colour is a line belonging to HEC-HMS modelling procedure

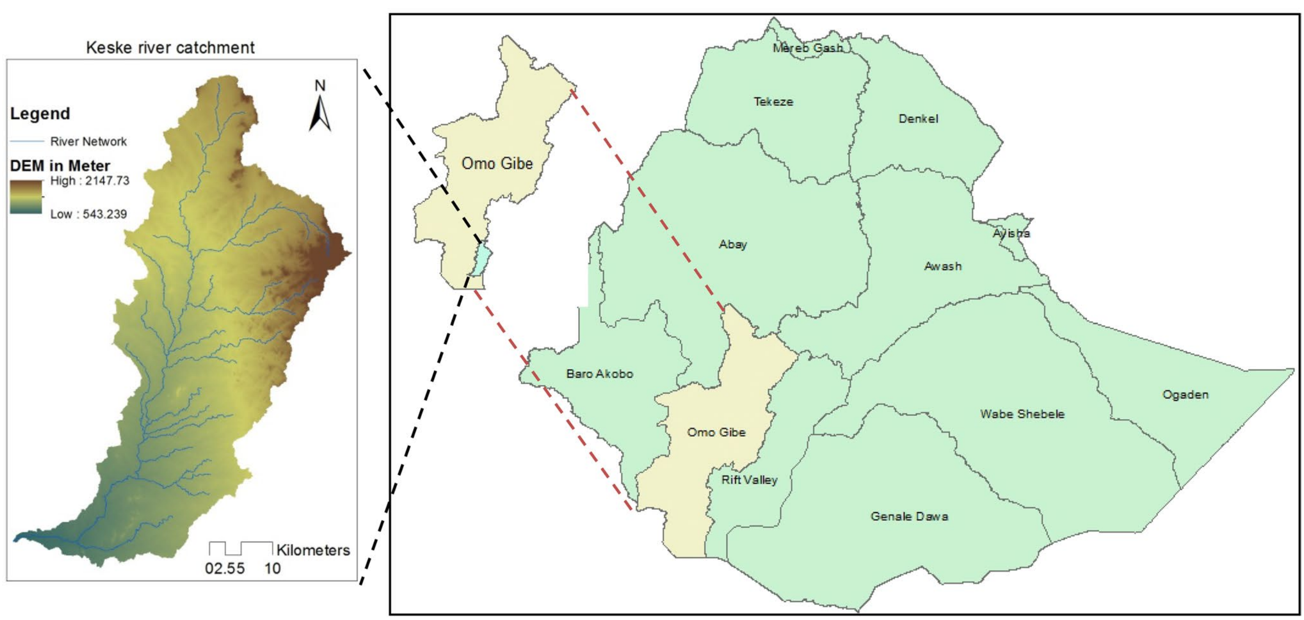

Fig. 1 Location of the study area

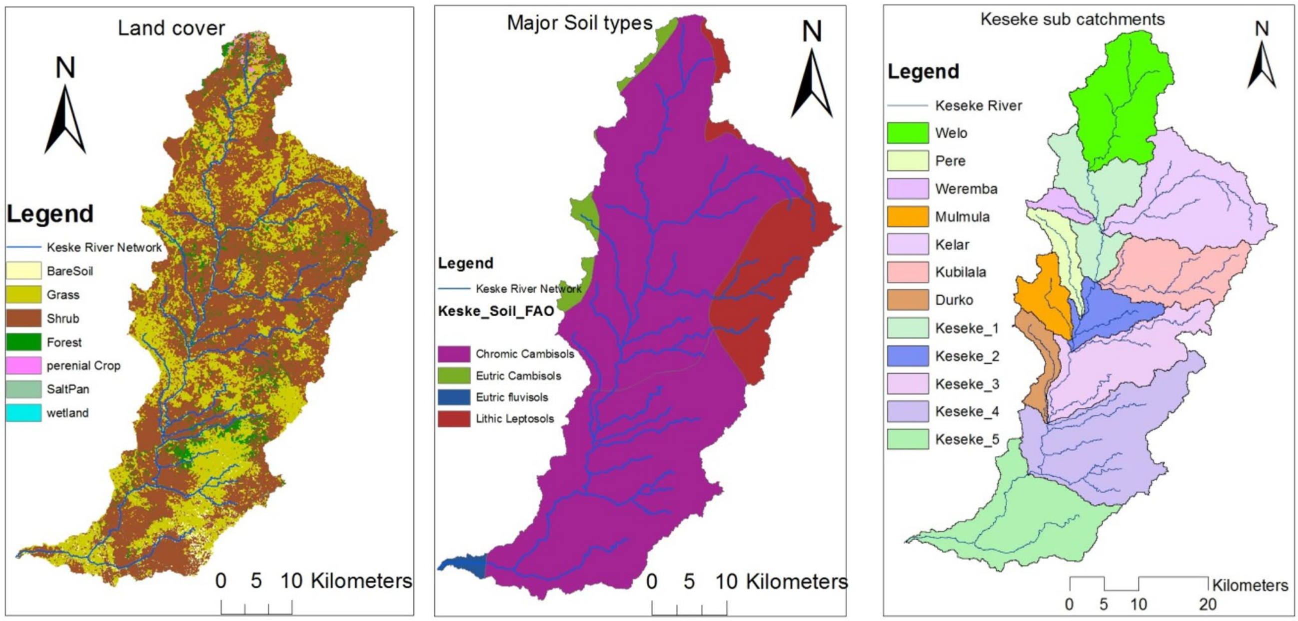

Fig. 2 Physiographic and location map of selected sub-catchments inside the Keseke River catchment **a** land cover map of Keseke catchment, and **b** soil type distribution of Keseke catchment, and **c** selected sub-catchments

Table 1 selected sub-catchments

	Sub-catchment	Outlet	X_utm (m)	Y_utm (m)	Area (km^2)
1	Welo	@Wele	227,610	577,122	194.04
2	Keseke1	Near Kubilala	228,589	560,923	602.81
3	Weremba	@Weremba	227,828	569,984	23.22
4	Kelar	@Kelar	218,885	533,222	243.21
5	Pere	@Pere	226,517	556,241	48.2
6	Kubilala	@Kubilala	229,047	561,031	153.29
7	Keseke2	Near Mulmule	225,129	550,917	932.45
8	Mulmule	@Mulmule	225,203	552,893	58.75
9	Durko	@Durko	221,586	540,658	42.84
10	Keseke3	Near Durko	221,767	540,733	1119.17
11	Keseke4	Near Bridge	229,613	568,138	1446.9
12	Keseke5	@Keseke	201,160	523,513	1683.81

(deterministic modelling), blue colour represents data driven modelling (ANN) and red colour stands for the empirical research procedure (SCS-CN). Thesemodelling approaches were developed at each sub catchment and compared with their mean value and 95% and 5% confidence interval.

Remote sensing data

We use remote sensing data as core source of data for this research work and runoff prediction at each sub-catchment. The main variables that are extracted from remote sensing data bases are: precipitation, temperature, soil moisture and Normalized Difference Vegetation Index (NDVI).

Climate data: Climate data were extracted from Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS) dataset. CHIRPS dataset is available globally and in 30 + year temporal length. This dataset covers a spanne of 50°S-50°N (and all longitudes) spatial coverage and starting in 1981 to near-present temporal length. The grid resolution of CHIRPS dataset is around 0.05° resolution scaleUptodate, many reserchs proved and recommended that the dataset has significant role for different research purposes (e.g. hydrological modelling, trend analysis and seasonal drought monitoring). The version 2.0 of CHIRPS is complete and freely available to the public (http://chg.geog.ucsb.edu/data/chirps/).

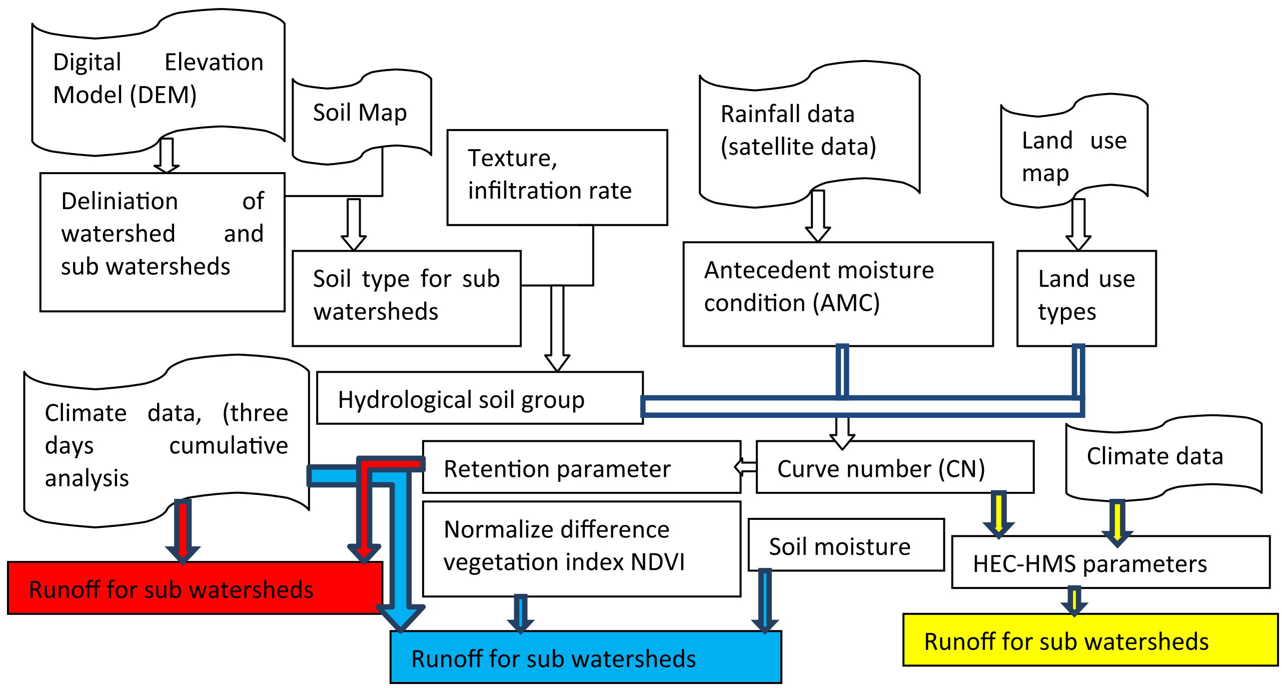

Fig. 3 Methodological framework to estimate runoff value in ungauged catchment. Three river flow prediction techniques: (i) Red: empirical (SCS-CN), (ii) Yellow: hydrological model (HEC-HMS), and (iii) Blue: data driven committee model (ANN)

In this research work, we use CHIRPS climate dataset for river run-off prediction in ungauged Keseke catchment. CHIRPS product is selected because of relatively high spatila-temporal resolutions, the availability of long time series upto 2017, and free access to the dataset. Before we applied the output of CHIRPS climate dataset to our study area, we have done a lot of post-processing data bias correction, evaluation and validations. As, one of the objectives of this research work, the dataset is evaluated and validated its application and presented how CHIRPS can be used to quantify the river flow in ungauged river catchment in South Ethiopia.

Soil moisture data: European Space Agency (ESA) has been released a new long-term and global grided dataset of soil moisture measurements time series from space by to help scientistis better understand the climate and water cycle, monitor agriculture activities and manage our water resources, and it is freely available at http://www.esa-soilmoisture-cci.org/. In this study, the daily soil moisture time series data extractedfrom level-3 (version 4) product with a spatial resolution of 36 km which is generated on Grid 2.0, is used in this paper. This dataset should evaluate and validate with respect to the observed/measured surface soil moisture values. However, do to lack of observed value, we have done only 1 day validation of the soil moisture time series.

Soil moisture plays a decisive role in soil hydrology, regulating the surface and sub-surface flow including interflow, infiltration and percolation capacity of the area. That is why soil moisture variable is selected in this research work. specially, soil moisture is a control variable in exchange of water and energy between theatmosphere and the land.

Normalized Difference Vegetation Index (NDVI) data: The scientistics in National Oceanic and Atmospheric Administration (NOAA) and Climate Data Records (CDR) provide historical hydroligcal and climate information using data from satellites. This dataset contains daily Normalized Difference Vegetation Index (NDVI) derived from earth surface reflectance temporal data acquired by the Advanced Very High Resolution Radiometer (AVHRR) sensor. This temporal long-term record spans from 1981 to 2017 and utilizes AVHRR data from NOAA polar orbiting satellites. NDVI has been prepared using the values of channel 1 and 2 of NOAA AVHRR and TERRA MODIS sensor. This NDVI spatial and temporal data time serious provides vital information on global change and resource management. Also, it is very important to understand the historical NDVI change and vegetation moniterign around the globe for land surfaces. The NDVI dataset is organized with 1 km spatial resolution globally and monthly temporal resolution time scale and every one can access from https://modis.gsfc.nasa.gov/data/dataprod/mod13.php website.

Normalized Difference Vegetation Index (NDVI) was intended to understand the status of vegetation using remotely sensed satellite data applied. It represents the vegetation quantity and activity status. That is why NDVI is selected as input to our ANN model together with climate and soil moisture data.

Satellite data correction: distribution based quantile mapping

Distributed Quantile mapping (DQM) equates observed cumulative distribution functions (CDFs) Fo, h and modelled cumulative distribution functions (CDFs) Fm, h, in a historical period(in this study from 1981 to 2017) which is denoted by the subscript h. DQM transfer function represents as fellows:

$$\bar{x}_{m,p}(t) = F_{o,h}^{-1}\left\{F_{m,h}\left[x_{m,p}(t)\right]\right\} \tag{1}$$

for bias correction of xm, p(t), a modeled value at time t within some the other station period, denoted by the subscript p. If inverse CDFs and CDFs (i.e., quantile functions) are estimated in single semi empirically from the data, the mathematical formula can be illustrated with the aid of a Q-Q (quantile–quantile) plot, which is a direct scatter plot between quantiles emerically estimated from observed and modelled data. In this case, DQM amounts to a lookup table whose entries are found by interpolating between points in the quantile–quantile plot of the historical data. The transfer function is mainly constructed using information from the base station historical period exclusively; information provided by the other station is ignored.

DQM, like all climatatological and hydrological statistical post processing algorithms, relies highly on an assumption that the satellite climate data biases to be corrected are stationary (i.e., the characteristics in the historical time period will persist into the other station). As it is beyond the scope of this paper to tackle this assumption, we instead direct to studies by Maraun et al. (2010) and Maraun (2012) for more insight.

Empirical runoff calculations

The empirical approach for estimation of river runoff in ungauged catchment is one of the most popular approach in hydrology. However, in this research work, we develop SCS-CN approach a bit different from the previous and conventional way of runoff estimation. Basically, we develop a novel approach using the physiographic and climate characteristics to estimate runoff.

Hydrologica Soil Group (HSG) classification: As per National Engineering Handbook developed by USDA, soils are classified into four main groups A, B, C and D based upon their infiltration rate, capacity and and other characteristics. ***Group A***: Soils in this group have low river runoff potential and high infiltration capacity and rate when thoroughly wet. River water is transmitted with high rate through the soil; ***Group B***: Soils in this group have moderately low river runoff potential and moderate infiltration capacity and rate when thoroughly wet. River water transmission with moderate rate through the soil; ***Group C***: Soils specifically in this group have moderately high river runoff potential and low infiltration capacity and rate, when thoroughly wet. River water transmission is somewhat limited through the soil; ***Group C***: Soils in this group have high river runoff potential and very low infiltration capacity and rate, when thoroughly wet. River water transmission is limited through the soil.

Antecedent Moisture Condition (AMC): AMC indicates the moisture content of soil layer at the beginning of the rainfall droplets. AMC highly correlated with the curve number of the area, and accounts for the variation in curve number under consideration from time to time. There are three levels of AMC were dominated and goverged by rainfall characterstics of the study area. The AMC I is related to CNI, AMCII with CNII and AMCIII with CNIII (Table 2). The classification of these three AMC classes are based on the characterstics of rainfall magnitude of previous cumulative 3 days and season (dominant season). AMC threshold is identified based on the local three class of rainfall for determination of curve number (Table 2).

SCS Curve Number Method: Soil Conservation Model is distributed catchment modeling and based on the AMC and HSG. It is widely used in hydrological modelling application. This approach computes direct river runoff through an empirical forumulation that requires the rainfall and a watershed characterstics as inputs (Nayak and Jaiswal 2003). The first concept is that the ratio of actual amount of runoff to maximum potential runoff is equal to the ratio of actual infiltration to the potential maximum retention. This proportionality concept of SCS curve number method is expressed as

$$\frac{\left(P - I_a - Q\right)}{S} = \frac{Q}{\left(P - I_a\right)}, \tag{2}$$

where, P = precipitation in millimeters (P > = Q); Q = runoff in millimeters; S = potential maximum retention in millimetres; Ia = Initial Abstraction.

Table 2 AMC for determination of CN value

CN	AMC	Total rain in previous 3 days Dominant seasons
I	I	Less than 13 mm
II	II	13 to 21 mm
III	III	More than 21 mm

The SCS-CN method defined the value of the initial abstraction I to be approximately equal to 20% of the watershed storage S by means of rainfall and runoff data from experimental small watersheds, I = 0.2S.

Solving Eqs. 1 and 2 simultaneously,

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \quad \text{where} \quad (\mathrm{P} >= 0.2\mathrm{S}), \tag{3}$$

which is the rainfall-runoff relation used to compute direct daily runoff from storm rainfall in the SCS method. The catchment storage, S, and the curve number CN are related by,

$$\mathrm{S} = 25400/\mathrm{CN} - 254. \tag{4}$$

The parameter curve number (CN), having a range of values between 0 and 100.. In this method, a CN is assigned to each sub-cathcment based on land use, soil type and treatment, and AMC.

Area weighted composite CN for various conditions of hydrologic soil and land use conditions are computed as follows:

$$CN = \frac{CN1 * A1 + CN2 * A2 + CN3 * A3 \cdots CNn * An}{A1 + A2 + A3 + \cdots An}$$

where A1, A2, A3, …, An represent areas of polygon having CN values CN1, CN2, CN3, …, CNn respectively and A is the total area.

Weighted curve number (AMC II) and also curve number (AMC I) and curve number (AMC III) were determined using the following equations respectively:

$$\text{CN for AMC I is calculated as} : CNI = {}^{CNII}/_{(2.281 - 0.01281 * CNII)}$$

$$\text{CN for AMC III as} : CNIII = {}^{CNII}/_{(0.427 - 0.00573 * CNII)}$$

Hydrological model for flow prediction: HEC-HMS

HEC-HMS is a hydrologic modele package developed by the United State Army Corps of Engineers-Hydrologic Engineering Centre (HEC). It is a semi-physically based and conceptual semi-distributed model designed to simulate continous and event based rainfall-runoff processes in a wide spatial scale range, from large river basin flood hydrology to small urban and natural catchment runoff. The software package includes runoff transform, losses, channel routing, base flow, canopy, surface, rainfall-runoff simulation and parameter estimation. HEC-HMS hydrological model uses different pachages to represent each component of the river runoff process, including models that compute runoff volume, models of base flow, and models of direct runoff. Each model run combines a meteorological model, basin modeland control specifications with run options to obtain results (Choudhari et al. 2014).

The hydrological modelling applied in this study is performed to predict continuous runoff on daily time step. The HEC-HMS hydrological model is process based physical model with parameters to be estimated directly from field data and remote sensing data. In ungauged catchment, the model parameters are calculated from the existing climatic and physiographic characteristics of the catchment. The model were implemented on the eleven reference catchments with two input data (daily precipitation and daily potential evapotranspiration) and calibrated against field data of flow.

Data driven model: artificial neural network model

There have been various studies regarding the applications of Artificial Neural Networks (ANN) in hydrology (Saliha et al. 2011; Kalteh 2013; Sabouri et al. 2013). The major advantages of ANN include their capability of modeling nonlinear relationships, providing flexibility and robustness in structure, and the ease of implementation. ANN models take into consideration both temporal changes in hydrologic and climatic conditions and the spatial variation of the catchment; therefore, they have gained popularity in flow estimation (Besaw et al. 2010; Maier et al. 2010). In many cases, ANN has outperformed other methods for prediction of flood flow, peak flow (Demirel 2009) and volume of surface runoff (Mondal et al. 2012). Besaw et al. (2010) concluded that an ANN trained at one basin is capable of accurately estimating the stream flow at a nearby basin.

Three major components of the ANN include, model structure (parameters and architecture), input data, and output data layers. Previous studies addressed the structure of ANN associated with model parameters through the alteration of datasets, which is governed by the input, hidden and output combination neurons. This involves training the network a number of times while varying initial weights and bias values. Similarly, the model architecture (type of ANN model, training time) is selected based on a trial and error approach, which optimizes the model. A key challenge for reliable adoption of ANN is embedded in the need to determine which input parameters significantly influence predictions. The sensitivity of these inputs for flow prediction is equally as important. Output uncertainty is typically addressed through prediction intervals (Srivastav et al. 2007; Solomatine and Shrestha 2009; Talebizadeh et al. 2010; Khosravi et al. 2011).

The Artificial Neural Network is generally used for modelling non-linear input–output relationship such as time series prediction of rainfall to runoff. The main objective of this ANN study is to predict the runoff from remote sensing data collected from 1981 to 2017.

In this study, based on the average mutual information analysis we selected temperature, soil moisture, normalized difference vegetation index and precipitation as input to ANN structure. Using these four input variables, we create 100 non-linear architecture to simulate river runoff at each sub-catchment. However, it does not mean that all the simulations are correct or exact values. Therefore, from the 100 simulations we estimate the average values which is the best representative river flow at specific site.

Flood magnitude and frequency

Flood frequency analysis is a statistical technique used by engineering hydrologiststo predict flow values (magnitude and frequency) corresponding to specific return periods or probabilities along a river. Statistical analysis in flow data is used to extract information such as mean, standard deviation, kurtosis, skewness, and recurrence intervals, which plays role in understanding the river flow character. These statistical values are then used to construct frequency distributions, which are curve graphs and tables that tell the likelihood of various river flows as a function of recurrence interval. Flood frequency analysis was employed for all selected sites in Keseke river catchment. These analyses deployed using annual daily maximum flow for the entire period from 1981 up to 2017 (at least 37 years of flow were considered), were conducted for selected eleven sites inside the Keseke river catchment.

After extracting of annual maximum flow data series, we select a best distribution from more 20 candidate distribution fitting and three parameter distributions. Such procedures are the most common application of the extreme values theory (Coles 2001).

Result and discussion

In this section we describe the results obtained from rainfall-runoff modelling using SCS-CN model, HEC-HMS model and ANN model; evaluation and validation of remote sensing data; spatial–temporal variability of hydro-climatic conditions; and flood frequency curve model development.

Remote sensing data evaluation

The climate satellite data is an important tool for the assessment of rianl, temperature characterstics of the catchment. The time scale of remote sensing data has similar time resolution with ground station which measures daily time scale values of precipitation depths, average daily temperature; the remote sensing data adjusted time series can be applied to determine historical flood events on the study catchment.

Rain gauge stations from the Keseke river catchment were used to correct the bias and non-uniform characterstics in the remote sensing rainfall data, which has a temporal time scale of 24 h, and corrected using a distribution quantile mapping technique. The time period of the rain gauge station used to correct the remote sensing product time series was from January of 1981 to December of 2017. The remote sensing product time series was obtained for the study area of interest using a Matlab platform script, which extracted the climate and hydrological daily values of a pixel.

The correction of the remote sensing data was performed in daily and monthly basis, this would help to understand the seasonal characterstics climate variables in the bias correction process. This technique showed that the remote sansing data biases were reduced significantly and the conscutiver rain spell and the intense rain events were well adjusted (Fig. 4a, b). The results also showed restrictions because it tends to accurate adjust the light rain events. Moreover, the Pearson correlation between corrected and observed values has shown a good correlation, specially, on intense rain events (Fig. 4b). The monthly bias correction shewed best agreement with the observed values due to inclusion of seasonal characterstics in the cbias correction process has the best adjustment of the approach; this is due to the inclusion of the seasonality in the correction process. The number of wet days, intense rianfall and light rain events are propoerly considered and adjusted.

Figure 4a, b show the comparison of the mean and maximum rain gauge station and the corrected satellite data. The correction of the satellite product correlates well to observed data including the values of the high quantiles that represent the high rain events (Fig. 4b). To compare the correction, the scatter plot was prepared between the observed data and the uncorrected satellite product and between the observed data and the corrected satellite values. The scatter plot of corrected and observed rainfall shows more straight (one to one relation) that concentrates in the diagonal line. Whereas, the scatter plot before correction is cloudier and not clearly show one to one relation. The change in correlation in this scatter plot shows a better fit to observed data with the corrected satellite data (Fig. 4b).

The rainfall satellite data is an important tool for the assessment of spatial and temporal precipitation distribution. As Fig. 5 shows the average annual maximum rainfall ranges from over 120 mm/year in the northern and western part of the catchment to less than 61 mm/year in the south part of the river catchment. Similarly, the annual mean rainfall shows similar pattern and variability with annual maximum rainfall in the Keseke catchment. Interestingly, the distributions of annual maximum and annual mean value of precipitation are more all less similar.

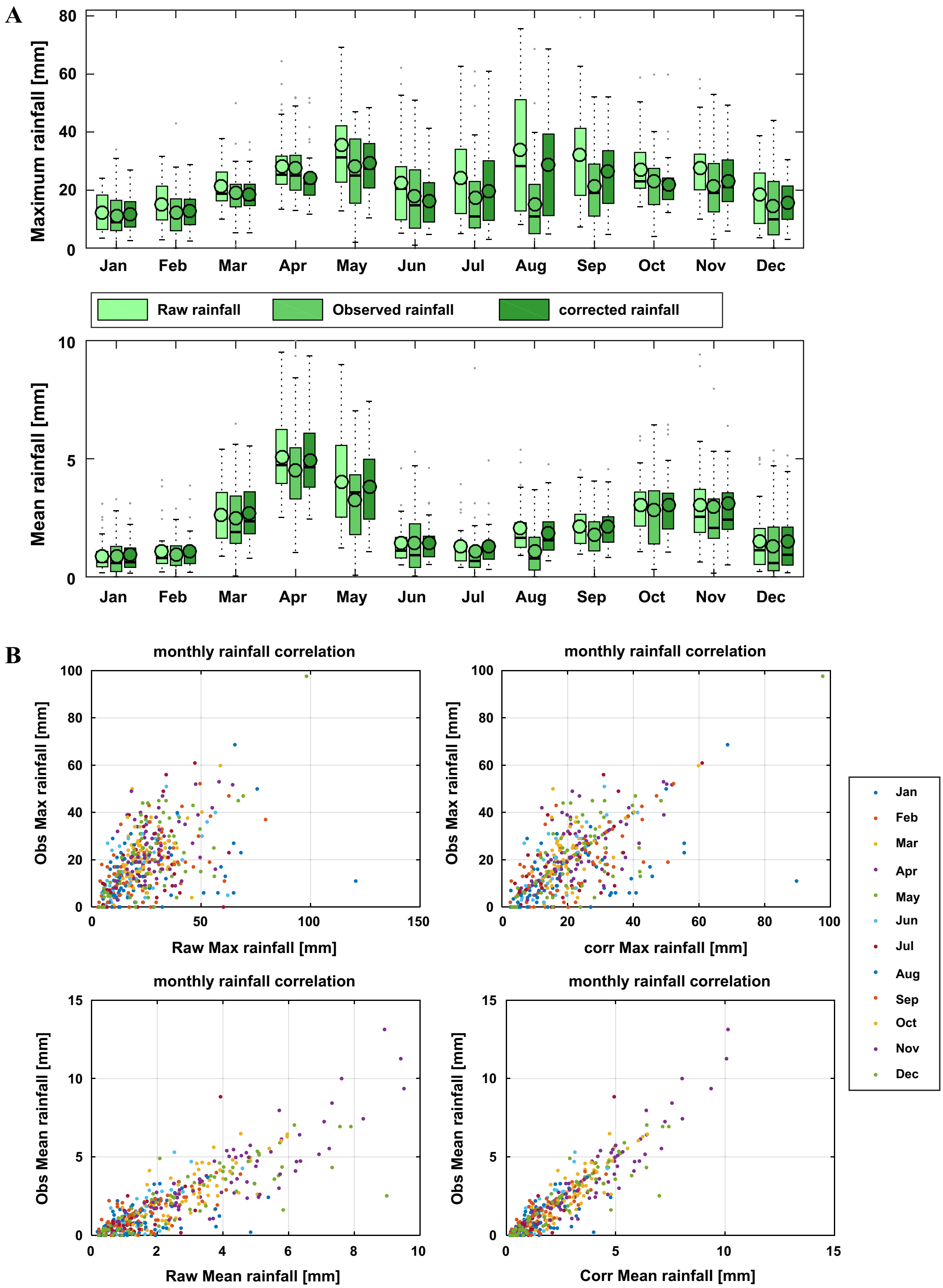

Fig. 4 **a** Raw, observed and corrected maximum and mean precipitation at Dimika station. **b** Scatter plot of seasonal raw, observed, and corrected maximum and mean precipitation at Dimeka station

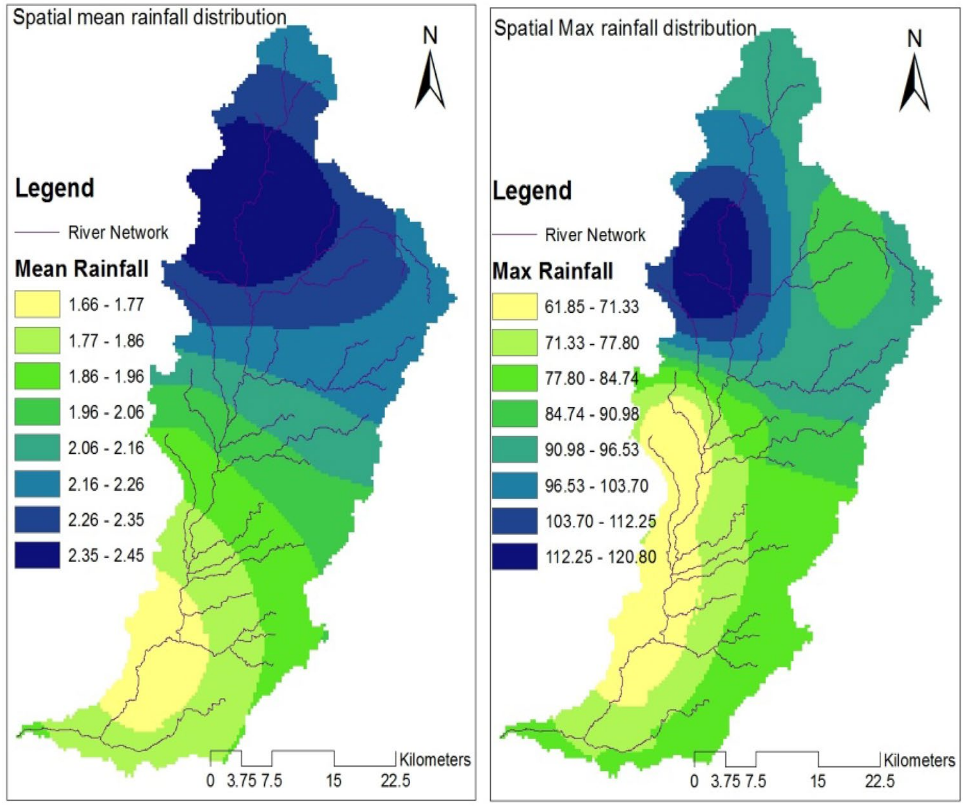

Fig. 5 Spatial mean (left) and maximum (right) rainfall distribution in Keseke catchment

Comparison of estimated runoff

The comparison of three approaches of river flow modelling was performed. HEC-HMS, ANN and SCS-CN methods were developed to estimated runoff in ungauged Keseke river catchment. Keseke river catchment is ungauged and highly heterogeneity catchment. In this way, it is impossible to calibrate the hydrological models because there is no observed flow in the catchment and it is also not feasible to use parameter regionalization and parameter transferring approach due to heterogeneity and non-stationarity of the catchment. Therefore, in this research paper, in order to evaluate the skill of these three runoff estimation techniques, we developed two way of rainfall-runoff models could validate and compare these three modelling approaches: (i) using field data, and (ii) using the median of confidence intervals (95% and 5% of the estimated runoff ensembles).

Figure 6 shows the mean and dispersion of the absolute value of the bias scores for each of the watersheds in the study. The box graphs are interpreted as follows. The highlighted bar extends from the 25th percentile to the 75th percentile, with the median shown as a horizontal line. Figure 6 indicates that the bias with respect to mean flow and spatial model performance and bias in the selected sub catchments. Clearly seen that the models were performed slightly different in spatially and flow regimes. More all less, the median (50%)values are almost comparable with small difference; which is appear equally located around + 10% and − 10% bias. whereas, the 75% and upper quartile values has shown large difference. The median of all models are appear equally located around + 10% and − 10% bias except Weramba sub catchment. Whereas, the bias variability estimated higher using HEC-HMS model in all selected sub-catchments. ANN and SCS-CN displays similar variability but different in median value. SCS-CN is performes better than the other two hydrological models interms of variability and median value as shown in Fig. 6. This is because SCS-CN method considered both climatic and physiographic characteristics of the catchment. While the others miss the integration and surface processes. There is a somewhat variable upper tail of the distribution, which is especially visible in the smaller watersheds. Another conclusion from reviewing the graph is the median percent bias exhibits more variability than the width of the 25/75 percentile box.

Thus, the above discussions on evaluation criteria and plots of estimated data could not provide explicit performances on different intervals of values. To address this problem, different ranges of flow (from very high to very low flow) were determined. The reproduction of the streamflow was analysed by the flow duration curve of selected river sub catchment for the 1981–2017 period (Fig. 7). The

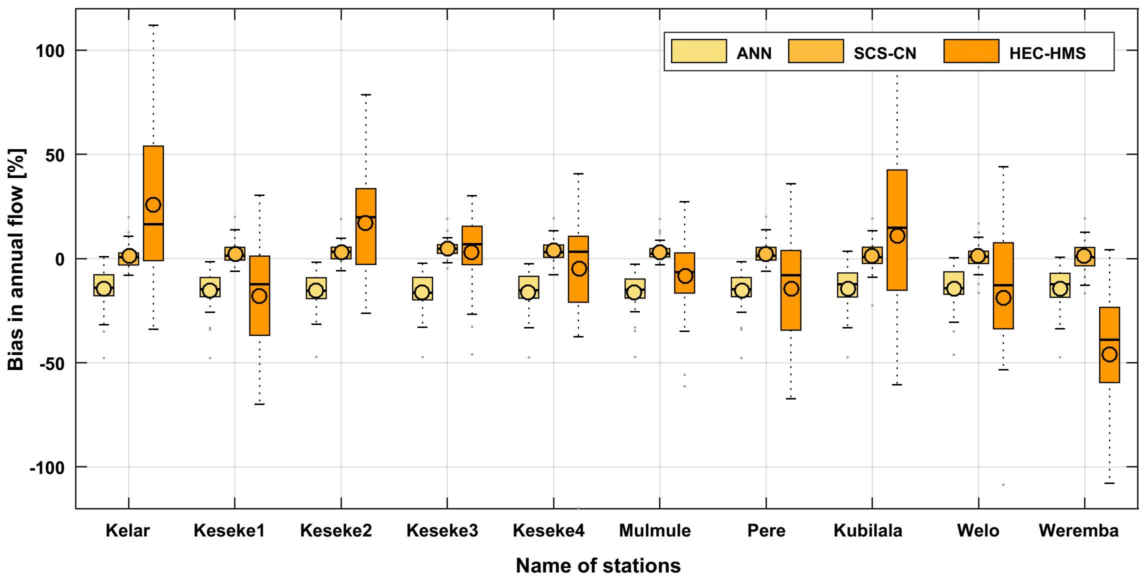

Fig. 6 Bias of annual estimated runoff in percent. In each box, the central black mark denotes a median from the temporal change, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to the most extreme data points not considered as outliers

exceedance probability of selected river flow shows that the SCS-CN and ANN performed generally better in the very high flow segment and ANN was better in the very low flow segment. The values obtained by HEC-HMS, SCS-CN and ANN has similar temporal pattern and lies in the 95% and 5% confidence interval. Interestingly noted that ANN is performed well in the hydrological low flow characteristics and SCS-CN for high flow characteristics, were graphically similar for the rest of the flow segments in Keseke river catchment. The result consolidates the result obtained in the bias analysis (Fig. 7).

The formulation confirms that remote sensing database can be used to solve water resource and hydrology problems, and important to asses daily and/or time based runoff modelling, and that the selected models calibrates itself. On the daily scale, the performance of this remote sesnsing-based approach rivals that of more conceptual and complex, and data-intensive hydrological models are important and feasible. The application of a grid-based approach, integrating different sources of open-access remote sensing data to evaluate the river flow hydrology and water resource modelling, is rather unique. Many models such as HEC-HMS, ANN and SCS-CN can ingest remote sensing products while performing calculations on a different catchmentscale. In comparison to varioues hydrology models, the modelling apreaoch applied here is slightly restricted to monthly and yearly temporal resolutions. For flood frequency applications, daily time steps are highly required, and the applied methods of advanced hydrological models provide robusta and substantial added value.

River flow simulation and evaluations

This section presented the simulated flow characteristics including correlation between precipitation and estimated runoff and temporal–spatial variability of estimated flow.

Simulated flow characteristics

The correlations between estimated runoff and correlated satellite rainfall for the selected river sub catchments were developed. The Pearson correlation matrix presented in Fig. 8 is the result of the inter and extra correlation among the sub-catchments. For the study catchment, the correlation between runoff and rainfall are found excellent and highly variable for all the selected sub catchment. The inter correlation (correlation of rainfall and runoff from the same site) is highly correlated each other. Whereas, the extra correlation (correlation between one another sites) are showed poor and highly variable except two sites (Kubilala and Pere). That means the catchment has heterogeneous and non uniform characteristics. This implies a warranty to hydrologist and water resource modelers that it is not possible to consider regionalization, regression and parameter transferring techniques for such catchment to model the river flow.

Correlations between runoff and precipitation are expected to be strong at the same site in comparison to extra correlation. In spatial rainfall characteristics of the catchment, the maximum and mean distribution is uneven and higher values were seen in the upper part of the river. Similarly, during our interview company, we proved that the river

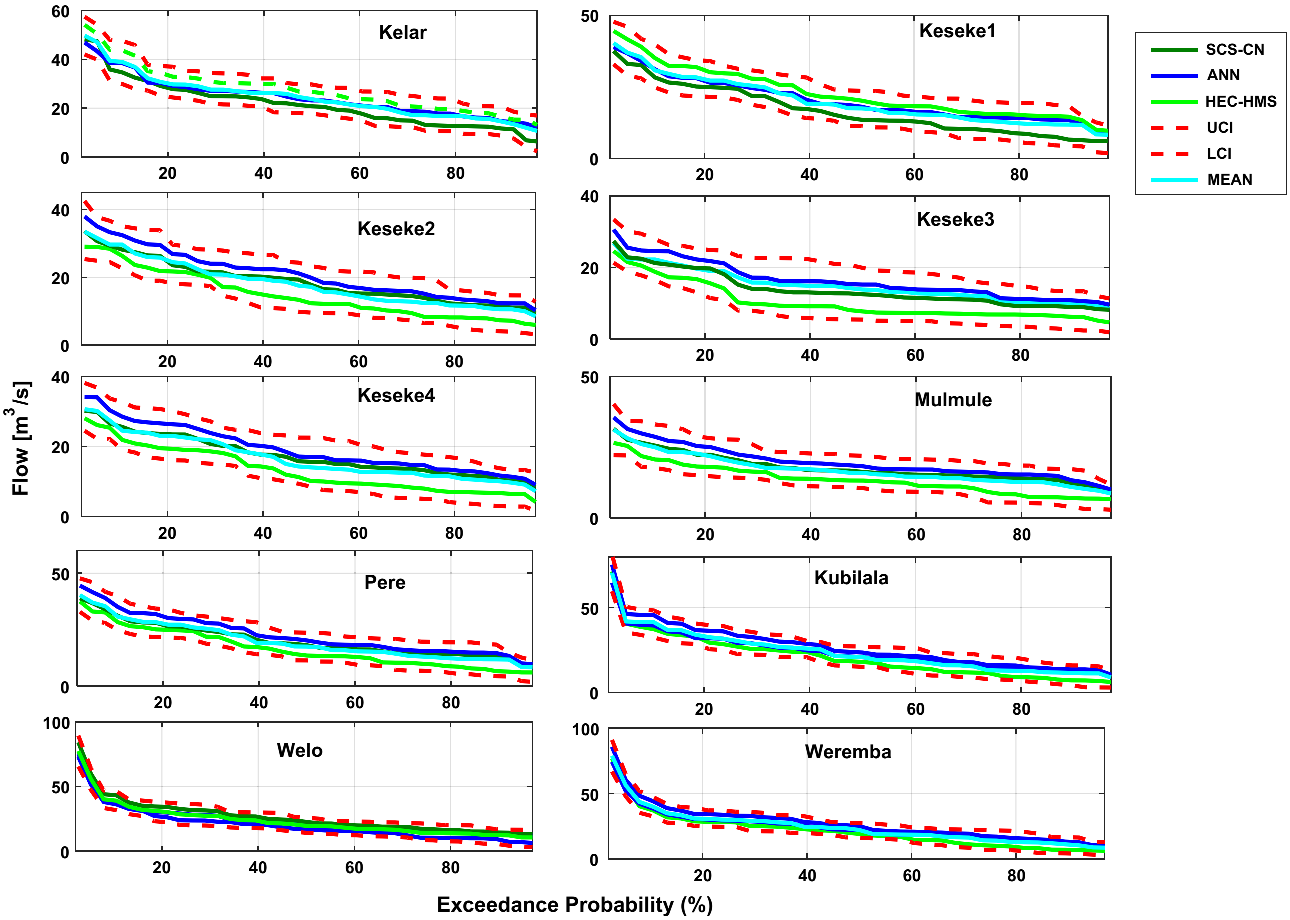

Fig. 7 Exceedance probabilities of the estimated runoff using SCS-CN, ANN, HEC-HM and the 95% upper confidence interval, 5% lower confidence interval and mean at the selected stations

flow mechanism derived mainly by rainfall and expected to get strong correlation as we shown in Fig. 8. Hence, rain contributes to the runoff at the outlet in a relatively shorter time period. However, sometimes intense rainstorms found in this catchment at the beginning of the rain season typically produced runoff immediately after a large storm.

Figure 9 shows graphical visualization of the annual maximum (upper panel of Fig. 9) and mean (upper panel of Fig. 9) estimate runoff time series for the selected ten stations. The highest maximam annual runoff was estimated in Keseke1 and Keseke 2 sites (77.3 m^3/s) and the lowest was estimated in Welo 4 site (8.9 m^3/s) according to the analysis of the present datasets (1981–2017). Similary, the annual mean values is also shows temporal variability ranges from 0.2 to 0.9 m^3/s. Generally, the annual maximum and mean runoff series are positively increased for all the ten stations and shows significant differences among the selected sub catchments. The temporal status of each sub catchment shows a positive trend and consistent inside the Keseke catchment. Also, possible to determine the coefficient of surface runoff from surface runoff value and rainfall data. So, it is mean that all sub catchment shows reliable surface runoff values and the estimated values important and applicable for design purpose in ungauged catchment.

Figure 10 shows the spatial variability of annual maximum and annual mean surface runoff within all 15 subcatchments as annual averages over the 37-year period (1981–2017). In general, the spatial patterns and variability's within the entire catchment are different. This is due to a combination of the main key factors, such as vegetation cover, slope and rainfall intensity, affects the spatial formation of surface runoff and, thus, the other flow components. Specially, a slight higher annual maximum surface runoff can be observed: in the mountainous and middle part of the Keseke catchment areas.

Figure 10 can be seen that different parts of Keseke river catchment exhibit different flow amount and variability at the same point in time. There is, in fact, a gradient in runoff regimes magnitudes across Keseke river catchment, with southern areas, especially lowland areas, experiencing low runoff flows, in opposition with the high flows exhibited in the north (mountainous) part of the catchment.

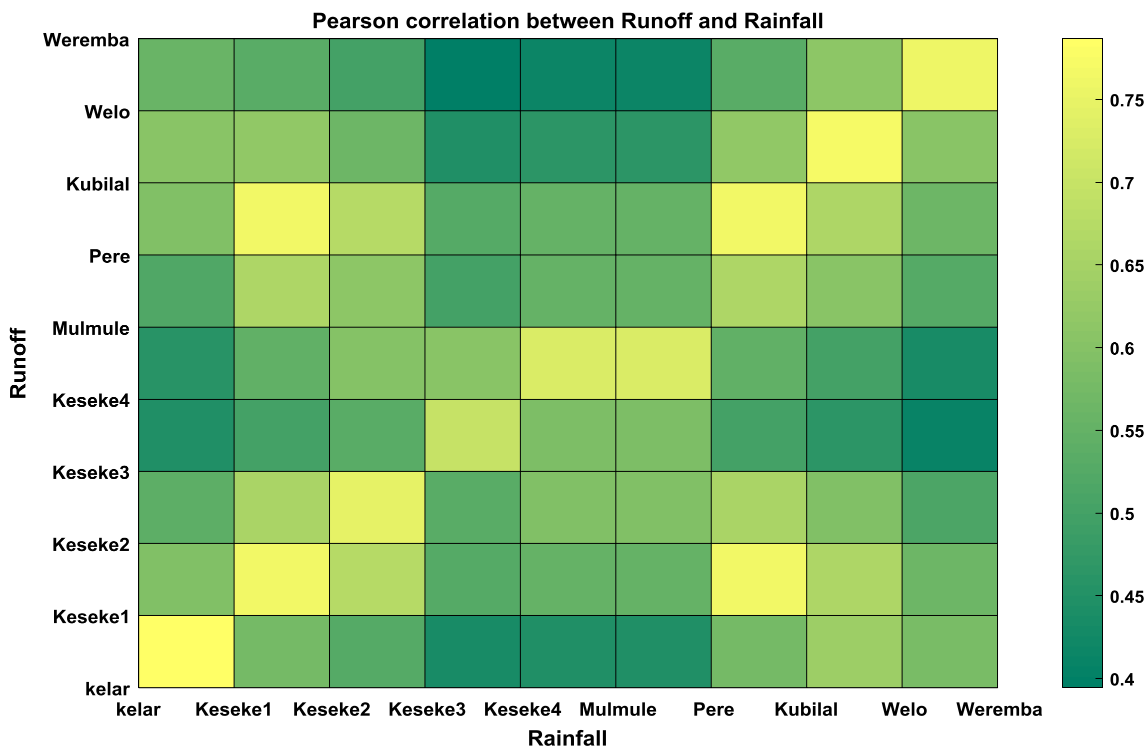

Fig. 8 The Pearson correlation between precipitation and estimated runoff of the selected sub catchments

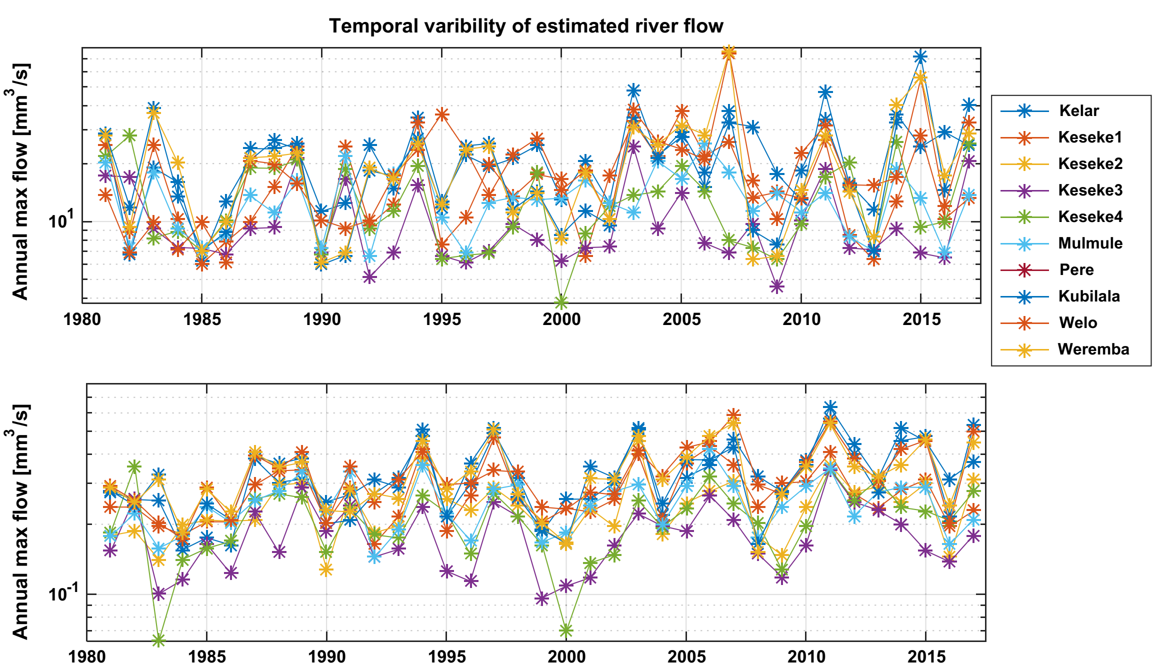

Fig. 9 Temporal variability of Annual maximum (upper) and annual mean (lower) surface runoff

Flood frequency analysis

Flood frequency analysis is a technique used by hydrologists to predict flow values corresponding to specific return periods or probabilities along a river. Flood frequency analysis is used to calculate statistical information such as mean, standard deviation and skewness which is further used to create frequency distribution graphs. Flood frequency

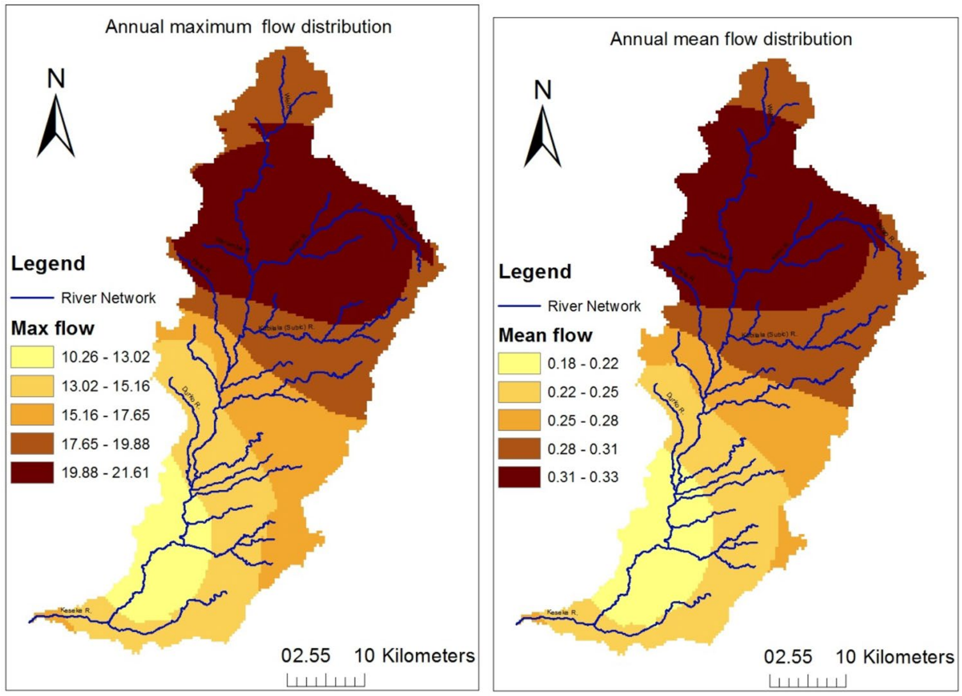

Fig. 10 Spatial variability of annual maximum (left) and mean (right) surface runoff distribution in Keseke catchment

analysis was employed for all selected sites. These analyses, using maximum daily flow for the entire period from 1981 upto 2017 (at least 37 years of flow were considered), were conducted for selected ten sites inside the Keseke river catchment.

For each station, pairs of coefficient of skewness (Cs) and coefficient of kurtosis (Ck) have been computed and plotted on the Cs–Ck diagram for each station, called moment ration diagram (MRD). The location of the sample estimate with respect to the distributions gives an indication of the suitability of the distribution to the data. However, if the sample size is small, the bias in the values of higher moments may be larger enough to give misleading results. In this study we have 37 years sample annual maximum flow, which is suitable to use moment ration diagram. Based on the smallest standard error of estimate, the best fitted candidate distributions and optimal parameters of annual maximum flow for all stations are selected. Generally, Gamma, Generalized perato, and birnbaumsaunder distributions are the most dominant distribution type with Maximum likely hood (ML) parameter estimation technique.

After choosing the probability distribution that best fits the annual maxima data and parameter estimation techniques, flood frequency curves were developed (Fig. 11). These graphs are then used to estimate the design flow values corresponding to specific return periods which can be used for flood protection, structure design and hydrologic planning purposes. Flood frequency plays a vital role in providing estimates of recurrence of floods which is used in designing structures such as dams, bridges, culverts, levees, highways, sewage disposal plants, waterworks and industrial buildings. for instance one can read from the flood frequency curve as the flow value corresponding to a 25-year return period event for the ten selected stations are approximately equal to 44.8, 39.2, 34.2, 37.9, 33.7,33.7 m^3/s respectively for Kela, Keseke1, Keseke2, Keseke3, Kaske4 and Mulmula.

Conclusions

Ungauged river understanding and modelling for water resource management and planning such as the Keseke River catchment in South Ome River basin, using empirical models, data driven models, hydrological models with GIS and remote sensing techniques can provide important information and analytical capability to hydrology and water resource assessment of the given river catchment. This study has confirmed the complementary framework approaches of remote sensing, various hydrological modelling techniques and observed hydro-climate data to refine the catchment process and balance of the Keseke river catchment. The methodology applied to a catchment where there is no hydrological gauged station with sparse meteorological stations, conclusions that the study may provide evidence and conformation for the utilization of remote sensing product data for hydrology and water resources assessment of the Keseke river catchment. The outputs of this study will help hydrologists to understand the efficiency and application of remote sensing data in river flow (rainfall-runoff) modeling.

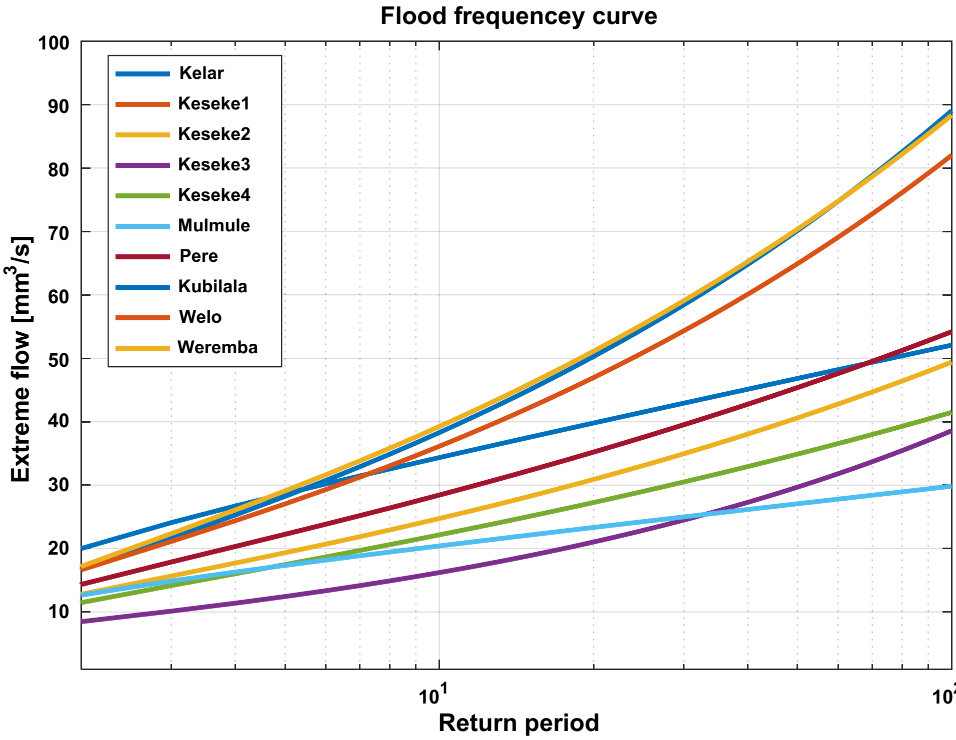

Fig. 11 Flood frequency curve for the selected study sites

The aims of this study were to explore the potential of satellite based precipitation estimates for flood frequency analysis under three umbrellas at different sub-catchments in Keseke catchment. First, the study focused on statistical evaluation of the remote sensing data products and evaluated their utility in river runoff prediction using three different hydrological modelling approaches in ten tributaries of Keseke catchment. Second, the three hydrological modelling approaches were evaluated and compared with respect to the mean and 95% and 5% confidence interval in ungauged Keseke river catchment. Third, based on the moment ratio diagram approach different distribution type and parameter estimation techniques were identified, and flood frequency analysis was performed using the 37 years flood series.

Validation of satellite-based climate product using rain gauges data within the time period from 1981 to 2017 in the selected ten sub catchments, Keseke river catchment, were performed. Both bias correction methods (Distribute Quantile Mapping and Emperical Quantile Mapping) satisfactorily improved daily raw climate data in the Keseke river catchment. Some statistical parameters such as correlation coefficient, bias and percent bias were used to evaluate the satellite data in comparison with the observed data. The results of the analysis show that the satellite data are reasonably correlated with observed climate data and highly cross-correlated with the observed climate data. Moreover, the bias correction technique was able to capture the daily observed climate data quite well in both timing and magnitude in all selected sub catchments.

The bias correction techque achieved significantly improved the capability of these products to predict runoff at a daily scale using ANN, HEC-HMS and SCS-CN. Improvements in hydrological predictions obtained by corrected remote sensing data can help to enhance the operation of hydropower, reservoirs, flood protection, planning for irrigation, and hydraulic structures, among other things. The three models performed well in the selected sub-catchments in most cases. However, relatively, SCS-CN and ANN performed better than HEC-HMS. Although the HEC-HMS model had higher relative peak flow errors and higher relative runoff errors than did ANN and SCS-CN in many cases. SCS-CN based modelling had lower peak flow errors and better hydrographs agreement with the mean simulated flow in most selected sites. Generally, HEC-HMS did not show better performance than the other two models as expected due the parameters that are extracted from field, which leads dueto the concept of stationerity and heterogeneity of the selected catchments.

Available global remote sensing data products present great opportunities to study extreme hydrology and water resource resource variability. We have confirmed that these products can be integrated with hydrological models to solve a typical water problems without the need for resource intensive and complex ancillary data. This research approach provides a rapid, accurate, reliable, and cost-effective solution to predict river runoff and assess hydrological characterstics in the selected sub catchments in unguaged or with out monitoring infrastructure, which is vital for water resource managers to make informed decisions on different sectorial activities (flood protection, water supply, irrigation…).

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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