

Hydroclimatology of Lake Victoria region using hydrologic model and satellite remote sensing data

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Abstract. Study of hydro-climatology at a range of temporal scales is important in understanding and ultimately mitigating the potential severe impacts of hydrological extreme events such as floods and droughts. Using daily in-situ data over the last two decades combined with the recently available multiple-years satellite remote sensing data, we analyzed and simulated, with a distributed hydrologic model, the hydro-climatology in Nzoia, one of the major contributing sub-basins of Lake Victoria in the East African highlands. The basin, with a semi arid climate, has no sustained base flow contribution to Lake Victoria. The short spell of high discharge showed that rain is the prime cause of floods in the basin. There is only a marginal increase in annual mean discharge over the last 21 years. The 2-, 5- and 10- year peak discharges, for the entire study period showed that more years since the mid 1990's have had high peak discharges despite having relatively less annual rain. The study also presents the hydrologic model calibration and validation results over the Nzoia basin. The spatiotemporal variability of the water cycle components were quantified using a hydrologic model, with in-situ and multi-satellite remote sensing datasets. The model is calibrated using daily observed discharge data for the period between 1985 and 1999, for which model performance is estimated with a Nash Sutcliffe Efficiency (NSCE) of 0.87 and 0.23% bias. The model validation showed an error metrics with NSCE of 0.65 and 1.04% bias. Moreover, the hydrologic capability of satellite precipitation (TRMM-3B42 V6) is evaluated. In terms of reconstruction of the water cycle components the spatial distribution and time series of modeling results for precipitation and runoff showed considerable agreement with the monthly

model runoff estimates and gauge observations. Runoff values responded to precipitation events that occurred across the catchment during the wet season from March to early June. The spatially distributed model inputs, states, and outputs, were found to be useful for understanding the hydrologic behavior at the catchment scale. The monthly peak runoff is observed in the months of April, May and November. The analysis revealed a linear relationship between rainfall and runoff for both wet and dry seasons. Satellite precipitation forcing data showed the potential to be used not only for the investigation of water balance but also for addressing issues pertaining to sustainability of the resources at the catchment scale.

1 Introduction

Climatologically most of East Africa is considered as a sub humid landscape that comprises arid and semi-arid regions, grasslands, savannahs, as well as a Mediterranean environment. East African climate is mainly influenced by the seasonal shift of the Intertropical Convergence Zone (ITCZ). However other regional factors that influence the climate are topographical variations, large inland lakes, land cover/land use, as well as the proximity to the Indian Ocean. Oscillations in the ITCZ, causes two rainy seasons in the equatorial East Africa, one from March to May and the other from October to December (Kaspar et al., 2008). This precipitation pattern can result in floods in this region with impacts on the food and agricultural security, human health, infrastructure, tourism, and other sectors. The rainy season that onsets from October through early December brings devastating floods in Uganda, Kenya, Tanzania, and other countries in East Africa almost every year. This region, surrounding Lake Victoria,



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is heavily populated with around thirty million people (Osano et al., 2003). These floods are a serious problem in East Africa, particularly in the Lake Victoria Basin, which impacts the livelihood of many people every year.

Hydro-climatology deals with the interactions of climate with hydrology. One of the main focuses of the hydro-climatic study is the interactions between precipitation, evapotranspiration, soil moisture storage, groundwater recharge, and stream flow (Shelton, 2009). The study of the water budget at a given location and time period essentially deals with the components of hydro-climatology. Hydrologic modeling is an efficient approach for understanding the relationship between climate, hydrologic cycle, and water resources. In East Africa, the current trend and future scenarios of unsustainable water resource utilization demands modeling studies that provide accurate spatial and temporal information on hydrological and climatological variables. The main obstacles for these investigations are the lack of sufficient geospatial data for distributed hydrologic model input and validation. Availability of observed data in regions with sparse ground based networks for hydrologic estimations is the key limitation in hydroclimatologic studies. However, advances in satellite remote sensing data can provide objective estimates on precipitation, evapotranspiration and land surface controlling factors for water budget calculations. The recent availability of virtually real time and uninterrupted satellite-based rainfall estimates is becoming a cost-effective source of data for hydro climatologic investigations in many un-gauged and under-gauged regions around the world. Furthermore, application of remotely sensed spatially distributed datasets has made possible the transition from lumped to distributed hydrologic models that accounts for the spatial variability of the model parameters and inputs (Hong et al. 2007; Li et al., 2009). The question remains whether with the existing spatial and temporal coverage of satellite precipitation and other estimates, how can we achieve their optimal use to compute a less uncertain water budget?

Hydrologic modeling has been constrained by the difficulty in precisely estimating precipitation, the key forcing factor, over a range of spatial and temporal scales. Several studies used satellite precipitation to examine the availability of water resources and the hydrologic extremes such as floods and droughts. Moreover, reliable satellite precipitation provides potential for hydrologic prediction around the world, particularly in developing countries where in situ observations are either sparse or nonexistent. One such example is the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al., 2007) product. TMPA is used for land surface modeling at global scale (Hong et al., 2007a, b; Collischonn et al., 2008; Curtis et al., 2007; Su et al., 2008) and local scale (e.g Li et al., 2009; Rahman et al., 2009; Valeriano et al., 2009).

The goal of this study is to examine the hydro-climatology of Nzoia basin, a sub catchment of the Lake Victoria region using observed and simulated data with particular emphasis

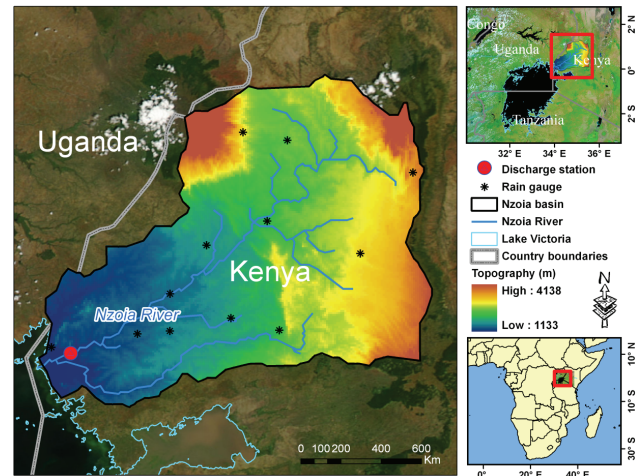


Fig. 1. Map of Nzoia river basin in Lake Victoria region, East Africa.

on distributed hydrology of the watershed (Fig. 1). More specifically, the objectives are to (1) quantify the hydroclimatology of Nzoia basin at decadal, annual, monthly and daily time scale using in-situ dataset; (2) model the rainfall-runoff relationship using a distributed hydrological model, calibrated by long-term observations, in terms of predictability at the daily scale; (3) investigate the hydrological capability of remote sensing data (primarily the precipitation) in terms of the reconstruction of water cycle components.

The paper follows with a brief description of the study basin, data, and model in Sect. 2. The hydroclimatology based on observational datasets are discussed in Sect. 3, followed by Sect. 4 with a model set-up, calibration, and verification. The hydrological model reconstruction results are outlined in Sect. 5, and finally summary and discussions are given in Sect. 6.

2 Study area, data and model

2.1 Study area

The study area is the Nzoia River located at latitudes 34° – 36° E and longitudes $0^{\circ}03'$ – $1^{\circ}15' N$ in East Africa. It drains into the Lake Victoria and Nile river basins. Lake Victoria, with an area of $68\,600\text{ km}^2$, is the second largest freshwater lake in the world (Swenson and Wahr, 2009). Nzoia, a sub-basin of Lake Victoria, is chosen as the study area because of its regional importance as it is a flood-prone basin and also one of the major tributaries to Lake Victoria (Fig. 1). The Nzoia sub-basin covers approximately $12\,900\text{ km}^2$ of area with an elevation ranging between 1100 to 3000 m. The Nzoia River originates in the southern part of the Mt. Elgon and Western slopes of Cherangani Hills (Li et al., 2009). The lowlands are characterized by predominant clayey soils

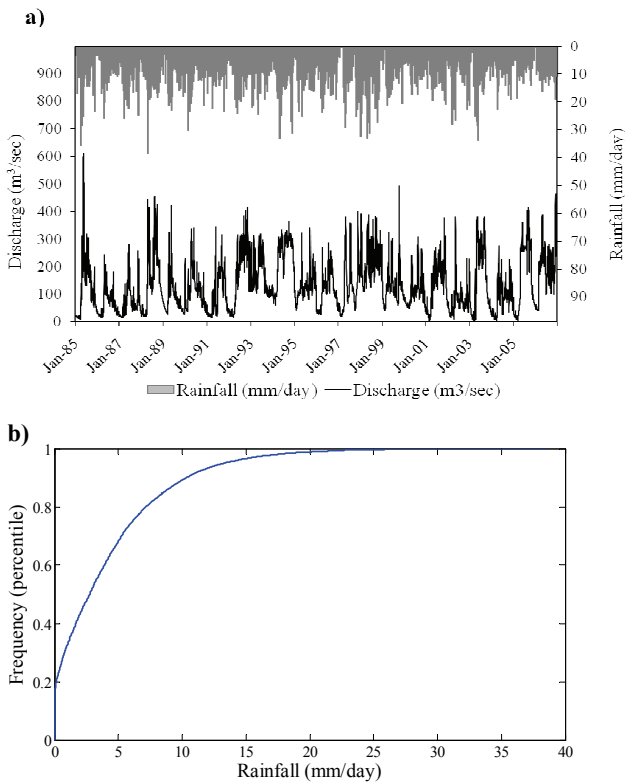


Fig. 2. (a) Nzoia basin average daily rainfall and discharge time series. (b) Cumulative distribution plot of observed basin average rainfall (mm day^{-1}) for 1985–2006.

at 77%. The other main soil type of the catchment is sand at 14%. Soil data is used from the Food and Agriculture Organization of the United Nations (FAO; <http://www.fao.org/AG/agl/agll/dsmw.htm>). The land use land cover data is from the Moderate Resolution Imaging Spectroradiometer (MODIS) land classification map. It is used in this study as a representation of land use/cover, with 17 classes of land cover based on the International Geosphere–Biosphere Programme classification (Friedl et al., 2002).

2.2 In-situ and remote sensing datasets

2.2.1 Gauged rainfall and discharge data

Daily observed rainfall data are obtained from the Africa Regional Centre for Mapping of Resources for Development (RCMRD) from 1985 to 2006 for the 12 rain gauge stations located within the Nzoia basin. They are then interpolated to fit the model grid resolution using the Thiessen polygon method (Kopeck, 1963). Also obtained are the daily discharge data (in $\text{m}^3 \text{s}^{-1}$) at the basin outlet for the same time period (Fig. 2a).

2.2.2 NASA TMPA

Precipitation is a critical forcing variable to hydrologic models, and therefore accurate measurements of precipitation on a fine space and time scale is very important for simulating land-surface hydrologic processes, and monitoring water resources, especially for semiarid regions (Sorooshian et al., 2005; Gebremichael et al., 2006). For the past decade, there have been several multi-satellite based precipitation retrieval algorithms for operational and research purposes (Hong et al., 2004; Huffman et al., 2007; Joyce et al., 2004; Sorooshian et al., 2000). For this study, we used one of the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) products, 3B42 V6 given its 10+ year data availability. It is used to drive the CREST model to simulate the water budget components such as runoff, evapotranspiration and, change in storage for the study basin. The standard TMPA provides precipitation estimates from multiple satellites at a 3-hourly, $0.25^\circ \times 0.25^\circ$ latitude-longitude resolution covering the globe between the latitude band of $50^\circ \text{N}–\text{S}$ (Huffman et al., 2007). This TRMM standard precipitation product has been widely used for hydrological applications such as flood and landslide prediction at the global and regional scope (Su et al., 2008; Hong et al., 2006, 2007; Yong et al., 2010).

2.2.3 Evapotranspiration

In the model, Potential Evapotranspiration (PET) values are from the global dataset based on the Famine Early Warning Systems Network (FEWS). Further details on these estimates can be found at (<http://earlywarning.usgs.gov/Global/product.php?image=pt>). The PET are estimates of climate parameter data that is extracted from the Global Data Assimilation System (GDAS) analysis fields. FEWS PET is at a 1-degree spatiotemporal resolution calculated using global-scale meteorological datasets.

2.3 The CREST model

A distributed hydrologic model, Coupled Routing and Excess STorage (CREST) (Wang et al., 2011; Khan et al., 2011) is used to simulate the spatiotemporal variation of water fluxes and storages on regular grids. The model accounts for the most important parameters of the water balance component i.e. the infiltration and runoff generation processes. The main CREST components are briefly described as; (1) data flow module based on cell to cell finite elements; (2) the three different layers within the soil profile that affect the maximum storage available in the soil layers. This representation within cell variability in soil moisture storage capacity (via a spatial probability distribution) and within cell routing can be employed for simulations at different spatiotemporal scales 3) coupling between the runoff generation and routing components via feedback mechanisms. This coupling allows for

Table 1. Main physically-based parameters in CREST model.

Symbols	Brief description	Source for estimation	Unit
DEM	Digital Elevation Model	Remote Sensing	m
ACC	Accumulation grids	Derived from DEM	N/A
Dire	Flow Direction	Derived from DEM	N/A
S	Slope between cells	Derived from DEM	degree
K	Cell mean infiltration rate	Soil Survey	mm-h-1
d	Vegetation coverage	Remote Sensing	N/A
l	Distance between cells	Derived from DEM	m
LAI	Leaf area index	Remote Sensing	m ² -m ²

Table 2. Seasonal variation of rainfall and discharge.

	Decades	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
Rainfall (mm day ⁻¹)	1985–1994	1.70	2.69	4.49	7.66	7.69	4.49	4.47	5.40	4.08	4.26	4.22	1.55	
	1995–2004	2.20	1.20	4.07	7.23	5.96	4.37	3.93	4.55	4.11	4.65	4.31	2.05	
	Change	0.50	-1.49	-0.41	-0.44	-1.74	-0.13	-0.54	-0.86	0.04	0.40	0.08	0.49	
	% Change	30%	-55%	-9%	-6%	-23%	-3%	-12%	-16%	1%	9%	2%	32%	-4%
Discharge (m ³ sec ⁻¹)	1985–1994	57	51	64	144	22	160	167	182	166	143	131	85	
	1995–2004	83	45	60	129	191	151	154	165	155	141	150	116	
	Change	25	-7	-4	-15	-29	-10	-14	-18	-10	-2	19	31	
	% Change	44%	-13%	-7%	-10%	-13%	-6%	-8%	-10%	-6%	-1%	14%	36%	2%

a scalability of the hydrological variables, such as soil moisture, and particularly important for simulations at fine spatial resolution.

In CREST model the vertical profile of grid cells is subdivided into four excess storage reservoirs representing interception by the vegetation canopy and subsurface water storage in the underlying three soil layers. In addition, two linear reservoirs simulate sub-grid cell routing of overland and subsurface runoff separately. In each cell, a variable infiltration curve originally proposed by Zhao et al. (1980) is employed to separate precipitation into runoff and infiltration. There are two cell-to-cell routing modules that move water overland as surface runoff and below ground as subsurface interflow. These modules run in parallel which enables a computationally efficient and realistic three-dimensional representation of water flux to downstream cells. CREST model description in Wang et al. (2010) and Khan et al. (2010) lists the sequential flow of water entering a cell as rainfall and subsequent redistribution back to the atmosphere via evapotranspiration, division of rainfall reaching the soil surface into infiltration and surface runoff components, sub-grid routing, routing of overland, channel and finally feedbacks between routing and runoff generation components.

Many of the parameters in the CREST model can be estimated based on the availability of field survey data, such as soil surveys, land cover maps, and vegetation coverage.

Other parameters are derived directly from a DEM such as flow direction, slope, and drainage area. These physically-based parameters are listed in Table 1 along with a suggested source of data to estimate them. There are approximately ten parameters that are much more difficult to estimate from ancillary data and need to be calibrated either manually or automatically (Wang et al., 2010).

3 Hydro-climatology of Nzoia basin

3.1 Rainfall

The mean monthly rainfall over Nzoia shows dual peaks over the year which is common to parts of the immediate equatorial zone especially in East Africa (Hulme, 2006). The first and second maxima occurred in April–May and July–November respectively. It is observed that for the given time period of 1985–2006, the basin average rainfall per annum is about 1500 mm. Observations of the rainfall since 1985 do not show any statistically significant trends. It is observed that half of the recorded rainfalls are below 5 mm day⁻¹ (Fig. 2a, b).

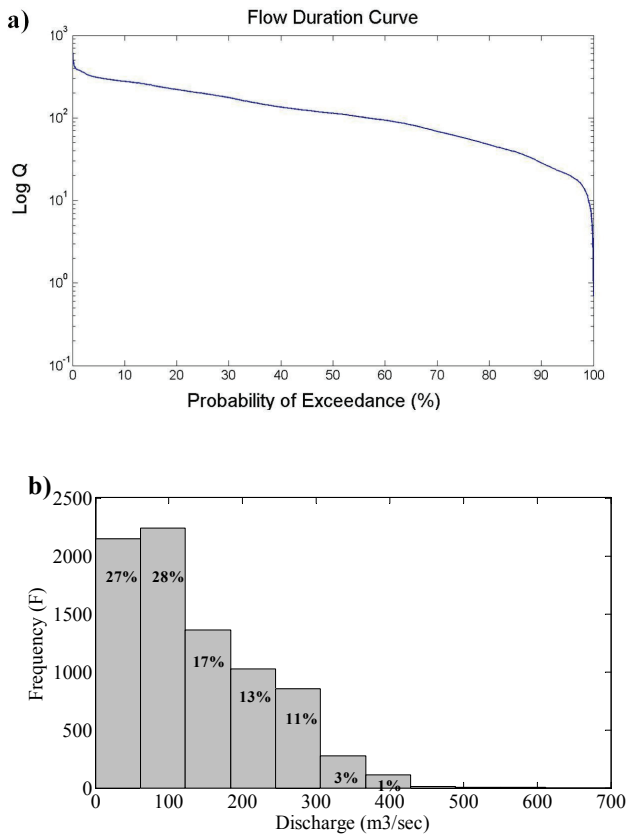


Fig. 3. Observed daily discharge ($\text{m}^3 \text{sec}^{-1}$) for 1985–2006 for Nzoia River (a) Flow duration curve (b) histogram.

3.2 Stream discharge

The highest river discharges occurred in the months of May through September while the lowest river discharges occurred in the months of December through February (Table 2). From 1985–2006, the average daily discharge is $134 \text{ m}^3 \text{ s}^{-1}$. The flow duration curve shows the average percentage of time that specific daily flows (Fig. 3a) are equaled or exceeded at Nzoia. The discharge histogram is skewed towards the lower values and more than half of the recorded daily discharges are less than $120 \text{ m}^3 \text{ s}^{-1}$ (Fig. 3b).

3.3 Return periods of rainfall and discharge

The annual peak discharge and precipitation for the given time period are shown in Fig. 4a. The calculated return periods for both the discharge and rainfall are given in Table 3. The peak discharges of 1985, 1988, 1999, and 2006 were all above the 5-year flow while 1985 and 1999 recorded discharges of 10-year return periods. In 1985, the recorded peak discharge was of the 100-year return period.

It is observed that the annual peak rainfall in the years 1985, 1988, 1990, 1994, 1998, and 2003 exceeded the 5-year return period values. Similarly, 1994, 1998 and 2003 have

Table 3. Discharge and rainfall return periods.

Return periods (year)	Discharge ($\text{m}^3 \text{sec}^{-1}$)	Rainfall (mm day^{-1})
2	370	26
5	443	31
10	486	34
20	526	37
50	573	40
80	591	41
100	608	43
200	641	45
500	684	48

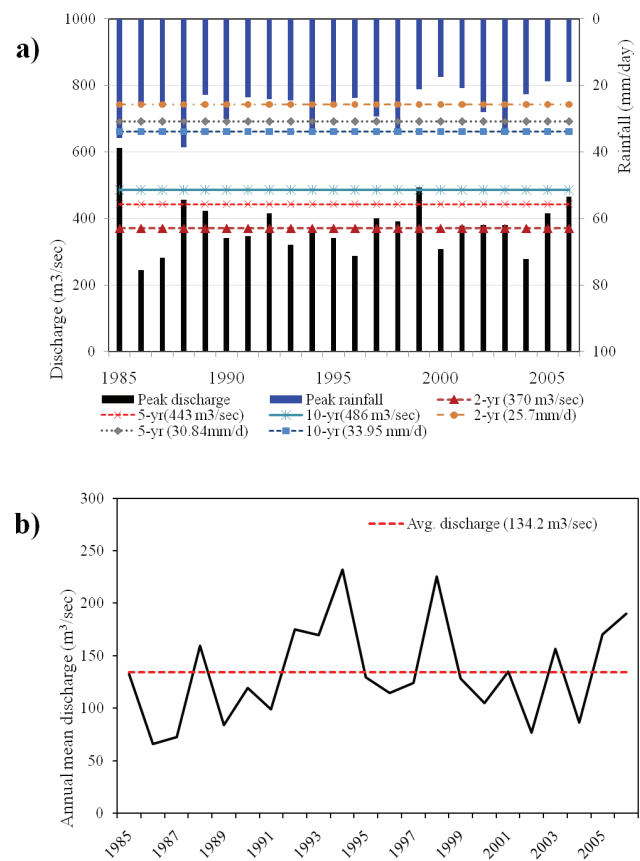


Fig. 4. Annual peak rainfall and discharge for 1985–2006 with (a) the 2-, 5- and 10-year return period (b) annual mean discharge.

the peak rainfall of 10-year. Finally, 1985 and 1988 recorded rainfall of a 20-year return period.

3.4 Annual mean discharge

The discharge time series provide information on the year-to-year variations of both low and peak discharges. Figure 4b shows the annual mean discharge for Nzoia River. The

lowest annual discharge is $66 \text{ m}^3 \text{ s}^{-1}$ in 1986 and the highest is $232 \text{ m}^3 \text{ s}^{-1}$ in 1994. The other wet years are 1998 and 2006 and the dry years are 1987 and 2002 (Fig. 4b). Overall we can observe a slight increasing trend in annual mean discharge. Seasonal cycles included in annual discharge are noticeable with a greater variability of monthly mean stream flow. The maximum monthly discharge is $421 \text{ m}^3 \text{ s}^{-1}$ for May 1985. All the wet years of 1994, 1998 and 2006 are marked by high monthly discharges (Fig. 4b). The dry years of 1986, 1987, and 2002 are not the result of a single dry month but due to continuous low monthly discharges throughout the whole year.

3.5 Decadal monthly trend

The observed data are also analyzed for any trends over the past two decades: 1985–1994 (first decade) and 1995–2004 (second decade). Overall there is some decrease (-4.2%) in rainfall in the second decade compared to the first. Similarly there is a marginal increase ($+2\%$) in discharge (Table 2). However, there is a more pronounced monthly variation both in rainfall and discharge. A maximum decrease in rainfall is recorded for the month of February (-55%) whereas December witnessed a maximum increase ($+32\%$). Similarly, there is a maximum drop in stream discharge in the months of February and May (-13%) while a surge of $+44\%$ is observed in the month of January (Table 2).

4 Hydrologic model setup, calibration and verification

A moderate resolution CREST model at a 30 arc-second resolution is implemented for the Nzoia basin to retrospectively simulate the main components of water cycles with both in-situ and remote sensing data sets. The model is implemented using digital elevation data to generate flow direction, flow accumulation, and contributing basin area that are required as basic inputs to run the CREST model. The local drainage direction and accumulation are derived from the Digital Elevation processed from the Model Shuttle Radar Topography Mission (SRTM) (Rabus et al., 2003). The primary forcing datasets enabling the development of a distributed hydrological model using the long term rain gauge and observed streamflow data provided by the local authorities previously discussed in Sect. 2.2. The CREST model is calibrated at the Nzoia basin outlet (Fig. 1) for the given time period of 1985–1998. A spin up period of one year is assigned to produce reasonably realistic hydrologic states.

The model utilizes global optimization approach to capture the parameter interactions. An auto-calibration technique based on the Adaptive Random Search (ARS) method (Brooks, 1958) is used to calibrate the CREST model. The ARS method is considered adaptive in the sense that it uses information gathered during previous iterations to decide how the simulation effort is expended in the current itera-

tion. The two most commonly used indicators for the model calibration in order to get the best match of model-simulated streamflow with observations are the Nash-Sutcliffe Coefficient of Efficiency (NSCE) (Nash and Sutcliffe, 1970) and relative bias ratio. Therefore, these are used as objective functions for the automatic calibration. The ideal value for NSCE is 1 and bias is 0%. CREST is calibrated using daily observed discharge data for the period between 1985 and 1999. A one-year period (1984) is used for warming up the model states. CREST calibration, performed using the ARS method described in Sect. 2.4, resulted in good performance with NSCE = 0.87 and bias = -0.23% (Fig. 5a).

The performance of CREST in discharge simulation at the drainage outlet is validated. The validation of the hydrological model is performed for the period 1999–2004. The simulation quality during the validation period is comparable, even with a decrease in model efficiency. One reason for the noise in the simulation might be due to the increase in human activities in the catchment area during the recent years. With this optimized parameter combination and model status at the last day from calibration (31 December 1998), discharge from 1999 to 2004 is simulated and compared to observations (Fig. 5b). The error metrics with NSCE of 0.65 and 1.04% bias for the validation period (Fig. 5b) indicates that the CREST model can reproduce observed discharge in the Nzoia basin with acceptable skill.

The simulation results for Nzoia using TRMM 3B42 V6 as precipitation forcing. It can be seen that from 1999 and 2003, the model simulated daily discharge with a NSCE of 0.48 and bias of -4.57% (Fig. 5c). The model for the validation period captures peak and low flows and there is acceptable agreement between simulation and observation at different flow conditions throughout the simulation period.

5 Hydrologic model reconstruction results

Basin-based water balance modeling studies are important in both hydrology and climate research since they provide information on the hydrological cycle and the amount of renewable water available for ecosystems at various land-atmosphere interaction scales ranging, in general, from daily, seasonal, annual, to decadal. Water balance for watersheds, lakes or over a unit land surface area is normally expressed as $P - R + ET = dS/dt$. Where P is Precipitation, R surface runoff, ET is evapotranspiration and dS/dt change in storage (Thornthwaite, 1948; Vörösmarty et al., 1989; Willmott et al., 1985). In this equation, precipitation is the important climate variable for accurate water budget estimation and measured directly on a regular basis. CREST model simulates the spatio-temporal variation of water fluxes and storages at grid cell resolution. The model can output many variables as a raster grid for any selected time period. The hydrologic variables were generated from CREST retrospective simulation from 1999 to 2003 using TRMM 3B42 V6. These four years

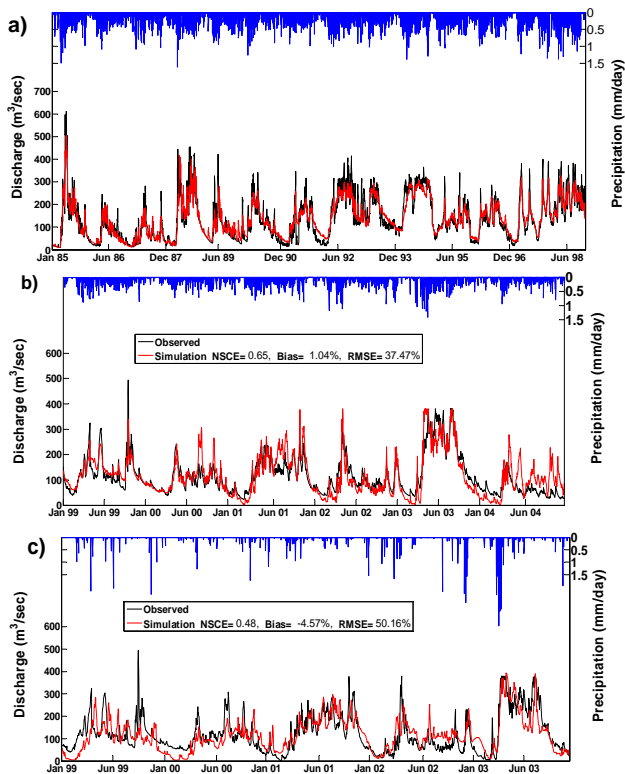


Fig. 5. Daily precipitation, observed and simulated runoff for (a) calibration period (1985–1998), (b) validation period (1999–2004), (c) validation with the TRMM 3B42 V6 from (1999–2003).

were selected to minimize the model run time. Since simulation of the model involves thousands of iterations, model run time in particular is a critical factor to complete a simulation. Water balance basin average calculations were made at daily and long-term mean monthly scale and are discussed hereunder.

5.1 Runoff

The results from the hydrologic water balance are shown in Fig. 6. The basin average monthly analysis shows that the model produces nearly the same basin-wide runoff. Model runoff is compared to the river discharge gauged at the catchment outlets of the basin. Spatially distributed runoff averaged over study period (1996–2006) during wet and dry season is illustrated in Fig. 7. The runoff estimates are expressed in mm/month, to allow inspection of the relative contribution of the catchment. The overall comparison of runoff estimates are reasonably well matched in magnitude and time evolution (Fig. 6). The model slightly underestimates R for the months of June, July, August and September. Model underestimation can be attributed to the accuracy of the TMPA V6 data. The model underestimates runoff for the validation period (Fig. 5c). Several articles evaluated satellite precipitation products by comparing time series of observed river

streamflow with simulated streamflow using rainfall – runoff models over Africa (Hughes, 2006; Nicholson, 2005; Li et al., 2009) and other ungauged or poorly gauged regions (Su et al., 2008; Collischonn et al., 2008). These studies showed that TMPA V6 underestimate the rainfall values that lead to under prediction by the hydrologic model. The observed values still fall under the ± 1 standard deviation (std dev) of monthly mean values. It is to be noted that there is fluctuation of observed streamflow which is an indication of water management practices on the Nzoia River; this is also depicted in Fig. 5b.

5.2 Precipitation

We utilized the TMPA 3B42 V6 dataset as a forcing parameter to characterize the hydrologic variables at the study basin. As expected, 3B42 V6 captures the seasonality of precipitation over the Nzoia basin. The monthly distribution of 3B42 V6 precipitation data also shows two rainy seasons that are comparable with the observed precipitation shown in Fig. 2. The spatial distribution of rainfall over the catchment is shown in Fig. 8. The TMPA product showed fairly good agreement throughout the year; similar results are reported in Li et al., 2009. The 3B42 V6 estimates fall under the ± 1 std dev of monthly mean values throughout the year (Fig. 6).

5.3 Evapotranspiration

Estimation of evapotranspiration, a key hydrologic variable provides better understating of the relationships between water balance and climate. In arid and semi arid biomes, around 90% or more of the annual precipitation can be evapotranspired, and thus ET determines the freshwater recharge and discharge from aquifers in these environments (Wilcox et al., 2003). Moreover, it is projected that climate change will influence the global water cycle and intensify ET globally (Huntington, 2006; Meehl et al., 2007) consequently impacting the scarce water resources. Therefore, estimation of average monthly and annual evapotranspiration is important. Figure 6 shows the simulated evapotranspiration for the time period. Generally in the drier months, evapotranspiration equals rainfall amounts. The evapotranspiration, however, does not vary as much as rainfall does in a given year.

6 Summary and conclusion

In this study, we used observed data from 1985–2006, for the hydroclimatology of Nzoia basin by studying (1) rainfall and stream discharge patterns, (2) return periods of rainfall and discharge, (3) annual mean discharge and decadal monthly trends of both rainfall and discharge. In addition, a distributed hydrologic model driven by satellite remote sensing data is used to study the water balance of the sub catchment. Runoff and precipitation observation have been used to evaluate the hydrologic model results.

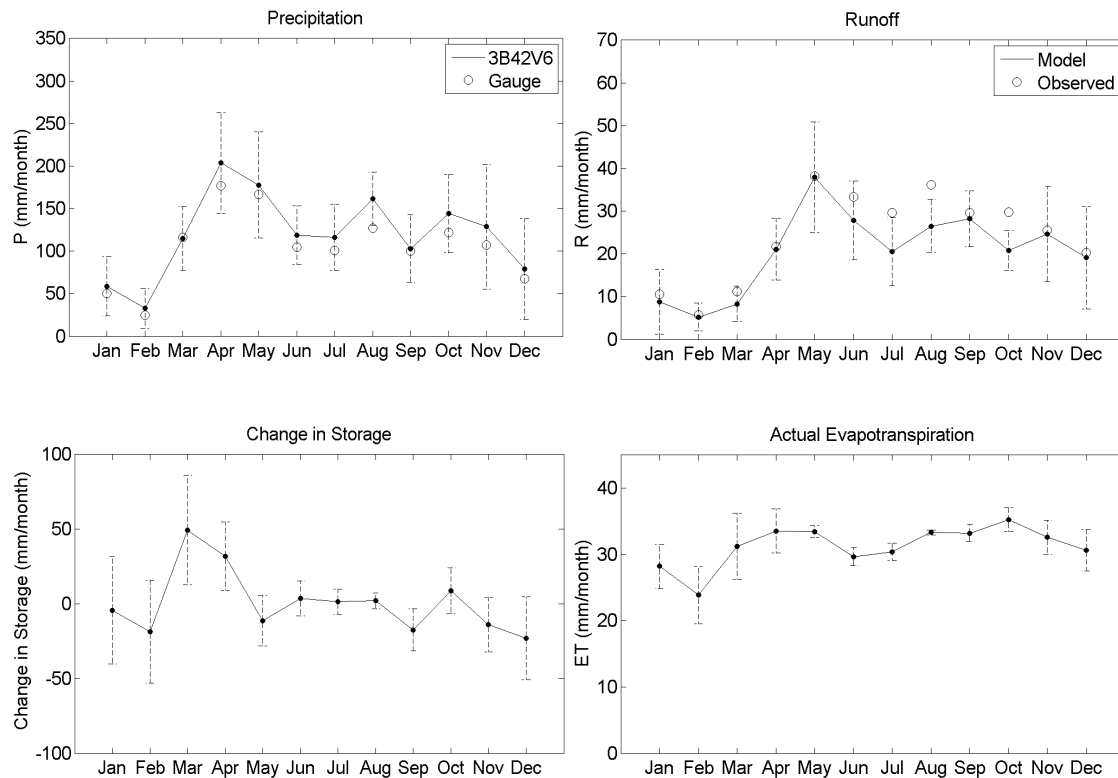


Fig. 6. Monthly model versus observed Runoff (R), Precipitation (P), Evapotranspiration (ET) (mean annual cycle 1996–2006). Error bars showing the ± 1 std dev of monthly mean values.

The observed record at Nzoia showed that for the 1985–2006 time period the basin received quite consistently 2-, 5- and 10-years rainfall in totality for the past 21 years (1985–2006). The second decade (1995–2004) however, received less 5-year and 10-year equivalent rainfalls compared to the first decade (1985–1994). The discharge data showed that the two year returned period equivalent discharge is observed more frequently in the second decade than in the first decade. There is only a marginal increase in annual mean discharge for the last 21 years. The 2-, 5- and 10- years peak discharges, for the entire study period shows that more years since the mid 1990's have high peak discharges even with relatively less precipitation. This might have been the effect of changing land-use and land cover types or increased channelization of the Nzoia basin over time. Githui (2008) revealed that the land use land cover changes during 1973–2001 have been significant and have contributed to a considerable increase in runoff. The agricultural area has increased from about 40 to 60% while forest area has decreased from 12 to 7%. Generally runoff was highest from agricultural lands while runoff from shrubland was greater than that from grasslands. This increase in agricultural in the basin can be attributed to the increased runoff.

The discharge data for the study period showed that the basin is dry and arid with no sustained base flow. The short

spell of high discharge shows the rain caused flooding in the basin. With a decrease in rainfall, the primary input flux into the Nzoia basin, the water budget situation might deteriorate over the coming years. Noticeable variations in monthly average rainfall and discharge were observed for the two decades (1985–1994 and 1995–2004). The rainfall fluctuated from as low as 55% (in February) to as high as 32% (in December) in drier months. Similarly, there are decreases in February and May monthly average discharge by 13% while January saw a surge of 44%. But overall, there is only a very slight increase (2%) in annual mean discharge suggesting an insignificant imbalance in water budget in the basin during the study period.

The study utilizes quasi-global satellite precipitation and other remote sensing data products. This helps to understand the utility of the remotely sensed data for hydroclimatology studies at a sub-catchment with sparse ground observations. Simulation of the key hydrological processes and their inter-connection with climate and basin characteristics is a critical step in estimating catchment water balance. Therefore, a distributed hydrologic model (CREST) is implemented to simulate hydrological states and flux variables such as runoff, ET , precipitation and soil moisture at a spatial resolution of 30 arc seconds at 3 hourly time steps. The CREST model is forced by satellite-based precipitation and evapotranspiration

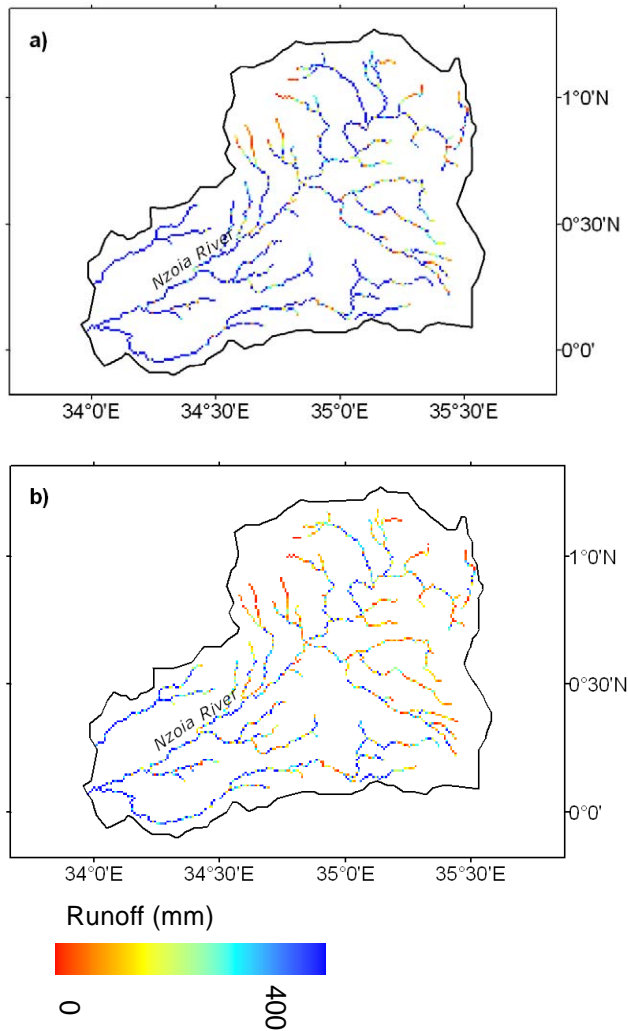


Fig. 7. Spatially distributed runoff averaged over study period (1996–2006) during (a) wet season from March to June and (b) dry season from November to February.

estimates, rain gauge observations, and other remote sensing products. Observations on runoff and precipitation have been used to evaluate the model results at the sub-catchment level. TMPA 3B42 V6 showed good agreement with gauge observations.

Spatially distributed CREST model output for runoff (R) is shown in Fig. 7 and precipitation (P), evapotranspiration (ET), and dS/dt is shown in Fig. 8. In general, the model reproduces P , ET , and dS/dt fairly well. Considerable agreement is observed between the monthly model runoff estimates and gauge observations reported for the Nzoia River (Fig. 6). Runoff values respond to precipitation events occurring across the catchment during the wet season from March to early June. The hydrologic model reasonably captured the soil moisture storage variability. An important advantage of spatially distributed hydrologic model, such as CREST, is

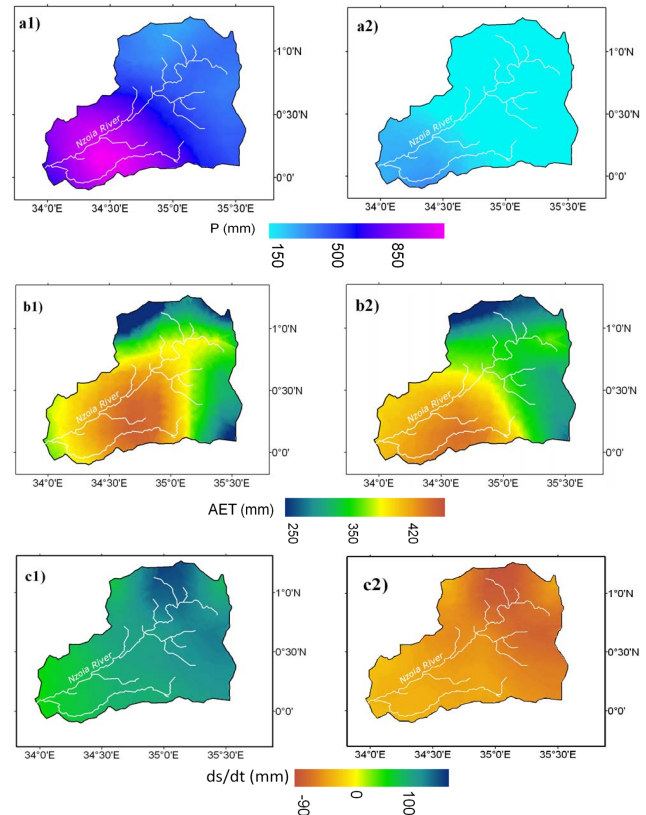


Fig. 8. Spatially distributed Precipitation (P) (a1, a2), Evapotranspiration (ET) (b1, b2), Change in storage (ds/dt) (c1, c2) for wet season (from March to June) and dry season (from November to February) respectively averaged over study period (1996–2006).

that it not only provides estimates of hydrological variables at the basin outlet, but also at any location as represented by a cell or grid within the given basin (Fig. 7). These spatially distributed model inputs, states, and outputs, are useful for visualizing the hydrologic behavior of a basin. These results reveal that relatively high flows were being experienced near the basin outlet from previous rainfall, with a new flood peak responding to the rainfall in the upper part of the basin.

Comparison of the model outputs such as evapotranspiration and soil moisture estimates against field measurements can help evaluate the model performance. The model developed from this study can be applied to poorly gauged catchments using satellite forcing data and also be used to investigate the catchment scale water balance. Implementing the CREST model resulted in spatiotemporally distributed hydrological variables that can be utilized in addressing issues pertaining to sustainability of the resources within the catchment.

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