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Continuous Modeling of the Mkurumudzi River Catchment in Kenya Using the HEC-HMS Conceptual Model: Calibration, Validation, Model Performance Evaluation and Sensitivity Analysis

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Academic Editors: Ali Assani, Christophe Kinnard and Mhamed Mesfioui

Received: 27 June 2018; Accepted: 10 August 2018; Published: 14 August 2018

Abstract: The Mkurumudzi River originates in the Shimba hills and runs through Kwale County on the Kenyan Coast. Study on this river has been informed by the many economic activities that the river supports, which include sugarcane plantations, mining, tourism and subsistence farming. The main objective of this study was to use the soil moisture accounting (SMA) model specified in the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) settings for the continuous modeling of stream flow in the Mkurumudzi catchment. Data from past years were compared with observed stream flow data in order to evaluate whether the model can be used for further prediction. The calibration was performed using data from 1988 to 1991 and validation for the period from 1992 to 1995 at a daily time step. The model performance was evaluated based on computed statistical parameters and visual checking of plotted hydrographs. For the calibration period of the continuous modeling, the performance of the model was very good, with a coefficient of determination R^2 = 0.80, Nash-Sutcliffe Efficiency NSE = 0.80, index of agreement d = 0.94, and a Root Mean Squared Error (RMSE)/observations' standard deviation ratio—RSR = 0.46. Similarly, the continuous model performance for the validation period was good, with R^2 = 0.67, NSE = 0.65, RSR = 0.62 and d = 0.88. Based on these performance results, the SMA model in the HEC-HMS was found to give a satisfactory prediction of stream flow in the Mkurumudzi Catchment. The sensitivity analysis of the model parameters was performed, and the different parameters were ranked according to their sensitivity in terms of percent change in simulated runoff volume, peaks, Nash-Efficiency, seven-day low flow and base flow index. Sensitivity analysis helped to understand the relationships between the key model parameters and the variables.

Keywords: continuous modeling; calibration; validation; model performance evaluation; HEC-HMS model

1. Introduction

The hydrology of any catchments depends highly on climatic conditions, especially rainfall. Hydrological modeling helps in the understanding of all the processes of rainfall transformation into runoff. The Hydrologic Modeling System (HEC-HMS), developed by the US Army Corps of Engineers Hydrologic Engineering Center in 1998, is designed for both continuous and event-based hydrologic modeling [1]. It offers different options for modeling various components of the hydrologic cycle. For watershed modeling, the HEC-HMS model contains four components: (1) Basin component, (2) Meteorological component, (3) Control specification, and (4) Input data component (time series, paired data and gridded data). For effective use of hydrological models, calibration, validation, performance evaluation and sensitivity analysis need to be undertaken. After calibration is done using one part of the data, the validation process follows in order to analyze the performance of the simulation using the remaining part of the data [2]. Then sensitivity analysis is done to find the most sensitive parameters, so as to understand how great the impact of each model parameter is on the results. This paper addresses three specific objectives: (1) calibration and validation of the HEC-HMS hydrologic model in the Mkurumudzi catchment, (2) Model Performance Evaluation by statistical measures, and (3) sensitivity analysis of the model's parameters.

2. Materials and Methods

The study site, the Mkurumudzi River basin, measures approximately 230 km^2, is located 50 km south of Mombasa, Kenya, and stretches 30 km inland from the Indian Ocean. The river, which is approximately 40 km long, is the main waterway flowing from the Shimba Hills and drains into the Indian Ocean. The river basin experiences a sub-humid climate, with average rainfall ranging from 800 mm to 1300 mm in the short (October–December) and long (March–May) rainfall periods, respectively, based on records from 1959 to 2012. Mean annual evaporation is about 2170 mm/year, giving an aridity index of approximately 0.55 [3]. The mean annual minimum and maximum temperatures are 22.8 and 30.0 °C, respectively. The warmest months are between November and April, with mean temperatures of 26.0 to 28.0 °C, while the cooler months have a temperature ranging between 24.0 and 26.0 °C. The mean daily evapotranspiration rate is 4.4 mm/day. The Mkurumudzi River has a gauging site (RGS-3KD06) near the Shimba Hills. The waterway has stable dry season base flows, which are sustained by groundwater. The catchment land is mainly used for agriculture (maize, beans, cowpeas, millet and sorghum, okra, cassava) (Figure 1) and livestock husbandry, commercial mining (Base titanium Ltd., Ukunda, Kenya), commercial farming of sugarcane (by Kwale International Sugar Company KISCOL, Kwale, Kenya), tourism associated with the sea and the Shimba Hills National Reserve, and for fishing, mainly in the Indian Ocean.

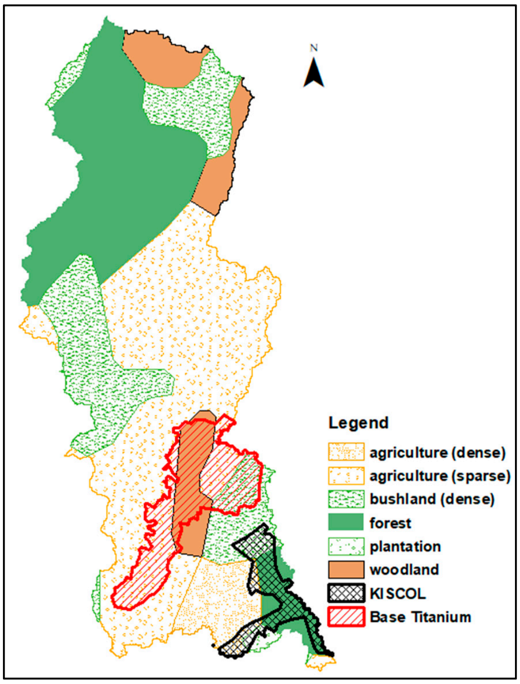

Figure 1. Land use in the Mkurumudzi basin.

Characteristics of the soils in the catchment are presented in Figure 2.

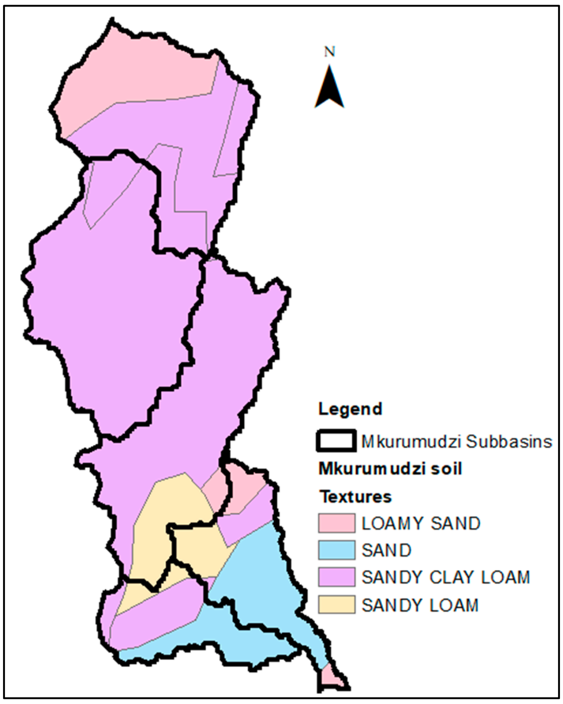

Figure 2. Soil description in Mkurumudzi basin.

2.1. Datasets

The data used in this study includes: rainfall, maximum and minimum temperature, insolation, wind speed and solar radiation, data for evapotranspiration calculation (Penman-Monteith method [4]) and flow data. Rainfall data are from the Kidongo Park Gate station, which is coded 9439065 (1984–2016). Maximum and minimum temperature, insolation, wind speed and solar radiation data are from the NASA POWER dataset. Flow data are from the gauging station 3KD06 for the period 1956 to 2002. The study period is chosen as the period where data are not having missing gaps (Table 1).

Table 1. Summary of annual hydrological data of the Mkurumudzi river basin and gauging station 3KD06.

Year	Annual Rainfall (mm)	Annual Observed Flow (mm)	Runoff Coefficients	Rainy Days
1988	887.59	41.31	0.05	130
1999	1394.1	175.23	0.13	92
1990	837.63	78.00	0.09	108
1991	1200.5	151.92	0.13	125
1992	1024.08	104.04	0.10	128
1993	900.79	66.60	0.07	92
1994	1868.87	335.01	0.18	113
1995	1203.9	244.34	0.20	111

2.2. Software

ArcGIS of ESRI was used to visualize and edit soil and land use data, while Microsoft Excel was used for data formatting and for evapotranspiration calculation using the Penman-Monteith equation. The Arc Hydro tool in ArcGIS [5] was used for watershed delineation based on a Digital Elevation

Model (DEM) and river maps. The Hydrologic Modeling System (HEC-HMS) was used to simulate the hydrological processes in the basin.

2.3. HEC-HMS Model Application

Before the HEC-HMS project can be run, we must have the following four components: basin, meteorological, input data and control specification components. The basin component is created based on a background map containing the delineated sub-basins derived from the Arc Hydro tool 10.3 from ESRI. The meteorological component contains the observed precipitation and discharge data; the control specification component determines the simulation period and the time step to be used. The observed historical data of the Kidongo Park Gate rain station representing each sub-basin and one stream gauge station (3KD06) were used for model calibration and validation. Due to the location of the 3KD06 station, only the two (02) upstream sub-basins M1 and M2 (Figure 3) were used. A daily time step was used for the simulation, given the time interval of the available observed data.

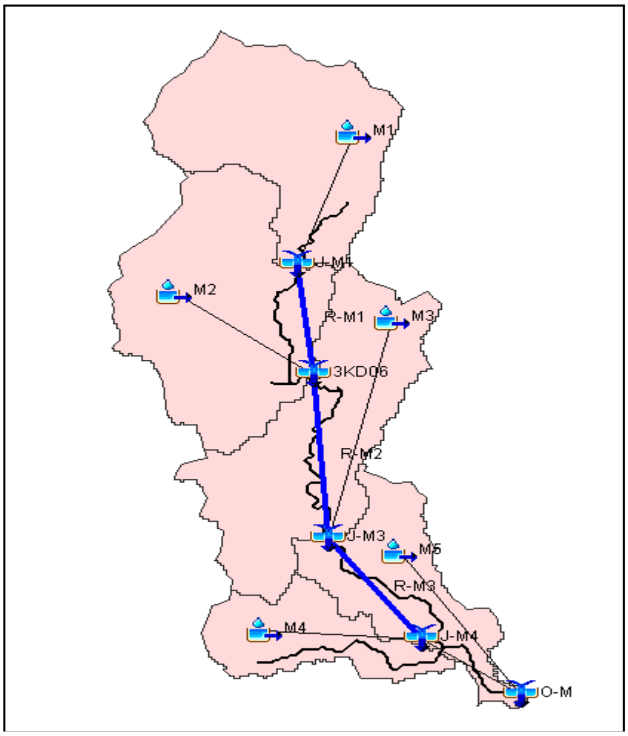

Figure 3. Mkurumudzi basin model.

The Soil Moisture Accounting (SMA) Loss Method included in HEC-HMS was employed to model infiltration losses combined with canopy and surface methods. The canopy is a component of the sub-basin which is intended to represent the presence of plants in the area. The canopy method specified in the HEC-HMS settings is mainly used for continuous simulations. All rainfall is trapped until the canopy storage capacity is filled. Subsequently, the excess precipitation falls on the soil surface after passing through the canopy. The surface method specified in the HEC-HMS settings represents the depression of the ground surface where water accumulates after the pores in the soil are filled to the soil's field capacity. The water on the surface then accumulates in the depression storage until runoff begins to occur as part of the precipitation percolating deep into the groundwater zone. Runoff begins when the precipitation rate exceeds the infiltration rate of the soil (Figure 4) and the storage in the depressions is full. Values for the canopy and surface storage were obtained from the analysis of Land Use and the DEM maps as derived from Tables 2 and 3, respectively.

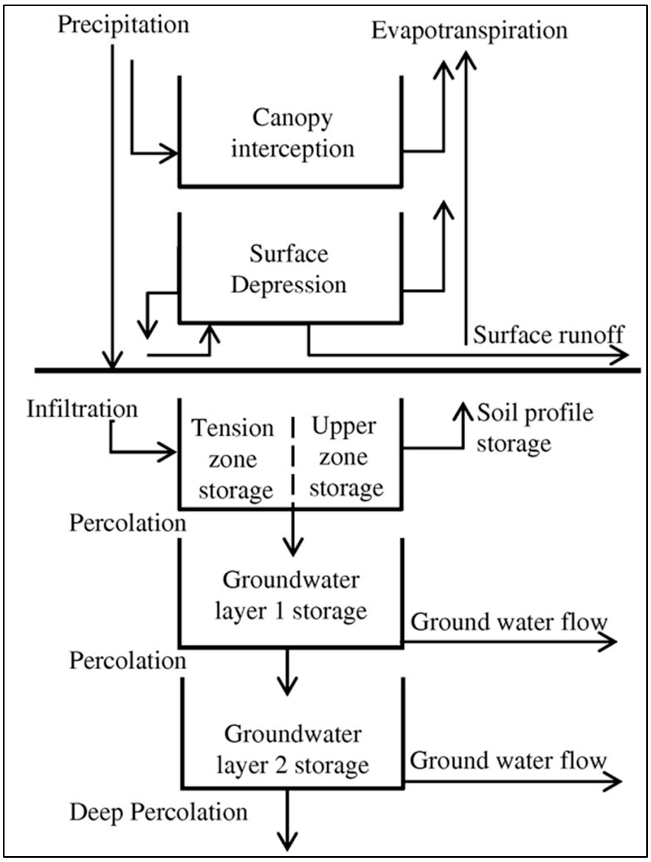

Figure 4. SMA conceptual framework [6].

Table 2. Canopy interception values [7].

Type of Vegetation	Canopy Interception (mm)
General Vegetation	1.270
Grasses and Deciduous Trees	2.032
Trees and Coniferous Trees	2.540

Table 3. Surface depression storage values [6].

Description	Slope (%)	Surface Storage (mm)
Paved Impervious Areas	NA	3.18–6.35
Flat, Furrowed Land	0–5	50.8
Moderate to Gentle Slopes	5–30	6.35–12.70
Steep, Smooth Slopes	>30	1.02

The required inputs for the SMA model are presented in Table 4. The maximum infiltration rate was determined as the upper limit of the rate of water entry from surface storage into the soil [8]. The values for maximum infiltration rate were obtained based on the soil analysis in the catchment and represent the saturated hydraulic conductivity (Table 5). Impervious area was defined as the percentage of the area under urban civilization for the sub-basin using Google Earth with the aid of the Land Use map. Soil water storage was defined as the porosity in Table 5, which is the available space that water can occupy in the soil. Tension storage was determined from Soil-Plant-Air-Water (SPAW) computer software (6.02.75, United States Department of Agriculture-USDA, Washington, DC, USA) [8] by considering it as the field capacity of the soil based on the soil texture values. The soil percolation rate and the first groundwater layer (GW1) percolation rate were chosen as the average hydraulic conductivity of all sub-basins as obtained from SPAW software based on soil texture [9]. Storage coefficients and depths of GW1 and GW2 were determined based on a stream flow recession analysis of historical flow data. The values of the percolation rate of GW2 were obtained during the calibration process.

Table 4. SMA model parameters [10].

Canopy	Initial canopy storage (%) Maximum canopy storage (mm) Crop coefficient
Surface	Initial surface storage (%) Maximum surface storage (mm)
SMA	Soil (%) Groundwater 1 (%) Groundwater 2 (%) Max infiltration rate (mm/h) Impervious (%) Soil storage (mm) Tension storage (mm) Soil percolation (mm/h) GW 1 storage (mm) GW 1 percolation (mm/h) GW 1 coefficient (h) GW 2 storage (mm) GW 2 percolation (mm/h) GW 2 coefficient (h)

The SCS (Soil Conservation Service) unit hydrograph method was used to model the transformation of precipitation excess into direct surface runoff. The other important parameter is the Lag time (T_{LAG}), an important concept in linear modelling of basin response which was calculated using Equation (1) [11]:

$$T_{LAG} = L^{0.8}(S + 1)^{0.7}/1900\sqrt{Y} \quad (1)$$

where

T_{LAG} = lag time (h).
L = hydraulic length of the watershed (ft.).
Y = watershed slope (%).
S = maximum retention in the watershed (mm) as defined by:

$$S = 25400/CN - 254 \quad (2)$$

CN = SCS curve number for the watershed

The Curve Number (CN) was manually estimated for the sub-basins, based on the hydrologic soil group (SHG) and the land cover type. After determining the required soil and land cover characteristics, the CN was estimated for each unit of the sub-basin, followed by area-weighting for the whole sub-basin. The tables used for computation are found in the Technical Release Number 55 [12].

Table 5. Soil textures and properties [13].

Sub Basins/Area (km^2)	Soils		Percentage (%)	Slope (%)	Texture	Saturated Hydraulic Conductivity (cm/h)	Bulk Density (kg/dm^3)	Porosity (cm^3/cm^3)
	Code	Name						
M1 (31.8)	ACf	Ferric Acrisol	20.0	11.3	Sandy Clay Loam	0.43	1.40	0.398
	RGd	Dystric Regosol	44.0		Sandy Clay Loam	0.43	1.41	0.398
	FRx	Xanthic Ferrasol	36.0		Loamy Sand	6.11	1.19	0.437
M2 (37.16)	ACf	Ferric Acrisol	93.0	8.4	Sandy Clay Loam	0.43	1.41	0.398
	RGd	Dystric Regosol	7.0		Sandy Clay Loam	0.43	1.19	0.398
M3 (42.32)	ACf	Ferric Acrisol	78.8	7.9	Sandy Clay Loam	0.43	1.41	0.398
	RGd	Dystric Regosol	0.2		Sandy Clay Loam	0.43	1.19	0.398
	FRx	Xanthic Ferrasol	3.1		Loamy Sand	6.11	1.40	0.437
	ALh	Haplic Alisol	17.9		Sandy Loam	2.59	1.40	0.453
M4 (22)	ACf	Ferric Acrisol	7.8	4.7	Sandy Clay Loam	0.43	1.41	0.398
	ARo	Ferralic Arenosol	47.5		Sand	21.00	1.56	0.437
	ALh	Haplic Alisol	10.8		Sandy Loam	2.59	1.40	0.453
	FRh	Haplic Ferrasol	33.9		Sandy Clay Loam	0.43	1.41	0.398
M5 (16)	ACf	Ferric Acrisol	0.2	5.0	Sandy Clay Loam	0.43	1.41	0.398
	FRh	Haplic Ferrasol	13.8		Sandy Clay Loam	0.43	1.41	0.398
	FRx	Xanthic Ferrasol	10.4		Loamy Sand	6.11	1.40	0.437
	ARo	Ferralic Arenosol	54.5		Sand	21.00	1.56	0.437
	ALh	Haplic Alisol	17.7		Sandy Loam	2.59	1.40	0.453
	LVf	Ferric Luvisol	3.4		Loamy Sand	6.11	1.39	0.437

The linear reservoir method was employed to model base flow with the following required parameters:

- Groundwater 1 initial (m^3/s): initial base flow at the beginning of the simulation for the first layer of groundwater.
- Groundwater 1 coefficient (h): the response time of the sub-basin as specified in the SMA model.
- Groundwater 1 reservoir is used so that the base flow is routed through several sequential reservoirs. The base flow is attenuated when the number of reservoirs is increased.

The same parameters are also defined for the second layer of groundwater.

The Lag routing model was used to model the reaches through the lag time, which is the time that falls between the rainfall and flow peaks.

2.4. Calibration and Validation

Before a hydrological model can be considered to have outputs that are reliable, it needs to be calibrated and validated using observed stream flow. The simulated stream flow must be compared to the observed stream flow to evaluate the goodness of fit and conclude whether the model is able to predict and present credible results. In this work, the model was calibrated using the identified parameters to achieve good fit between the simulated and observed data. The auto-calibration (through optimization trials) tool available in the HEC-HMS model was used for optimizing the estimates of the model parameters. The Nelder-Mead [14] method was used as the search method for optimization. However, the auto-calibration process in HEC-HMS does not necessarily converge to the desired optimum results, so in addition, a manual calibration was performed. The input parameters can be determined by estimating, observing and measuring the watershed and stream characteristics, except for the percolation rate of the groundwater through the second layer (GW2), which is estimated during calibration and optimized to obtain the best fit of simulated flow to observed flow.

The validation process entailed using the optimized parameters of a different period and confirming the goodness of fit for the observed and simulated stream flow.

2.5. Model Performance Evaluation

The HEC-HMS model performance evaluation involved assessing the goodness of fit in the observed and simulated stream flow using:

1. The Percentage Error in Volume (PEV)

$$\mathrm{PEV} = \left| \frac{Vol_o - Vol_s}{Vol_o} \right| \times 100 \quad (3)$$

   where Vol_o, Vol_s are the observed and simulated volumes, respectively.

2. The percentage Error in Peak Flow (PEPF)

$$\mathrm{PEPF} = \left| \frac{Q_{o(peak)} - Q_{s(peak)}}{Q_{o(peak)}} \right| \times 100 \quad (4)$$

   where $Q_{o(peak)}$, $Q_{s(peak)}$ are the observed and simulated flows, respectively.

3. The Coefficient of correlation (R^2)

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - \overline{O}) \times (S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2 \times \sum_{i=1}^{n} (S_i - \overline{S})^2}} \right]^2 \quad (5)$$

   where O_i, S_i are the observed and simulated flows at time i, respectively; and $\bar{O}$, $\overline{S}$ are the average observed and simulated flows during the calibration period, respectively.

R^2 is a standard regression criterion which is limited because it only evaluates the linear relationships between observed and simulated variables. Legates and Mccabe [15] and Moriasi et al. [16] recommended that a good model efficiency criterion have at least three important components, which are improvements over the coefficient R^2: one dimensionless statistic, one absolute error index statistic and one graphical technique. That means that none of the statistics should be used alone; applied together, they form a set of model selection criteria which offsets each other's limitations [17,18]. According to the categorization of the most used statistics, we added the following criteria:

4. The dimensionless statistic: index of agreement (d) given by:

$$\mathrm{d} = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}\left(\left|S_i - \overline{S}\right| + \left|O_i - \overline{O}\right|\right)^2} \tag{6}$$

5. The dimensionless statistic: Nash-Sutcliffe model Efficiency [19] given by:

$$\mathrm{EFF} = \frac{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2 - \sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \tag{7}$$

6. The absolute error index represented by the Root Mean Squared Error (RMSE)—standard deviation ratio (RSR) of observations given by:

$$\mathrm{RSR} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2}} \tag{8}$$

RSR ranges from 0 (optimal value) to 0.5 (very good performance) ratings for both calibration and validation periods. Lower values of RSR indicate a lower root mean square error normalized by the standard deviation of the observations, which indicates the appropriateness of the model simulation [16,20].

To interpret the results, Tables 6 and 7 from [16] were used as a guide.

Table 6. General performance ratings for recommended statistics [16].

SI. No.	Performance Rating	PEPF (%)	R^2	d
1	Very good	<15	0.75 to 1	0.90 to 1.00
2	Good	15 to 30	0.65 to 0.75	0.75 to 0.90
3	Satisfactory	30 to 40	0.50 to 0.65	0.50 to 0.75
4	Unsatisfactory	>40	<0.50	<0.5

Table 7. General performance ratings for recommended statistics [16].

SI. No.	Performance Rating	NSE	PEV (%)
1	Very good	0.75 to Unity	<±10
2	Good	0.65–0.75	±10–±15
3	Satisfactory	0.50–0.65	±15–±25
4	Unsatisfactory	<0.50	>±25

2.6. Sensitivity Analysis

Sensitivity analysis is a critical component of rainfall-runoff modeling that helps to identify influential parameters. Each of the optimized parameters must be used as inputs into the model to get the desired simulated results. Some of these parameters are more sensitive than others. That is, a minor change in the value can lead to a big difference in the simulated flow. Thus, the most sensitive parameters of the model need to be precisely estimated.

To do so, the model was first run with the optimized model parameters obtained after calibration and validation. Next, one parameter at a time method was applied: the value of each parameter was varied from −30% to +30% in increments of 10%, keeping all other parameters constant. The output values (simulated runoff data, volume, peaks, seven-day low flow (7-MALF) and baseflow index (BFI)) were analyzed to determine variation with respect to the initial estimates of the parameters. The elasticity ratio (e) [21] was used to rank the parameters in descending order from most to the least sensitive. Also called the relative sensitivity, e expresses the relative change in the dependent variable with respect to the independent variable. The elasticity ratio is invariant to the dimensions of the variables and is given by Equation (9) [22,23]. A greater elasticity ratio indicates a more highly sensitive variable.

$$e = \frac{\Delta O/O}{\Delta I/I} = \frac{\%\text{change}_{\text{output}}}{\%\text{change}_{\text{input}}} \tag{9}$$

where O, I are the output and the input variables, respectively.

3. Results

3.1. Calibration and Validation

The manual calibration of thirteen HEC-HMS parameters was conducted using observed stream flow data from the 3KD06 gauging station for the period 1988 to 1991. The calibration was started using the basic values that were also used for sensitivity analysis. These values were manually modified until a good fit between the simulated and observed stream flows was obtained. The goodness of fit was evaluated using hydrograph visualization and computed statistics values. The observed and simulated stream flow comparison graphs are shown in Figure 5 for the calibration period (1988 to 1991). The comparison shows a close agreement between simulated stream flow and observed stream flow in terms of peak values and an acceptable agreement in terms of stream flow distribution. The parameters were optimized to obtain a closer agreement between the simulated and observed stream flow.

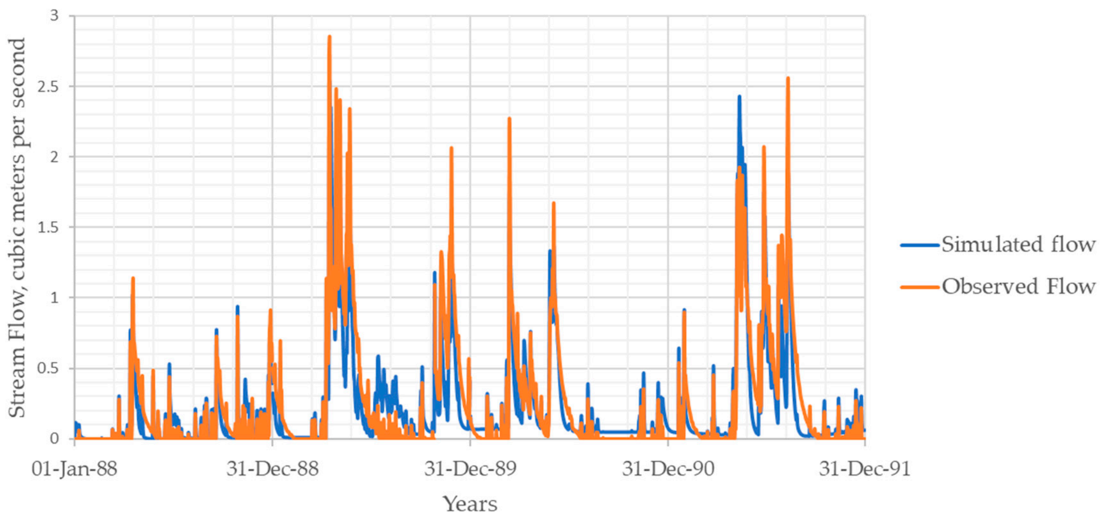

Figure 5. Daily observed and simulated discharge for the entire calibration period (1988–1991).

Table 8 shows the optimized values of the calibration parameters for the study area. Model validation involved running the model using the same input parameters used for the calibration process. Based on the optimized parameters, the model was run for the validation period (1992 to 1995) to check the capability of the model to predict runoff at the 3KD06 gaging station. The observed and simulated stream flow comparison graphs are shown in Figure 6 for the validation period (1992 to 1995). The comparison shows an acceptable agreement between the simulated stream flow and the observed stream flow in terms of peak value, as well as the stream flow distribution.

Table 8. Optimized model parameters.

Parameters	Sub-Basins	
	M1	**M2**
Max canopy storage (mm)	2.5	2.5
Max surface storage (mm)	30	30
Max infiltration rate (mm/h)	18.415	18.415
Impervious (%)	5	5
Soil storage (mm)	150	150
Tension storage (mm)	90	90
Soil percolation (mm/h)	10	10
GW1 storage (mm)	85	85
GW1 percolation (mm/h)	1.98	1.98
GW1 coefficient (h)	111	111
GW2 storage (mm)	200	200
GW2 percolation (mm/h)	1.35	1.35
GW2 coefficient (h)	1000	1000

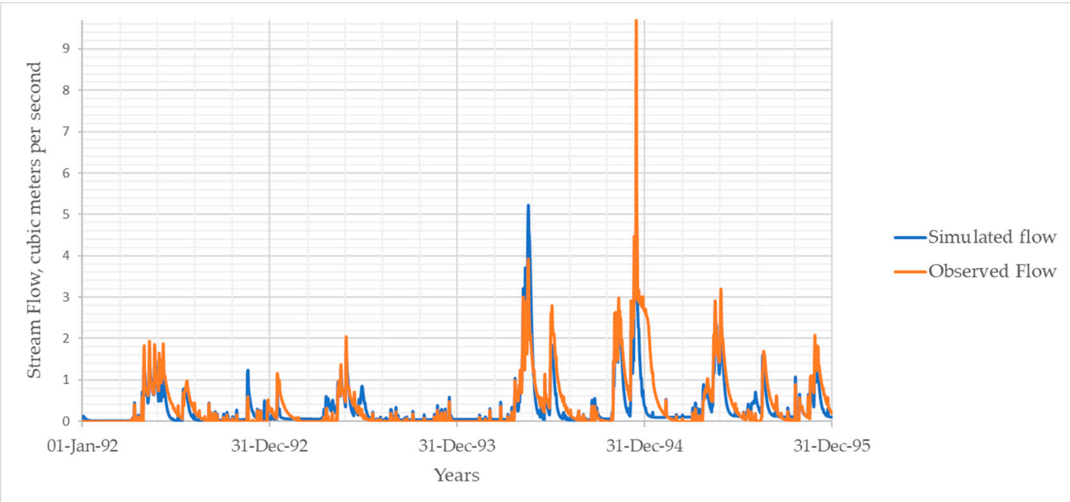

Figure 6. Daily observed and simulated discharge for entire validation period (1992–1995).

3.2. Model Performance Evaluation

Continuous model performance evaluation was conducted for each year and for the calibration and validation periods. The time series of simulated and observed flows from the results of the simulation run in the HEC-HMS model were analyzed in Microsoft Excel to compute the statistics used for performance evaluation. The statistics that were used are described in Section 2.5, presented earlier. The performance ratings of these parameters are presented in Tables 6 and 7. During calibration for the 3KD06 gauging station, the values of PEV, PEPF, R^2, d, NSE and RSR were found to be 8.2%, 10.8%, 0.80, 0.94, 0.80 and 0.46, respectively. Similarly, during the validation, the model evaluation criteria for PEV, PEPF, R^2, d, NSE and RSR were found to be 21.7%, 46.1%, 0.67, 0.88, 0.65 and 0.62, respectively. Table 9 displays the performance evaluation of the SMA model specified in the HEC-HMS settings for individual years and for the calibration and validation periods. According to Tables 6 and 7, the model performance ranges from satisfactory to very good, except for the year 1995, which may be due to various uncertainties in the observed stream flow data. According to the results, and based on the values of NSE, PEPF, PEV and R^2 calculated, the model performance is satisfactory. Furthermore, the index of agreement (d) ranges from 0.81 to 0.96, and the RSR from 0.37 to 0.74, which are also indicators of good model performance.

Table 9. Performance evaluation of the continuous HEC-HMS model.

Years	PEV (%)	PEPF (%)	R^2	d	NSE	RSR
1988	**1.8%**	**11.9%**	**0.75**	**0.92**	**0.75**	**0.50**
1989	**18.2%**	**11.3%**	**0.77**	**0.94**	**0.76**	**0.49**
1990	**16.0%**	**27.5%**	**0.87**	**0.96**	**0.86**	**0.37**
1991	**16.1%**	**5.0%**	**0.81**	**0.96**	**0.79**	**0.45**
1992	**15.6%**	**11.2%**	**0.76**	**0.92**	**0.75**	**0.50**
1993	**2.9%**	**19.5%**	**0.62**	**0.89**	**0.60**	**0.63**
1994	**23.6%**	**46.3%**	**0.68**	**0.91**	**0.65**	**0.59**
1995	**49.4%**	**24.1%**	**0.52**	**0.81**	**0.45**	**0.74**
Calibration	**8.2%**	**10.8%**	**0.80**	**0.94**	**0.80**	**0.46**
Validation	**21.7%**	**46.1%**	**0.67**	**0.88**	**0.65**	**0.62**

Legend
Very Good
Good
Satisfactory
Unsatisfactory

3.3. Sensitivity Analysis

The sensitivities of thirteen SMA parameters (except the five initial conditions for the five storage layers in the SMA model; see Table 4) were analyzed by separately varying each parameter from −30% to +30% in increments of 10%. A one-parameter-at-a-time method was used for this sensitivity analysis; changing one parameter while keeping the others constant. The percentage of variation in simulated volume, peak, seven day low flow (7-MALF), baseflow index (BFI) and Nash-Sutcliffe Efficiency (NSE) were plotted against the percentage of variation of each parameter, as shown in Figures 7–11.

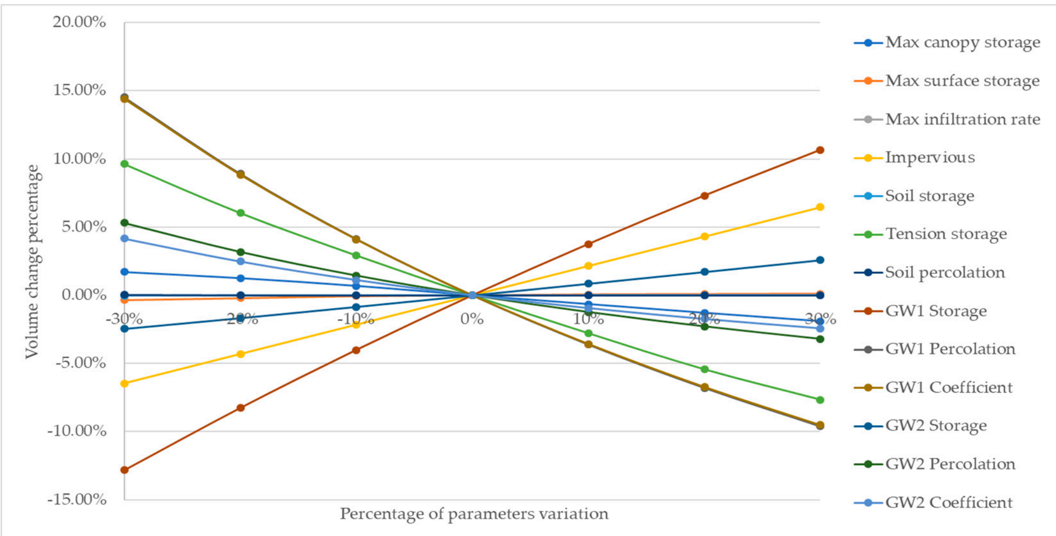

Figure 7. Percentage changes in simulated volume plotted against the percentage variation of each parameter.

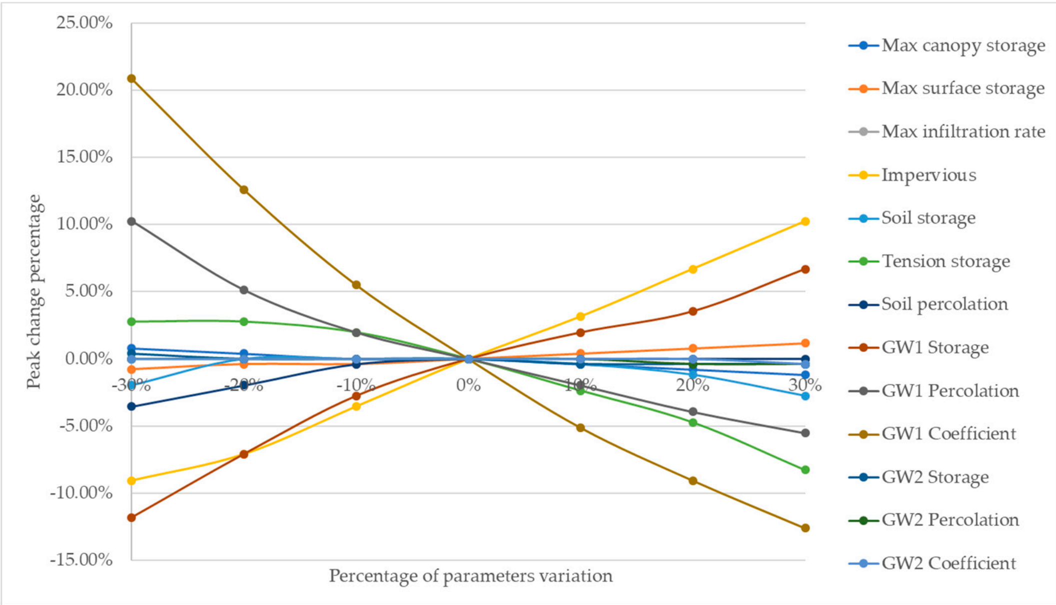

Figure 8. Percentage changes in simulated peak plotted against the percentage variation of each parameter.

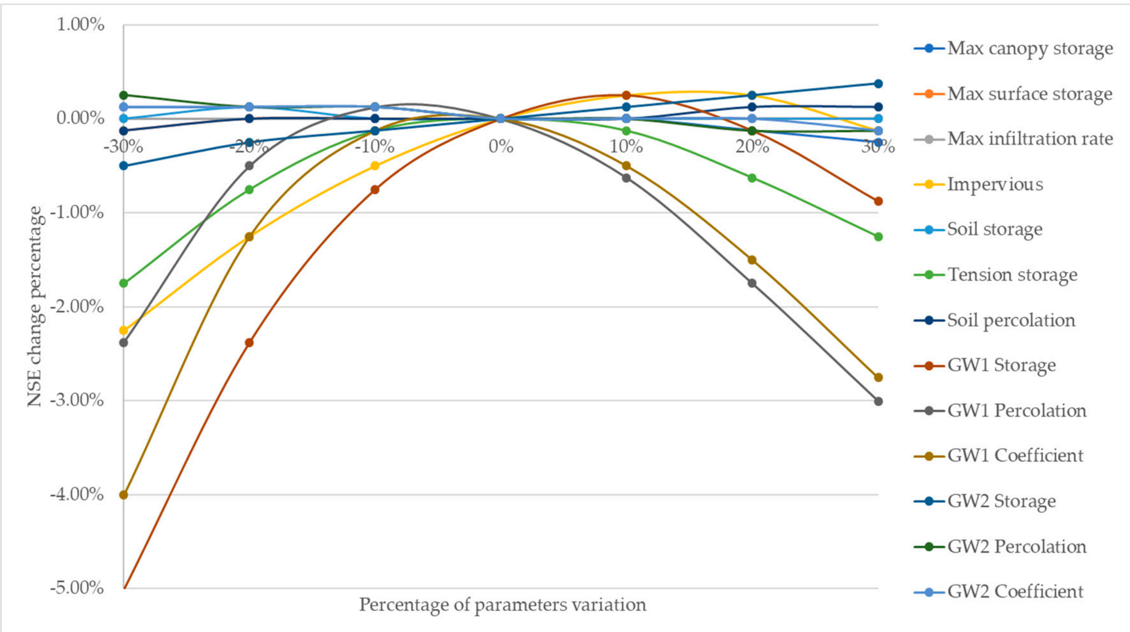

Figure 9. Percentage changes in simulated NSE plotted against the percentage variation of each parameter.

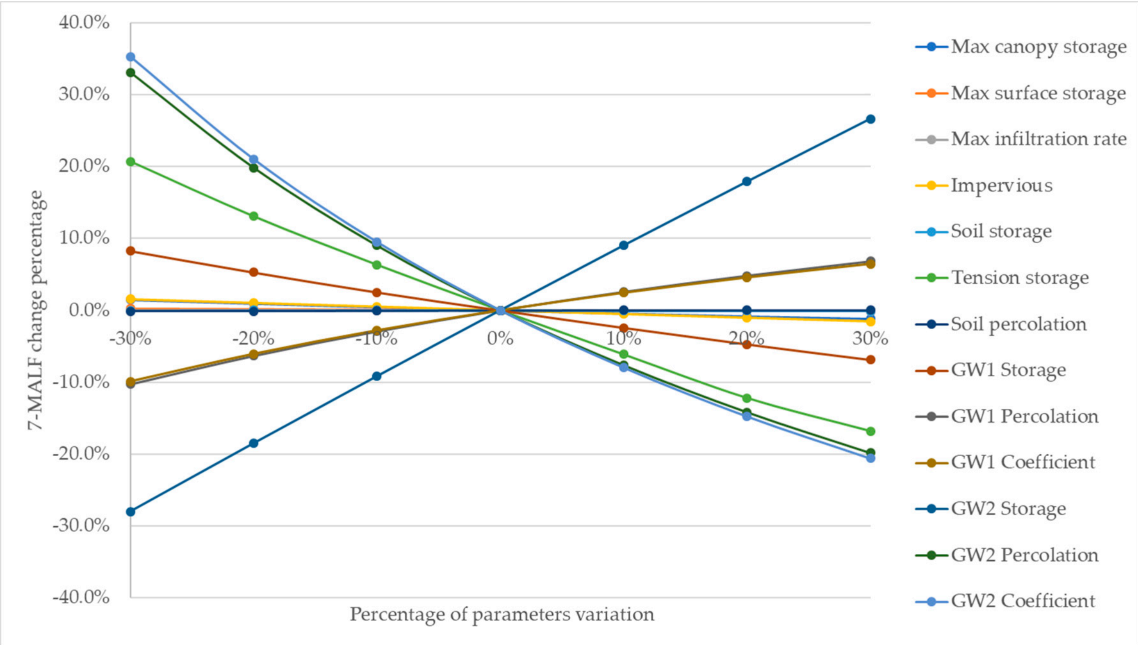

Figure 10. Percentage changes in simulated 7-MALF plotted against the percentage variation of each parameter.

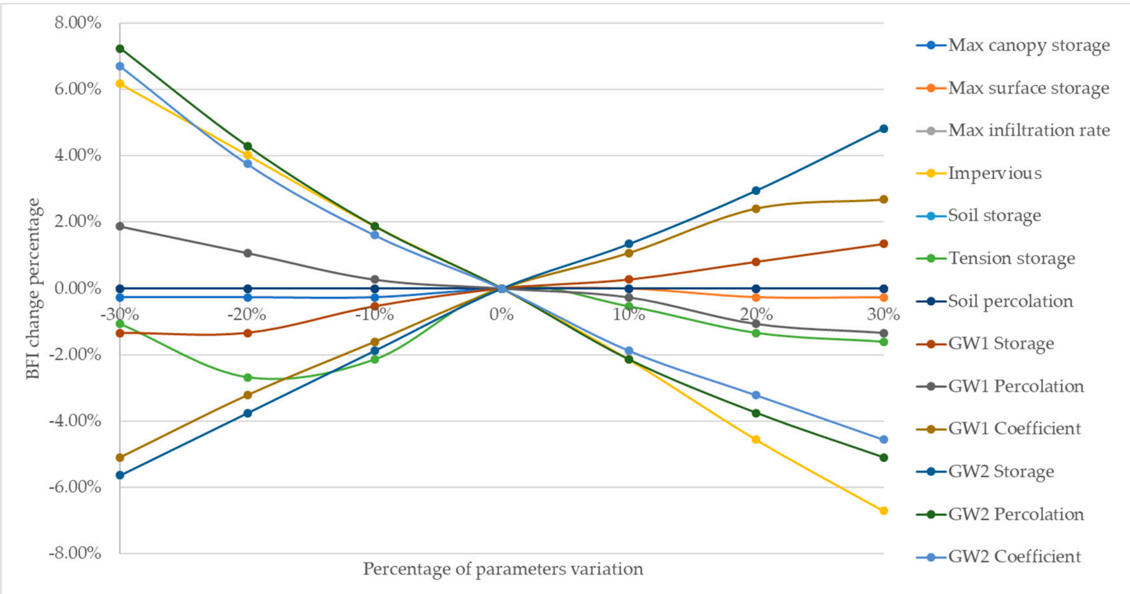

Figure 11. Percentage changes in simulated BFI plotted against the percentage variation of each parameter.

After analyzing the elasticity of the different parameters, they were ranked from the most to the least sensitive. The sensitivity analysis was done to determine the sensitivity of the computed runoff volume, the computed peak, the Nash-Sutcliffe, the seven day low flow (7-MALF) and the baseflow index (BFI) to the SMA model parameters. The runoff volume was found to be more sensitive to the GW1 percolation rate, the GW1 storage coefficient and the GW1 water storage (Table 10), while the peak volume was found to be more sensitive to the impervious area, the GW1 water storage, the GW1 percolation rate and the GW1 storage coefficient (Table 11). At the same time, the Nash-Sutcliffe Efficiency was found to be more sensitive to GW1 water storage, GW1 coefficient storage and GW1 percolation rate respectively (Table 12). The seven-day low flow was found to be more sensitive to the GW2 storage coefficient, the GW2 water storage and the GW2 percolation rate (Table 13). Finally, the baseflow index was found to be more sensitive to the impervious area, the GW2 percolation rate and the GW2 storage coefficient (Table 14).

Table 10. SMA parameters sensitivity ranking for runoff volume.

Rank	Parameter	Average Elasticity Ratio
1	GW 1 percolation (mm/h)	0.39
2	GW 1 coefficient (h)	0.39
3	GW 1 storage (mm)	0.39
4	Tension storage (mm)	0.29
5	Impervious (%)	0.22
6	GW 2 percolation (mm/h)	0.14
7	GW 2 coefficient (h)	0.11
8	GW 2 storage (mm)	0.08
9	Max canopy storage (mm)	0.06
10	Max surface storage (mm)	0.01
11	Soil storage (mm)	0.00
12	Soil percolation (mm/h)	0.00
13	Max infiltration rate (mm/h)	0.00

Table 11. SMA parameters sensitivity ranking for runoff peaks.

Rank	Parameter	Average Elasticity Ratio
1	Impervious (%)	0.33
2	GW 1 storage (mm)	0.27
3	GW 1 percolation (mm/h)	0.23
4	GW 1 coefficient (h)	0.23
5	Tension storage (mm)	0.20
6	Soil percolation (mm/h)	0.04
7	Soil storage (mm)	0.04
8	Max canopy storage (mm)	0.03
9	Max surface storage (mm)	0.03
10	GW 2 storage (mm)	0.01
11	GW 2 percolation (mm/h)	0.01
12	GW 2 coefficient (h)	0.00
13	Max infiltration rate (mm/h)	0.00

Table 12. SMA parameters sensitivity ranking for NSE.

Rank	Parameter	Average Elasticity Ratio
1	GW 1 storage (mm)	0.07
2	GW 1 coefficient (h)	0.06
3	GW 1 percolation (mm/h)	0.06
4	Impervious (%)	0.04
5	Tension storage (mm)	0.03
6	GW 2 storage (mm)	0.01
7	Max canopy storage (mm)	0.01
8	GW 2 percolation (mm/h)	0.01
9	Soil percolation (mm/h)	0.00
10	GW 2 coefficient (h)	0.00
11	Max surface storage (mm)	0.00
12	Soil storage (mm)	0.00
13	Max infiltration rate (mm/h)	0.00

Table 13. SMA parameters sensitivity ranking for 7-MALF.

Rank	Parameter	Average Elasticity Ratio
1	GW 2 coefficient (h)	0.91
2	GW 2 storage (mm)	0.90
3	GW 2 percolation (mm/h)	0.85
4	Tension storage (mm)	0.63
5	GW 1 percolation (mm/h)	0.28
6	GW 1 coefficient (h)	0.28
7	GW 1 storage (mm)	0.25
8	Impervious (%)	0.05
9	Max canopy storage (mm)	0.04
10	Max surface storage (mm)	0.01
11	Soil percolation (mm/h)	0.00
12	Soil storage (mm)	0.00
13	Max infiltration rate (mm/h)	0.00

Table 14. SMA parameters sensitivity ranking for BFI.

Rank	Parameter	Average Elasticity Ratio
1	Impervious (%)	0.21
2	GW 2 percolation (mm/h)	0.20
3	GW 2 coefficient (h)	0.18
4	GW 2 storage (mm)	0.17
5	GW 1 coefficient (h)	0.09
6	GW 1 percolation (mm/h)	0.05
7	Tension storage (mm)	0.04
8	GW 1 storage (mm)	0.04
9	Max canopy storage (mm)	0.01
10	Max surface storage (mm)	0.00
11	Max infiltration rate (mm/h)	0.00
12	Soil storage (mm)	0.00
13	Soil percolation (mm/h)	0.00

4. Discussion

Before using the HEC-HMS model to get an accurate prediction of runoff in the Mkurumudzi catchment, the model needed to be well calibrated using the SMA parameters. Most of these parameters are related in nature to the soil properties and require careful observation and some field investigations to reach a given level of accuracy. However, in the Mkurumudzi catchment, such records are lacking, and no investigations were conducted for the present study; instead, the parameters were obtained from the literature and other secondary sources. With this kind of data estimation, the results obtained are highly satisfactory. Evapotranspiration is one of the most important factors for continuous modeling and was estimated using the Penman-Monteith equation [4].

The percentage error in volume (PEV) for the continuous model ranges from 1.8% to 49.4%, with satisfactory global model performance, except in 1995. The percentage error in peaks ranges from 10.8% to 46.3%, indicating very good and good model performance, respectively, except for 1994. The Nash-Sutcliffe efficiencies of the model range from 0.45 (1995) to 0.80, indicating satisfactory to very good model performances, except for the year 1995. The coefficient of correlation R^2 ranges from 0.52 to 0.87, which, according to Table 6, indicates a satisfactory to very good performance. These results are similar to the NSE and the RSR results. As noted, the years 1994 and 1995 exhibit very low model efficiencies and low correlation between observation and simulation; these differences can be attributed to uncertainties in the stream flow dataset. Probably, the use of data from multiple gauging stations would have improved the model performance.

During the sensitivity analysis of the soil moisture accounting (SMA) parameters, the groundwater layer parameters and the impervious area were found to be some of the most sensitive parameters for runoff simulation. Fleming and Neary [24] performed a similar sensitivity analysis of a continuous HEC-HMS model for the Dale Hollow basin in Kentucky and Tennessee. They found the maximum infiltration rate, the maximum soil depth, and the tension zone depth to be the most sensitive parameters. However, Ouedraogo et al. [25], in 2017, also used HEC-HMS to perform runoff simulation in Ruiru reservoir catchment. They found soil storage to be the most sensitive parameter, followed by the groundwater storage coefficient and the soil tension storage capacity. These findings are different from the current study results. Singh and Jain [9] also conducted continuous hydrological modeling in Vamsadhara River Basin (India) using the SMA model and found the soil storage to be the most sensitive parameter.

5. Conclusions

The HEC-HMS conceptual model was successfully calibrated and validated for the Mkurumudzi catchment for continuous modeling. The global Nash-Sutcliffe Efficiency criteria were 0.80 and 0.65 for the calibration and validation periods, respectively, indicating a good and very good model fit. Percentage errors in volume (PEV) for the calibration and validation periods were found to be 8.2% and 21.7%, respectively, indicating a very good and good model fit. The percentage errors in peak (PEPF) were found to be 10.8% and 46.1% for the calibration and validation periods, respectively, with the performance of the model being rated as satisfactory. The coefficients of determination (R^2) for the calibration and validation periods were 0.80 and 0.67, respectively, indicating a very good and good model fit. Similarly, the indices of agreement (d) were found to be 0.94 and 0.88 during the calibration and validation periods, respectively, indicating a very good and good model fit. The RSR, which assesses the appropriateness of the model, ranged from 0.37 to 0.50 (0.50 to 0.74) for the calibration (validation) period, indicating acceptable to very good performance. Regarding these results, the SMA model in the HEC-HMS model can be used to predict continuous daily stream flow in the Mkurumudzi catchment. Sensitivity analysis of the continuous model was performed and showed that the groundwater layer storage coefficients and impervious area were the most sensitive parameters. The maximum infiltration rate was found to be the least sensitive parameter.

Author Contributions: Conceptualization, W.A.A.O., J.M.R. and J.M.G.; Methodology, W.A.A.O., J.M.R. and J.M.G.; Validation, W.A.AO., J.M.R. and J.M.G.; Writing and Original Draft Preparation, W.A.A.O.; Writing, Review and Editing, J.M.R. and J.M.G.

Funding: This research and the APC were funded by the Pan African University of Basic Sciences, Technology and Innovation (PAUSTI).

Acknowledgments: The authors would like to thank the Pan African University of Basic Sciences, Technology and Innovation (PAUSTI) for funding this research project and for the administrative and technical support and the UPGro Gro for GooD Project (upgro.org) for providing some of the hydrometeorological data.

Conflicts of Interest: The authors declare no conflict of interest.

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