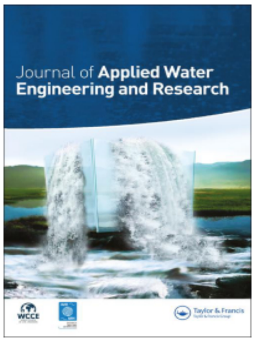

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Comparison of SWAT and HEC-HMS model performance in simulating catchment runoff

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Globally, surface water sources are important sources of drinking water and knowledge on their availability and sustainability is important for their protection. Such studies in data-poor regions are very limited. This paper compares the performance of SWAT and HEC-HMS in the event and continuous modeling of rainfall–runoff in two tropical catchments, a low laying and a mountainous one. Model calibration and validation were done using observed streamflow data at Busiu station for Manafwa and at Sezibwa falls for Sezibwa for the period 2000–2013. The results were compared based on objective functions and also the *t*-test was used to test the statistical significance of the difference in performance. The results show that HEC-HMS performed better than SWAT in Manafwa catchment ($p = .003$ and $p = .000$ during calibration and validation, respectively) while in Sezibwa the difference in model performance was not statistically significant ($p = .63$) although, during calibration, HEC-HMS performed better ($p = .01$).

Keywords: SWAT; HEC-MS; Hydrological simulation

1. Introduction

Globally many water professionals worldwide are exploring options for reducing the uncertainty of hydrological models in the estimation of runoff volumes from rivers as one of the ways to increase the accuracy of model results as the first step to enhancing sustainable development and management of water resources (Cosgrove & Loucks 2015; De Mello et al. 2016; Melsen et al. 2018). In data-scarce regions in many developing countries, modeling is particularly important to understand the quantity and variability of water resources to improve access to safe water supply while at the same time protecting available resources. Moreover, there are increasing global change pressures such as rapid urbanization, population growth and anthropogenic pressures which require hydrologists and water resources planners to achieve more accurate and suitable hydrologic models as a prerequisite for the planning, efficient, and sustainable management of the scarce and dwindling water resources (Zhang et al. 2013; Bredesen and Brown 2018).

This position has been reiterated by the official recognition of the United Nations Sustainable Development Goal (SDG) number 6.3–6.6 that targets improved water quality, increased water-use efficiency, integrated water resources management, and protection and restoration of water-related ecosystems (United Nations 2015). However, progress towards attaining these SDG targets cannot be accelerated without focusing on the performance of hydrological models in planning water resources for large river basins particularly in data-scarce scenarios.

Hydrologic models are a simplification of a real-world hydrologic system that enables us to understand how to predict and how catchments respond to different inputs and impacts. Hydrologic models widely used are classified into empirical models, lumped models and recently distributed physical models (Khakbaz et al. 2012). Open source hydrological models such as Soil and Water Assessment Tool (SWAT) (Abou Rafee et al. 2019; Bahati et al. 2021), MIKE-SHE (Ma et al. 2016), WEPP (Flanagan and Nearing 1995), HEC-HMS (Tassew et al. 2019) have gained wide acceptance in assessing catchment responses to management practices and assessment of climate impacts over the last decade. However, little is known about model performance and efficiency in simulating flows for the different terrains particularly in data-scarce scenarios that characterize developing countries that lack the infrastructure to collect hydrological and metrological data. As a result, water professionals lose a lot of productive time in modeling rainfall–runoff relationships for sustainable water resources management as they try out several models in a bid to choose the most appropriate. To reduce these uncertainties that emanate from data scarcity, there is need to establish the accuracy of different hydrological models in simulating streamflow.

Hydrological model studies are criticized for yielding heterogeneous results. For example, Van Griensven et al. (2012) reported that the application of SWAT in the upper

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Nile basin gave heterogeneous results. The most suited way to deal with this disparity is undertaking model inter-comparisons. However few comparative studies have been undertaken particularly in Sub-Saharan Africa.

According to literature, variability of hydrologic model structures such as the one for HEC-HMS and SWAT has a significant impact on model performances (Xie and Lian 2013; Zhang et al. 2016). A study by Thirel et al. (2015) reported that the same hydrological model yielded varying performances in different catchments. Catchment properties coupled with the type of event simulation have a significant impact on the responses and accuracy of hydrology models. From the available models, choosing a suitable model for a given terrain and event is quite challenging particularly because the choice of a model is based on the modelers preference rather than the technical merits of a model (Bormann et al. 2018).

Data scarcity is another factor cited in literature that affects model performance (Garibay et al. 2021) and as such recently, reanalysis data has gained wide acceptance as an alternative to measured data in data-poor regions (Saha et al. 2010; Bahati et al. 2021; Byakatonda et al. 2021). For example, Nakkazi et al. (2022) compared the different reanalysis data sets for a tropical catchment in Uganda and found that all gave satisfactory results. However, it is criticized for being more suitable where there is a lack of data than in a data-poor scenario. Moreover, the use of this data requires correction (Garibay et al., 2021). Therefore, comparison-based evaluation studies are required to aid decision-makers in choosing suitable models that fit a specific situation such as terrain, event and data availability. Although model comparison studies have been widely carried out, few studies have compared model performance under different catchment physical characteristics like altitude and temporal ability of the models. For instance, Verma et al. (2010) compared the performance of WEPP and HEC-HMS in the Baitarani watershed in Eastern India. The results show that HEC-HMS was better than WEPP on a daily time scale while WEPP was better on a continuous time scale. In a similar study, Otieno (2014) studied the performance of seven different models with respect to latitude, altitude and catchment size. The study showed that HEC-HMS and SWAT performance decreased with an increase in altitude while VIC and HEC-HMS performed better in smaller catchments. The study is criticized for not comparing HEC-HMS and SWAT performance. Golmohammadi et al. (2014) also evaluated the performance of three distributed models, SWAT, APEX and MIKE-SHE in continuous modeling of runoff. Despite both APEX and SWAT modeling the water losses using the curve number (CN) method, SWAT performed better than APEX. Nguyen Khoi Ho Chi and Nguyen Khoi (2016) compared the performance of SWAT and HEC-HMS in simulating streamflow in Srepok River Catchment in Vietnam. Whereas this study agrees that models can simulate runoff with varying levels of accuracy, it is criticized for not having considered variability of performance in the different terrains and events. From the literature review, it is evident that studies on a comparative assessment of hydrologic model performance in different terrains and events are limited particularly in developing countries such as Uganda.

This study, therefore, addresses the aforementioned research gap and compares the performance of SWAT and HEC-HMS in simulating rainfall–runoff on two small watersheds, a mountainous one and one in the plain/low land. SWAT and HEC-HMS were chosen in this study because they are widely used in Uganda and many Tropical catchments for being open source and relatively easy to calibrate. The findings of this study will enable potential users of these models to choose the most efficient and appropriate model that fits the objective of a particular study in a given catchment under consideration.

2. Materials and methods

The main objective of this paper is to compare the performance of SWAT and HEC-HMS in simulating runoff in low land and mountainous catchments. Details of the methodology followed are presented in Figure 1.

2.1. SWAT and HEC-HMS model description

Both SWAT and HEC-HMS are physically based, semi-distributed conceptual models. SWAT uses two models for assessing loss, i.e. the SCS curve number and the Green and Ampt method while HEC-HMS has a total of 11 different loss methods provided in the releases of HEC-HMS 4.4 which was used in this study (Zhang et al. 2016; Bennet and Peters 2000) and later versions. For this study, the SCS curve number method was used for computing both rainfall loss and also for transforming it to a runoff because it is simple and the most widely used loss model in SWAT. The transform methods used in HEC-HMS include Clark Unit hydrograph, ModClack and other Unit hydrographs while SWAT uses SCS for loss transform as well. A summary comparison of the two models is elaborated in Table 1 below.

2.2. Sites and data for model set up

2.2.1. Study area

Manafwa catchment The Manafwa watershed is located in eastern Uganda bordering Kenya. The total area of the basin is 2289 km^2 and spreads through the Districts of Bududa, Mbale, Manafwa, Budaka, Butaleja and Tororo. The Manafwa River originates from the hills of Mountain Elgon at an elevation of 2161 m a.s.l. and its stage measures are done at Busiu bridge a small town located at the center of the watershed, 34.16° E and 0.94° N near a

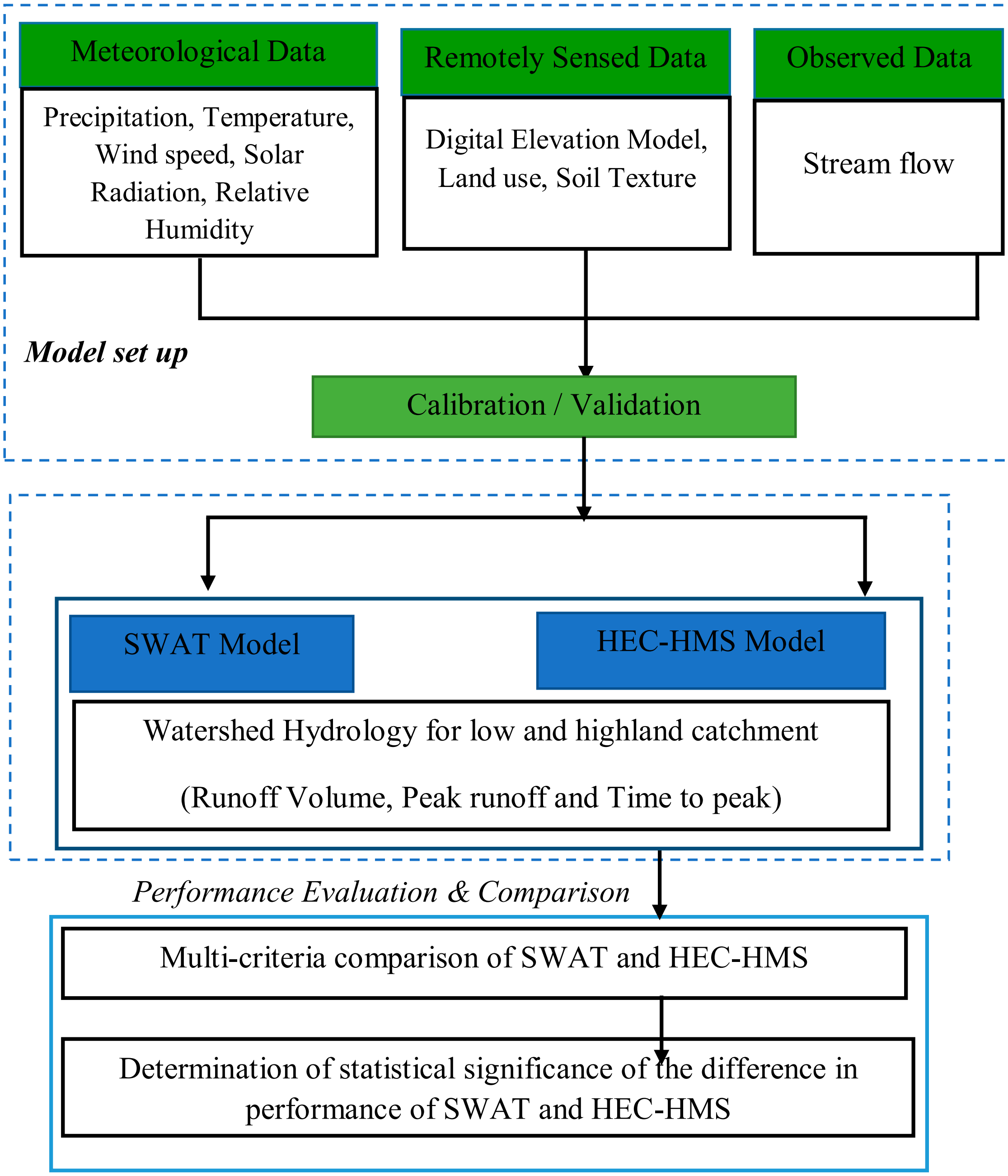

Figure 1. Study flow chart.

bridge connecting Mbale District to Manafwa District. The Manafwa catchment has an area of 475 km^2 and receives seasonal and an annual average rainfall of 905 mm and 2058 mm, respectively (Kansiime et al. 2013). The temperature of the Manafwa catchment varies between 14°C and 33°C with an average of 23°C.

Sezibwa river catchment Sezibwa catchment is located in the south-central part of Uganda and is shared among the districts of Lugazi, Buikwe, Mukono and Kayunga (Figure 2). The catchment has a total area of 175 km^2 and drains into river Sezibwa that spans a total length of around 165 km before entering Lake Kyoga. The catchment lies at an elevation that ranges from 1353 m a.s.l. to 1122 m a.s.l. The geology of the catchment is majorly characterized by Precambrian rocks.

2.2.2. *Data for model set up*

The data used for model setup is shown in Table 2 below.

Precipitation from CFSR (Fuka et al. 2014) was corrected for bias using the method proposed by Berhanu et al. (2016).

Table 1. Comparison of SWAT and HEC-HMS.

Criterion	SWAT	HEC-HMS
Model structure	A semi-distributed computer model simulates infiltration and surface runoff by lumping these processes at the HRU scale (Arnold et al. 1998; Arnold et al. 2012).	The relative lumped model simulates infiltration and surface runoff by lumping these processes at the sub-basin scale (Hydrologic Modeling System 2000).
Model Parameters	26 – for runoff necessitating a tedious sensitivity analysis and requires more computation time especially during calibration.	20 – Requires fewer parameters; approximately 20 depending on the loss method used and it requires less computational time.
Calibration time for the current study	4 hr for Manafwa, 1 hr Sezibwa-SWAT	10 min, 5 min
Calibration parameters	8	7, 3 for SMA, 2 for Clark Model and 2 for Initial and constant loss rate
Loss method Used in the current study	SCS Curve Number – the most widely used method in SWAT for both event and continuous modeling. Assumes constant rate infiltration rate throughout the rainfall duration against the fact that it will approach zero during a storm of long duration.	Initial and constant loss rate method used for the event. It is an empirical formula where parameters have no direct relationship with the physical characteristics of the watershed. 14 parameters with the soil moisture accounting model (SMA) used for continuous simulation accounting for the loss of up to three soil layers.
Transform methods used in the current study	SCS Curve number The SCS CN method assumes that the excess rainfall is uniformly distributed throughout the whole drainage area and reaches the outlet at the same time and is therefore based on the infiltration excess model (Gassman et al. 2007). Runoff is computed as a function of the rainfall depth of the day and the retention parameter S which is, in turn, a function of curve number $SW_f = SW_i + \sum(P_{\text{day}} - R_{\text{surf}} - ET - S_{\text{deep}} - G_w)$	Clark Unit hydrograph The Clark UH method (Sabol 1988) accounts for the time required for water to move to the watershed outlet and its derivation is based on the principle of linear reservoir model solved by finite differences. In application, its parameters are the time of concentration and storage coefficient which can be obtained during calibration.
Calibration Method	Uses both manual method and automatic optimization methods: Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Sequential Uncertainty Fitting (SUFI-2).	Uses both manual method and automatic optimization methods: Univariate gradient algorithm Nelder and mead algorithm/Simplex Markov Chain Monte Carlo In this study, the Nelder method was used because it uses the downhill simplex to evaluate all parameters simultaneously (Gebre 2015) similar to the SUFI2 in SWAT.

2.3. SWAT and HEC-HMS model set up and calibration

2.3.1. SWAT

Model setup A 30 × 30 m digital elevation model, land use map and climate data were processed in Arcgis run SWAT software and a simulation of eight years with three years of warmup was run. Table 3 shows the details of the input data and the model setup processes for both Manafwa and Sezibwa catchments. A summary of the model setup for Manafwa and Sezibwa is presented in Table 3 below.

SWAT model calibration and validation Following the guidelines by Abbaspour et al. (2017), Abbaspour et al. (2015) and Arnold et al. (2012), sensitivity analysis was done using the two methods: Latin hypercube one-at-a-time (LH-OAT) and global sensitivity analysis using the computationally efficient SUFI2 optimization algorithm (Uniyal et al. 2015) in SWAT-CUP. SUFI-2 was selected for calibration because all sources of uncertainty (model, input data, parameter and modeler skill) are accounted for by parameter uncertainty thereby performing optimization and uncertainty analysis at the same time using a global search method involving plenty of parameters (Khoi et al. 2017; Khoi and Thom 2015). Amongst the 19 parameters initially identified from the literature and after 500 simulations, 10 parameters were found to be sensitive during the LH-OAT analysis and ranked using the global sensitivity analysis run for 500 simulations with the most sensitive having a p-value of .05 or less. Calibration involved running SUFI 2 up to four iterations of 500 simulations each while adjusting the new parameter sets within reasonable and practical ranges. To validate the model, the parameter ranges used for the best iteration

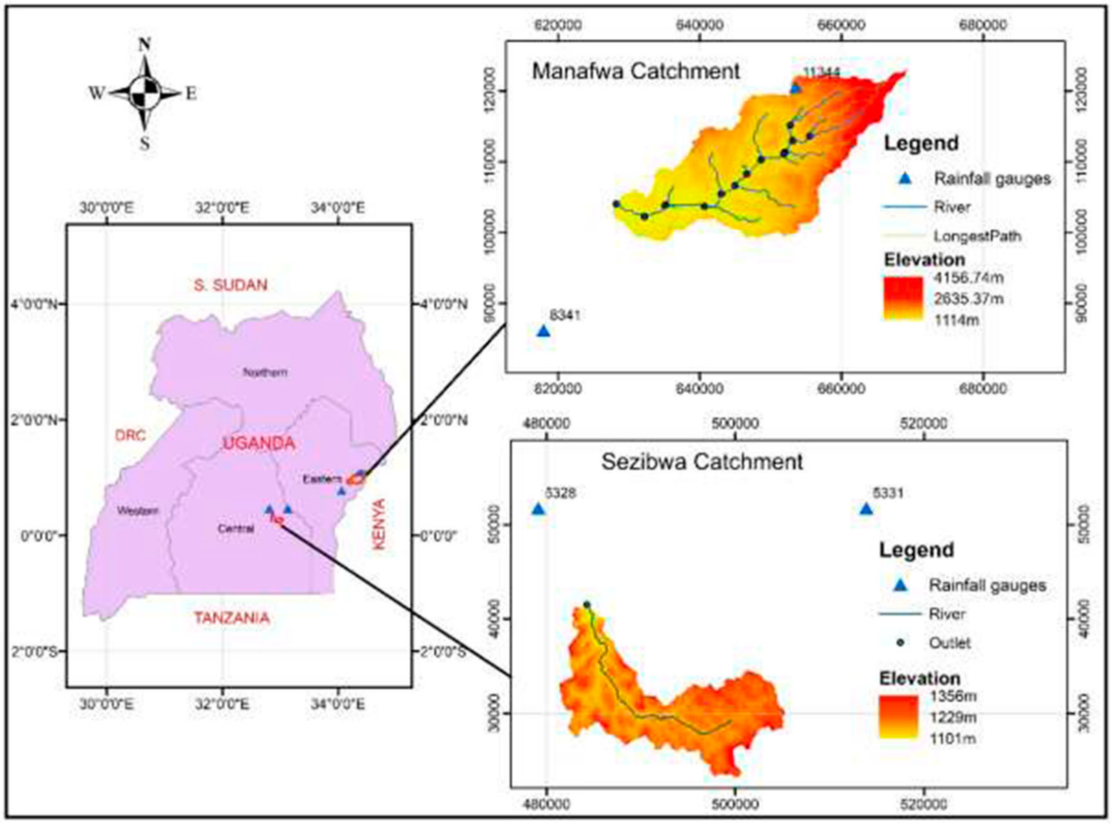

Figure 2. Location of the study area.

Table 2. Data used for model set up.

Data type	Description and use	Scale	Data source
Uganda Digital elevation models (DEMs).	Used to delineate the watershed, define hydrological response units.	30 m	SERVIR-ESA (http://opendata.rcmrd.org/datasets/uganda-srtm-dem-30-meters).
Land usage map-2009	Used in the SCS CN method in SWAT and for creating basin model in Hec-geohms.	300 m	European space agency (ESA)-http://due.esrin.esa.int/files/GLOBCOVER_L4_200901_200912_V2.3.color.tif
Soil data-digital soil map for Uganda	Together with land use data are required to generate a curve number map.	10 km	Harmonized World Soil Database.
Streamflow	Streamflow data is necessary for model calibration.	Daily & Monthly	Directorate of water resources management Entebbe.
Climate data	Monthly DataPrecipitation, temperature, Daily climatic data: precipitation, temperature, wind speed, solar radiation and relative humidity were obtained for the years 2000–2013.	Daily	Climate forecast system reanalysis (CFSR) data-accessed from https://globalweather.tamu.edu/.

during calibration were used to run another validation iteration with 500 simulations. Calibration data ranged from 2000 to 2007 with three years of warmup and four years for Validation (2010–2013). A summary of the SWAT model calibration parameters is presented in Tables 7 and 8.

2.3.2. *HEC-HMS model setup and calibration*

Model set up The basin model and meteorological models were created using HEC-GEOHMS in Arcgis together with Archydro. Despite its wide application (e.g. Nandalal and Ratmayake 2010; Martin et al. 2012; Asadi and

Table 3. SWAT model setup for Manafwa and Sezibwa catchments.

Input feature	Manafwa	Sezibwa
Soil type	Three soil types (Sandy clay loam-Fe47-2ab-501, Loam-Nh2-2c-848 and Loam-Tm9-2c-948-Loam)	Three soil types with the same texture (Sandy-clay-loam-Fo44-2b-500, Loam-Gh7-29-57 and Loam-Nh2-2c-848)
Land use	Five land use categories (agricultural land generic, forest mixed, forest deciduous, range-grasses and Barren)	Three land use classes (agriculture-generic, forest mixed and wetland forested)
Sub-basins and HRUS	27 sub-basins and 58 HRUs	2 sub-basins and 24 HRUS
Catchment area	475 km^2	175 km^2
Length of weather data	13 years (2000–2013)	13 years (2000–2013)

Table 4. HEC-HMS model setup for Manafwa and Sezibwa catchments.

Input feature	Manafwa	Sezibwa
Basin model	Derived using HEC-GEOHMS	Derived using HEC-GEOHMS
Sub-basins	13 sub-basins	Three sub-basins
Evapotransportation formula	Monthly derived using Hagreaves method	Monthly derived using Hagreaves method

Boustani 2013; Kamali et al. 2013; Kaatz 2014), the SCS curve number was not used in model simulation because it is criticized for not being sensitive to rainfall intensity (Hydrologic Modeling System Applications Guide 2008). The HEC-HMS model was therefore set up using the soil moisture accounting model (SMA) for continuous modeling. Table 4 below presents the HEC-HMS model setup for Manafwa and Sezibwa catchments.

Determination of parameters for initial and constant loss rate method and soil moisture accounting model (SMA) The initial values for the parameters were obtained by following guidelines proposed by Ahbari et al. (2018), Holberg (2014) and Merwade (2016). The hydraulic conductivity values for the different soil classes were also obtained from SPAW-Soil, Plant, Air and Water database (Saxton and Willey 2005). The initial parameter values were obtained from streamflow recession analysis based on the daily discharge at the outlet of the basins. The equations for determining all the recession curves (overland flow, interflow and baseflow) are given by Barnes 1939 cited in Singh and Stall (1971).

To rout the river, the Muskingum method was used. This method has two parameters; K – the travel time of water in a reach and X – a constant coefficient the value of which varies between 0 and 0.5. K was obtained by using a formula that relates reach length with wave celerity (Hydrologic Modeling System 2000). While X was initially set at 0.2, a value typical for natural channels. Celerity depends on the type of the channel (physical properties and Shape-Hydraulic radius and Manning's roughness coefficient) and is a function of average velocity in the channel under kinematic conditions/steady flow. Tewolde and Smithers (2006) give relationships of Wave velocity/celerity and average velocity as presented by Viessman and Lewis (1998) for the three different types of channels, that is, wide rectangular, triangular and parabolic. The velocities for Manafwa were obtained from a previous study by Kaatz (2014) while that for Sezibwa was measured at a straight section of the river and the reach length was obtained using HEC-GeoHMS processing. The calculated values were just initial estimates but the final values were obtained during calibration.

Calibration and validation To eliminate model uncertainties due to differences in flow data, the same data used in SWAT was also used in HEC-HMS for both calibration and validation.

Sensitivity analysis was also done for the initial and constant loss rate parameters and the SMA parameters. The one-at-a-time method was used and the direction of change in peak discharge, discharge volume was observed. After identifying the sensitive parameters, manual calibration was first conducted before employing the automatic optimization tool using the Simplex method. The simplex method was used because it evaluates all parameters simultaneously (Gebre et al. 2015) similar to the SUFI2 in SWAT. Automatic optimization was carried out concurrently with manual calibration similar to HEC-HMS; parameters produced during automatic optimization were adjusted within reasonable ranges based on literature. Details of the HEC-HMS model calibration parameters for Manafwa and Sezibwa catchments are presented in Table 5.

Table 5. Calibrated parameters for the HEC-HMS model for Manafwa and Sezibwa catchments.

Parameter name	Description of parameter	Manafwa initial values	Sezibwa initial values
Soil Moisture Accounting Model (SMA)			
Soil (%)	Initial soil content – upper part	0	0
Groundwater 1 (%)	Groundwater 1 initial content (middle part of the soil)	0	0
Groundwater 2 (%)	Groundwater 2 initial content (lowest part of the soil) percent, %. These three initial parameters were set to zero %, assuming that with a simulation starting after a prolonged no rainfall converge to 0%	0	0
Maximum Infiltration (mm/hr)	Equal to basin average hydraulic conductivity	17.312	7.84
Impervious (%)		1	2
Soil profile storage (mm)		591.35	561.6
Tension storage (mm)		349.59	367.9
Soil Percolation (mm)	Equal to basin average hydraulic conductivity	8.74	7.84
Groundwater 1 storage (mm)		0.08	0.085
Groundwater 1 percolation (mm/hr)	Equal to basin average hydraulic conductivity	8.74	7.84
GW1 coefficient (hr)	From recession curve	1.15	1.725
Groundwater 2 storage (mm)	From recession curve	5.4	13.09
Groundwater 2 percolation (mm/hr)	Equal to basin average hydraulic conductivity	8.74	7.84
Groundwater 2 coefficient (hr)	From recession curve	19.5	10.603
Transform method: Clark Unit Hydrograph			
Tc	Time of Concentration	4.86–12.71	12.1–23.873
R	Storage coefficient	3.63–20.33	12.24–35.01
Muskingum			
K	Travel time	3.2	
X		0.2	0.055
Base flow recession			
Initial discharge		1.28	2.5
Recession constant		0.95	0.91
Ratio to peak		0.58	0.58

2.3.3. *Model performance evaluation and comparison*

The models' performance was evaluated using Nash Sutcliff efficiency (NSE), Nash and Sutcliffe (1970) estimated using Equation (1) below, coefficient of determination (R^2), and Percent bias coupled with the graphical method.

$$\mathrm{NSE} = 1.0 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2} \quad (1)$$

where O_i = observed data, P_i = predicted data and $\bar{O}$ = mean of observed values and n is the total number of observations.

While R^2 used to estimate the combined dispersion against the single dispersion of the observed and predicted (Lee Rodgers and Alan Nice Wander 1988; Ayele et al. 2017) was estimated using Equation (2) below:

$$R^2 = \left\{ \frac{\sum_{i=1}^{N} (O_i - \bar{O})(P_i - \bar{P})}{\left[\sum_{I=1}^{N} (O_i - \bar{O})^2\right]^{0.5} \left[\sum_{I=1}^{N} (P_i - \bar{P})^2\right]^{0.5}} \right\} \quad (2)$$

The PBIAS the measure widely applied to assess the performance in watershed modeling (Gupta et al. 1999; Golmohammadi et al. 2014) was estimated using Equation (3).

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

Deciding on the best-performing model is a multi-criteria decision problem because a model might have a poor NSE and good R^2 and PBIAS indicators. Hence, a multi-criteria

Table 6. Model parameters used for sensitivity analysis.

SWAT Parameter name	Description of parameter	Rank
V__ALPHA_BF.gw	Base flow alpha factor	1
R__CN2.mgt	SCS Curve number for moisture condition II	2
V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	3
V__CH_K2.rte	Effective hydraulic conductivity in the main channel alluvium	4
R__SOL_AWC(..).sol	Available water capacity of the soil (mm)	5
V__EPCO.bsn	Plant up take compensation factor.	6
V__GW_DELAY.gw	Ground water delay (days)	7
R__SOL_K(..).sol	Saturated hydraulic conductivity (mm/hr)	8
V__ESCO.bsn	Soil evaporation compensation factor	9
HEC-HMS:		
Initial and constant loss rate parameters	Soil moisture accounting model	Clark unit hydrograph
Maximum infiltration (MM/HR)	Initial soil content-Soil% Percent impervious-%	Time of concentration
Impervious (%)	Groundwater 1 initial content % (middle part of the soil Groundwater 2 initial content (lowest part of the soil) (%):	Storage coefficient
Soil profile Storage (MM)	Soil profile Storage (mm) and tension zone storage (mm)	
Tension Storage (MM)	Max infiltration (mm/hr), soil percolation (mm/hr), groundwater 1 percolation (mm/hr), groundwater 2, percolation (mm/hr) Groundwater 1 coefficient and Groundwater 2 coefficient	

analysis method was used to determine the best model. Details of the multi-criteria methodology can be found in Mutikanga et al. (2011).

Moriasi et al. (2015) and Moriasi et al. (2007) developed criteria for evaluation of models applicable to continuous, long-term simulations for medium to large-scale studies, using measured data for calibration and validation obtained under typical data quality scenarios. The American Society of Agricultural and Biological Engineers (ASABE 2017) recommend that the criteria can be adjusted to be stricter or relaxed depending on the purpose of the simulation. The approach was adopted to score model performance during the multi-criteria assessment since this study is daily, continuous and uses reanalysis data as opposed to measured data, the criteria were relaxed and adopted the one used by Jimeno-Sáez et al. (2018)) since the study was an exploratory one. To accomplish multi-criteria comparison, the calculated values were assigned a score of 1–4 where 1 = Un satisfactory, 2 = satisfactory, 3 = Good and 4 = very good.

2.3.4. *Statistical comparison of SWAT and HEC-HMS*

To complement the multi-criteria approach used, a *t*-test was used to give a statistical inference on the difference or agreement of the two model results. The test was based on the null hypothesis that the differences between SWAT and HEC-HMS simulation results are zero. This helps to eliminate the subjectivity in the multi-criteria analysis. Statistical significance of the difference in simulated performance results for the two models was determined using the student *t*-test. A data analysis software R (https://cran.r-project.org/bin/windows/base/) was used to perform the Wilcoxon-rank sum test.

3. Results and discussion

3.1. *Sensitivity analysis*

The results show that the most sensitive parameters for Manafwa were CN2, SOL_AWC, ALPHA_BF, GWQMN, listed in order of decreasing sensitivity. For Sezibwa, the order of sensitivity from most sensitive to least sensitive was CN2, SOL_AWC, CH_K2, SOL_BD, SOL_Z and GWQMN, GW_DELAY, ESCO. The results for the sensitivity analysis for Manafwa are presented in Table 6 below.

The most sensitive parameters for both the initial and constant rate loss method and the soil moisture accounting model were the percent impervious, soil profile storage and Tension storage.

3.2. *Calibration and validation results for Manafwa and Sezibwa*

Tables 7 and 8 present the calibration results for Manafwa and Sezibwa. Whereas both models have a comparable number of calibration parameters, the calibration time for SWAT was considerably much higher than that for HEC-HMS.

Table 7. Manafwa Calibrated parameters for SWAT.

Parameter	Min. value	Max. value	Fitted value
r__CN2.mgt	– 0.41	– 0.20	– 0.39
r__SOL AWC().sol	– 0.17	– 0.06	– 0.09
v__ALPHA_BF.gw	0	0.03	0.00
v__GWQMN.gw	2000	4500	4052.50

Table 8. Sezibwa calibrated parameters for SWAT.

Parameter name	Min. value	Max. value	Fitted value
R__CN2.mgt	– 0.20	0.3	0.08
V__ESCO. hru	0.70	0.95	0.94
R__SOL_Z(..).sol	– 0.59	– 0.1	– 0.29
R__SOL_AWC(..).sol	– 0.56	– 0.1	– 0.26
R__SOL_BD(..).sol	0.40	0.5	0.48
V__GW_DELAY.gw	10.00	500	477.95
V__CH_K2.rte	300.00	500	325.40
V__GWQMN.gw	0.00	1000	757.00

Figures 3–6 show hydrographs of predicted streamflow by SWAT and HEC-HMS compared with observed flow. The secondary axis shows rainfall and temperature.

3.3. *Comparison of SWAT and HEC-HMS model performance*

The Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS) and coefficient of determination (R^2) were used to compare model performance. The combination of the four performance criteria was undertaken using multi-criteria analysis and both models gave acceptable results. The results are presented in Table 9.

Both models were calibrated several times to reach their maximum performance. Generally, the results show that both SWAT and HEC-HMS produce acceptable calibration and validation results following the criteria by Jimeno-Sáez et al. (2018). Using multi-criteria comparison to measure the aggregate performance based on the three objective functions, it was found that the aggregate score for HEC-HMS and SWAT was 2.3, 3.3 during calibration and 3, 2.6 during validation, respectively. This shows that HEC-HMS performed slightly better during calibration while SWAT performed better during validation for the Manafwa catchment. For Sezibwa, the average score was the same which means equal performance.

3.4. *Prediction of high and low flows*

For a better understanding of the performance of the models in simulating high and low flows, the figure below shows scatter plots of simulated values for SWAT and HEC-HMS against observed values. From the graphs, it is observed that SWAT performed poorly in simulating both high and low flows during calibration in the Manafwa catchment. This is seen from the big distance the points are from the 1:1 line. During validation, both models simulated high flows quite well although HEC-HMS was better in simulating the low flows.

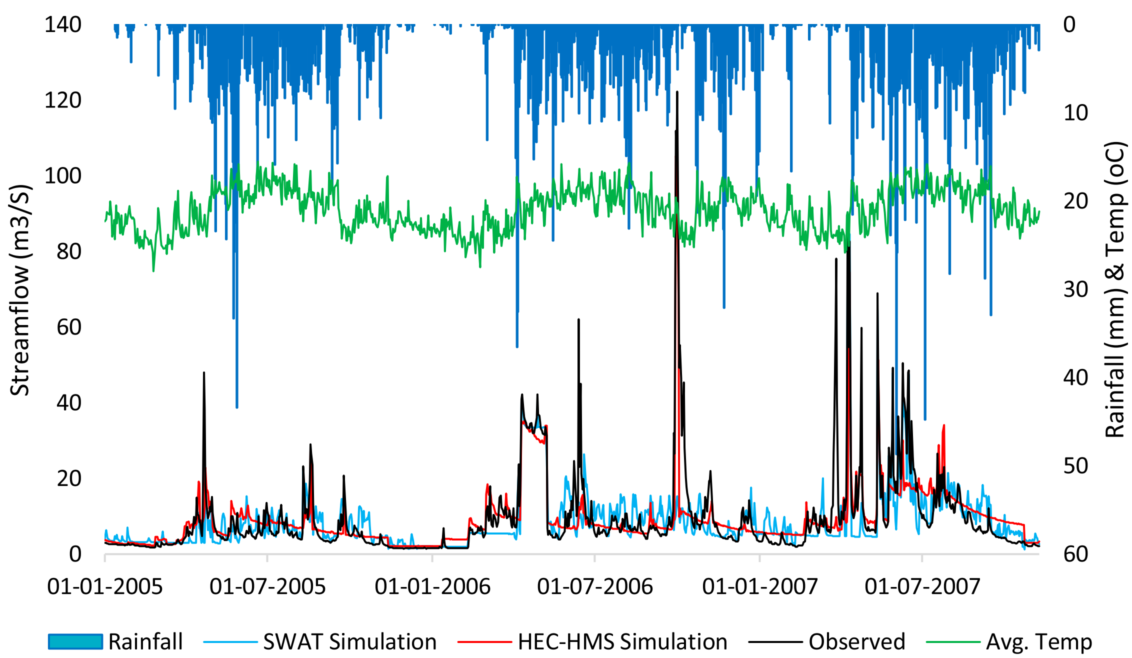

Figure 3. Variations of daily simulated and observed discharges in Manafwa (mountainous) catchment using SWAT and HEC-HMS from 2005 to 2007 – calibration period.

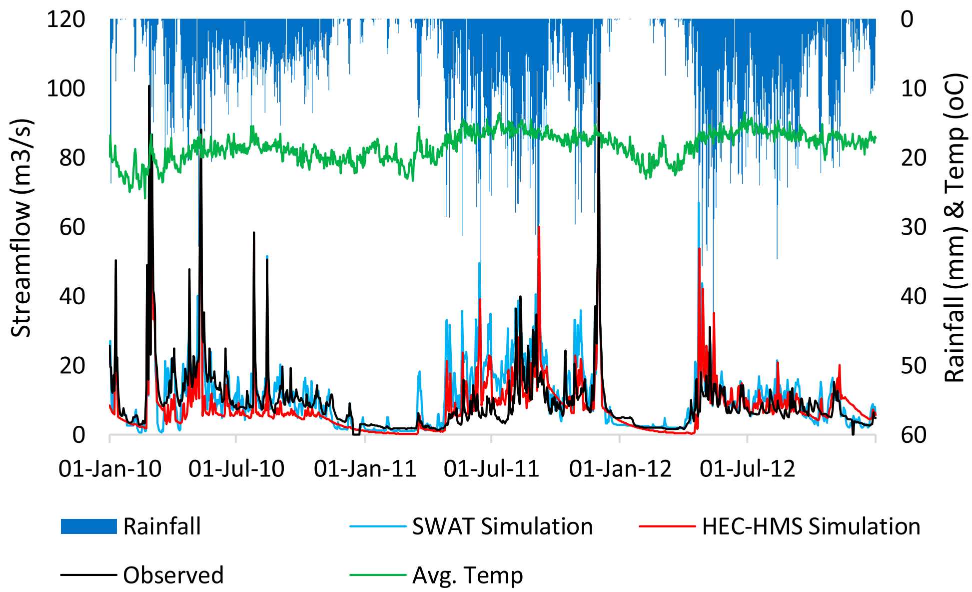

Figure 4. Variations of daily simulated and observed discharges in Manafwa (mountainous) catchment using SWAT and HEC-HMS from 2010 to 2012 – Validation period.

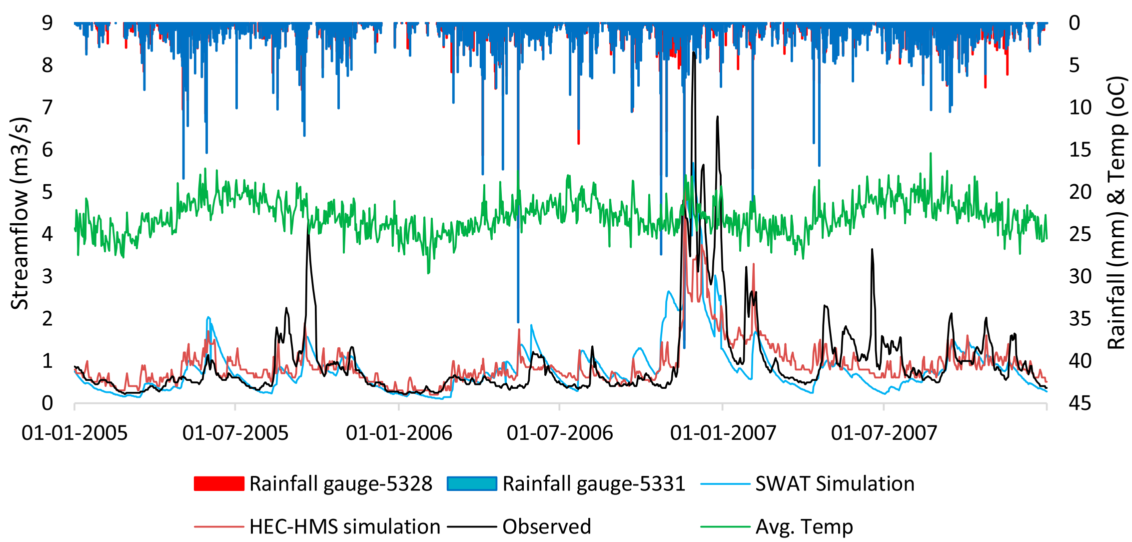

Figure 5. Variations of daily simulated and observed discharges in Sezibwa (low land) catchment using SWAT and HEC-HMS from 2005 to 2007 (calibration period).

Comparison of the models in the low-lying Sezibwa catchment shows that SWAT was better in predicting high flows while HEC-HMS was better in predicting low flows while during validation HEC-HMS performed better in predicting both the low and high flows (Figures 7 and 8).

3.5. *Statistical significance*

The test for statistical significance was used in combination with the Multi-criteria analysis to serve as a confirmatory test. The student *t*-test was used for this comparison, the means μ were compared. The results for Manafwa and Sezibwa catchments are presented in Table 10 below.

For Manafwa, the absolute values for NSE, R^2 and PBIAS were 0.44, 0.36 and 7.27 for SWAT and 0.66, 2.61 and 2.61, respectively, for HEC-HMS. Similarly, validation results for SWAT were 0.47, 0.62 and -22.55 while those for HEC-HMS were 0.49, 0.57 and 5.15, respectively. The results of the *t*-test with a *p*-value of .003 and .000 for calibration and validation, respectively, show that HEC-HMS performs better than SWAT.

For Sezibwa, the absolute values for NSE, R^2 and PBIAS were 0.50, 0.52, 14.22 for SWAT and 0.52, 0.57, 6.46, respectively, for HEC-HMS. Similarly, validation results for SWAT were 0.40, 0.45 and 10.44 while those for HEC-HMS were 0.49, 0.51 and 9.46, respectively. The

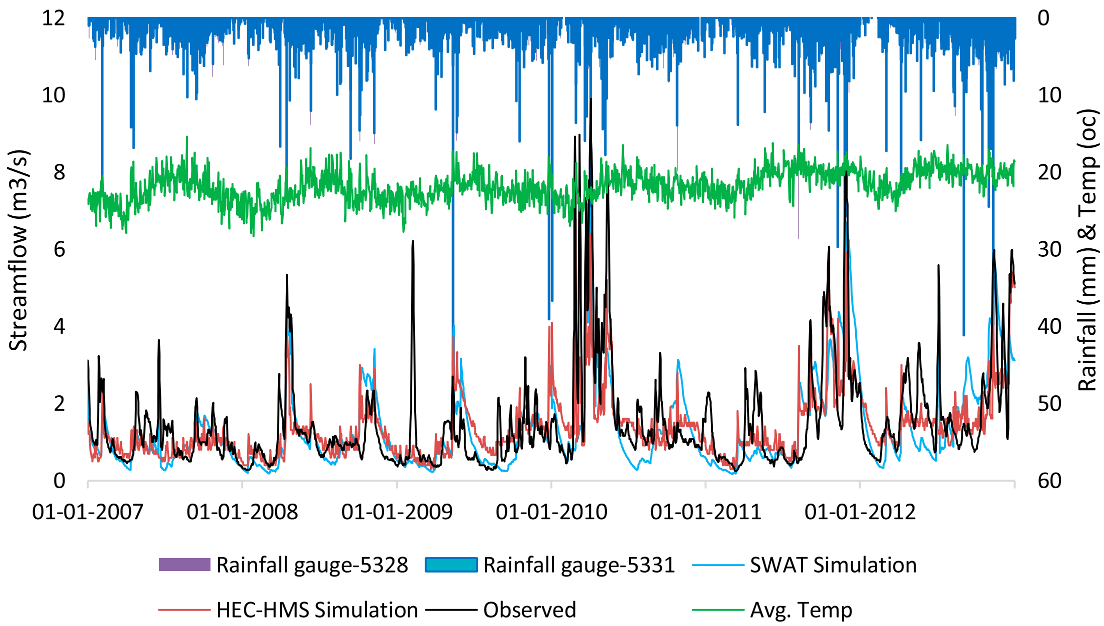

Figure 6. Variations of daily simulated and observed discharges in Sezibwa (low land) catchment using SWAT and HEC-HMS from 2007 to 2012 (validation period).

Table 9. Multi-criteria comparison of SWAT and HEC-HMS in Manafwa and Sezibwa.

Objective function	Manafwa Calibration		Validation	
	SWAT	HEC-HMS	SWAT	HEC-HMS
NSE	0.44 … 2	0.65 … 3	0.47 … 2	0.49 … 2
R2	0.36 … 1	0.66 … 3	0.62 … 3	0.57 … 2
PBIAS	7.27 … 4	2.61 … 4	− 22.55 … 4	5.15 … 4
Average score	2.3	3.3	3	2.6
	Sezibwa			
	SWAT	HEC-HMS	SWAT	HEC-HMS
NSE	0.44 … 2	0.52 … 3	0.40 … 2	0.49 … 2
R2	0.52 … 1	0.57 … 2	0.45 … 1	0.51 … 1
PBIAS	14.22 … 4	6.46 … 4	10.44 … 4	9.46 … 4
Avg. score	2.3	3	2.3	2.3

Table 10. Statistical significance results for Manafwa and Sezibwa Catchments.

	Objective function values-calibration		Calibration p-value	Objective function values-validation		Calibration p-value
	SWAT	HEC-HMS		SWAT	HEC-HMS	
Manafwa			μswat = 8.733 μHec-hms = 9.173			μswat = 11.277 μHec-hms = 8.435
NSE	0.44	0.65	0.003	0.47	0.49	0.0000
R2	0.36	0.66		0.62	0.57	
PBIAS	7.27	2.61		− 22.55	5.15	
Sezibwa			μswat = 0.8229 μHec-hms = 0.8926			μswat = 1.335 μHec-hms = 1.350
NSE	0.50	0.52	0.01	0.40	0.49	0.63
R2	0.52	0.57		0.45	0.51	
PBIAS	14.22	6.46		10.44	9.46	

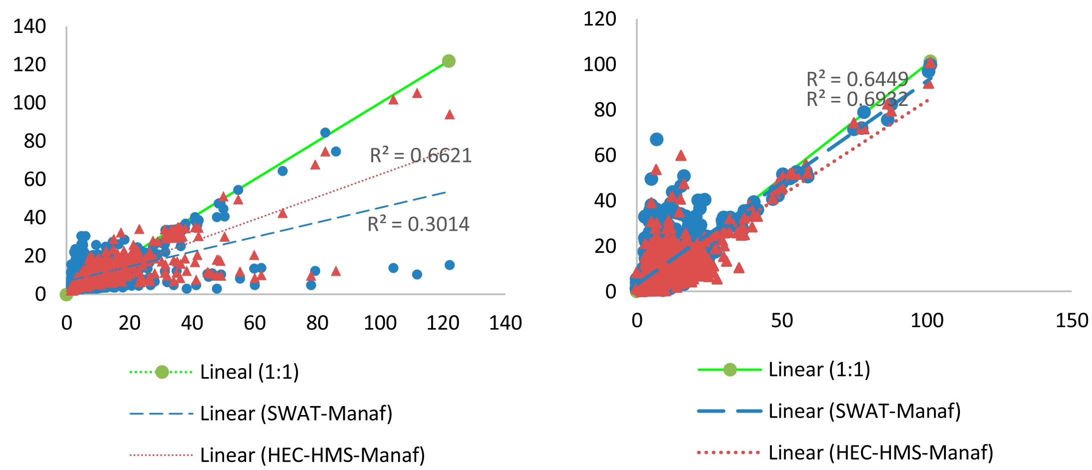

Figure 7. Scatterplots for daily streamflow obtained in Manafwa with SWAT and HEC-HMS during calibration (Left) and validation (Right).

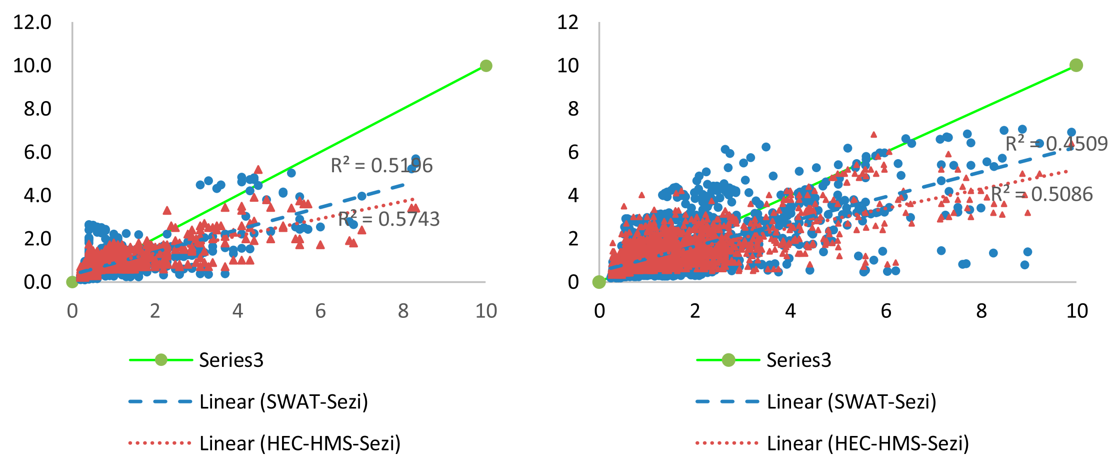

Figure 8. Scatterplots for daily streamflow obtained in Sezibwa with SWAT and HEC-HMS during calibration (Left) and validation (Right).

results of the Wilcoxon test with a p-value of .01 and .63 calibration and validation, respectively, show that the difference in statistical performance was not statistically significant which agrees with the multi-criteria comparison.

4. Conclusion

In this study, the performance of SWAT and HEC-HMS, both semi-distributed models were compared. Both models were used to simulate flow on a continuous time scale in a mountainous and low land catchment. Both models produced acceptable results but HEC-HMS performed better than SWAT in the mountainous catchment while the performance of the models was not statistically significantly different in the low-lying Sezibwa catchment.

The study has demonstrated that the complexity in the model structure, e.g. in SWAT does not necessarily make it superior to less complex ones. Also, in the absence of a measured date, reanalysis data can be used for continuous simulation studies with acceptable metric indices.

For mountainous and law-lying terrains, each of the models presented individual strengths and weaknesses. The results showed that HEC-HMS performed better than SWAT for the mountainous catchment. This means that in addition to selecting a model based on the skill and experience of the modeler and ease to use, the different altitudes also have to be considered. It is also worth noting that because HEC-HMS has a relatively simple structure, it requires less data to set up, less time to run, and is easier to run whereas SWAT requires a lot of data and data computations. On the other hand, there is no significant difference between the performance of HEC-HMS and SWAT for low-lying catchments.

This, therefore, means that whereas model structural representation capability (extent of physical catchment representation) does not necessarily make it superior over less-distributed models, there is no significant difference in model accuracy. None the less both models can be applied in applications that are not very sensitive to the level of accuracy especially for continuous modeling as the case is always. However, applications for event simulation always care about the degree of accuracy, and in this case, we recommend that HEC-HMS is used for such applications. It is also worth noting that because HEC-HMS has a relatively simple structure, it requires fewer data to set up, less time to run, and is easier to run.

Another interesting study that was outside the scope of this study but is worth undertaking is to compare the performance of the models with a short length of observed data (streamflow) for calibration especially during continuous modeling. Research conducted on the latter will be very valuable especially for catchments with little observed data for calibration. The introduction of uncertainty analysis can also help in the detailed comparison. Hydrologists and water resource professionals must consider model performance when choosing a suitable model for different events and terrains amidst data-scarce scenarios.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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