Simiyu River catchment parameterization using SWAT model

By [1]Deogratias M.M. Mulungu and [2]Subira E. Munishi

University of Dar es Salaam, Department of Water Resources Engineering,
P.O. Box 35131 Dar es Salaam, Tanzania.
Emails: [1]deo@wrep.udsm.ac.tz; [2]evasubira@yahoo.com

Abstract

The paper presents advances in hydrologic modelling of Simiyu River catchment using Soil and Water Assessment Tool (SWAT). In this study, the SWAT model set-up and subsequent application to the catchment was based on high-resolution data such as land use from 30 m LandSat TM Satellite, 90 m Digital Elevation Model and Soil from Soil and Terrain Database for Southern Africa (SOTERSAF).

The land use data was reclassified based on some ground truth maps using IDRISI Kilimanjaro software. The Soil data was also reclassified manually to represent different soil hydrologic groups, which are important for the SWAT model set-up and simulations.

The SWAT application first involved analysis of parameter sensitivity, which was then used for model auto-calibration that followed hierarchy of sensitive model parameters. The analysis of sensitive parameters and auto-calibration was achieved by sensitivity analysis and auto-calibration options, which are new in the recent version of SWAT, SWAT 2005.

The paper discusses the results of sensitivity and auto-calibration analyses, and present optimum model parameters, which are important for operation and water / land management studies (e.g. rain-fed agriculture and erosion / sediment transport) in the catchment using SWAT. The river discharge estimates from this and a previous study were compared so as to evaluate performances of the recent hydrologic simulations in the catchment.

Introduction

The Simiyu River catchment in the Lake Victoria basin is important for agricultural and other economic activities such as fishing and livestock. These activities and increasingly population bring much pressure on utilization of land and water resources in Simiyu River catchment. Land use / cover changes has significant impact on generation of runoff and other water fluxes, pollutant transport to water courses and rates of erosion. In order to have effective and sustainable use of land, availability and utilization of water resources, comprehensive hydrological models need to be used to aid management of land and water in the catchment. One of the hydrological model for this purpose is the Soil and Water Assessment Tool (SWAT) model (Arnold *et al*., 1998), which was applied in the Simiyu catchment and previous results showed that rainfall distribution, land cover and soil data were underrepresented (Mulungu and Mkhandi, 2005a; 2005b). Since SWAT applications in Tanzania are new, it was recommended a step-by-step model application for effective use of SWAT in Tanzania. This study will address improved spatial data as pointed out in the previous studies by using high-resolution spatial data such as land use from 30 m LandSat TM Satellite, 90 m Digital Elevation Model and Soil from Soil and Terrain Database for Southern Africa (SOTERSAF). Previously course spatial data of 1 km resolution were used. The spatial data is very valuable for providing cost-effective data input and estimating hydrological model parameters (Engman and Gurney, 1991; Drayton et al., 1992; Mattikalli et al., 1996). The data will also enable us to relate agricultural and other economic / land activities to water

through a distributed hydrological model such as SWAT. For example, Wang (2001) related urban growth to distributed hydrological modelling.

In this study, the SWAT application first involved analysis of parameter sensitivity, which was then used for model auto-calibration that followed hierarchy of sensitive model parameters. The analysis of sensitive parameters and auto-calibration was achieved by sensitivity analysis and auto-calibration options, which are new in the recent version of SWAT, SWAT 2005 (Griensven, 2005). The SWAT 2005 has two main features: sensitivity and uncertainty algorithms and auto-calibration algorithms for objective functions.

Objectives

The objective of the study is to parameterize the Simiyu River catchment using high resolution spatial modelling, with a view to use these baseline results for effective application of SWAT in Tanzania and for ungauged catchments.

Methods

For potential use of the model, and to ungauged catchments and other purposes in Simiyu or Tanzania, more detailed input data preparation and use has to be presented. Since land cover/use and soil classification has influence on results from a comprehensive and complex model, the details of the land use and soil reclassification for SWAT input are presented below for comments and criticism so as to improve the land use and soil data inputs into the model.

Land use data classification and reclassification

Classification of land use data from LandSat TM, where Satellite images of Landsat TM for 1985 were used as presented in the Table 1.

Table 1: Land use data from LandSat TM

Scene	Image Scene	Satellite Sensor	Platform	Date of Acquisition	Cloud Cover (%)
1.	P169R062	TM	Landsat 5-4 TM	05/03/1985	20% but not on the study area
2.	P170R062	TM	Landsat 5-4 TM	09/01/1985	0%

The data were imported into IDRISI32 from Geotiff format to IDRISI raster format. The images were enhanced after geometric correction using some control points and the two scenes were Mosaiced to merge them together and finally the study area was extracted (windowed) using the basin boundary prepared from the 90m DEM. The geometric correction left an error of 0.71 of a pixel for scene one and 0.91 for scene two. This was not bad compared to the recommended less than 1 RMS error by Clarks Lab 2001 manual.

For the purpose of classification, the false colour composites of the bands that carry most of the information, Band 3, 4 and 5 were created and used for better interpretation of landuse and land cover of the Simiyu catchment.

Prior to the classification process, the training sites were developed by on-screen digitization of the area representing the different land cover types. The software then developed the signatures using ‘makesig’ command.

The supervised classification process was done separately for each scene, the P170r062 and the P169r062 and the result was merged. Table 2 shows the reclassified land cover/use data for the SWAT simulations.

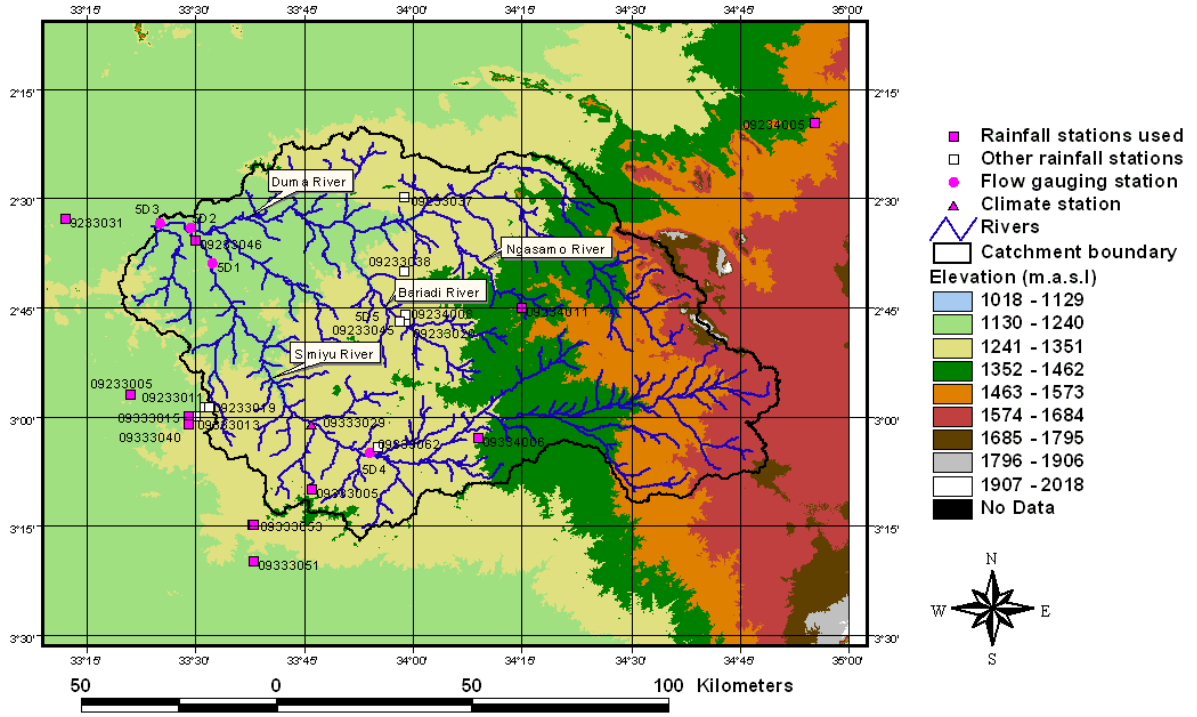


Fig. 1: The Simiyu River catchment: hydro-climatic and topographic distribution

Table 2: Simiyu Land use classes matched with the SWAT land use classes

Land use Class	SWAT Land use Class	% Total catchment area	Dominancy Rank
Grassland	Pasture (PAST)	47.35	1
Cultivated Land	Agricultural Land-Row Crops (AGRR)	36.18	2
Bush Land	Range-Brush (RNGB)	8.62	3
Open Grassland	Range-Grasses (RNGE)	6.45	4
Wood Land	Forest-Deciduous (FRSD)	1.37	5
Urban area	Residential-Medium/Low Density (URML)	0.02	6
Water	Inland Water (WATR)	0.01	7

Soil data classification and reclassification

The soil data was from the new 1:2 million scale Soil and TERrain (SOTER) database developed for Southern Africa by FAO and the International Soils Reference and Information Center (ISRIC) (Batjes, 2004). The detail and quality of primary information available within the various countries varies widely (Dijkshoorn, 2003) and therefore there was a need to use more detailed soil survey data and reclassification for the Simiyu River catchment in Tanzania.

The soil data was accessed through ArcView shapefiles with all soil parameters attribute tables linked. The reclassification of soil data from SOTERSAF was achieved as follows: The soil polygon was compared with the surveyed soil / geology map of Shinyanga region (NEDECO, 1974) covering the Simiyu River catchment to give geological description and hydrological group for the SOTER value of a polygon as presented in Table 3 - 5 below:

Table 3: Description of soils in Simiyu River catchment

Polygon SOTER value	Geological Description	FAO Drainage class (DRAIN)	FAO Texture class (PSCL)	Assigned USDA Hydrologic group (HYDGRP)
48	Alluvial sands and Mbuga clay	W	M	B
49	Alluvial sands and Mbuga clay	W	V	B
51		W	M	B
56	Alluvial sands and Mbuga clay	I	M	D
57	Granite	I	M	D
58	Cemented terrestral sands and gravels (LATERITE Hardcrust)	I	M	D
60	Alluvial sands and Mbuga clay	M	F	C
62	Granite	W	M	B
65	Granite	W	M	B
116	Alluvial sands and Mbuga clay	M	M	C
117		W	M	B
118	Alkaline volcanics	W	M	B
141	Alluvial sands and Mbuga clay	M	M	C
996	Granite	E	M	A
997	Water body			D

Table 4: FAO drainage classification for soils

DRAIN	Definition	Description
E	Excessively drained	Water is removed from the soil very rapidly
S	Somewhat excessively drained	Water is removed from the soil rapidly
W	Well drained	Water is removed from the soil readily but not rapidly
M	Moderately well drained	Water is removed from the soil somewhat slowly during some periods of the year. The soils are wet for short periods within rooting depth
I	Imperfectly drained	Water is removed slowly so that the soils are wet at shallow depth for a considerable period
P	Poorly drained	Water is removed so slowly that the soils are commonly wet for considerable periods. The soils commonly have a shallow water table
V	Very poorly drained	Water is removed so slowly that the soils are wet at shallow depth for long periods. The soils have a very shallow water table

Table 5: FAO textural class description

Textural class (PSCL)	C	M	Z	F	V
Description	Coarse	Medium	Medium fine	Fine	Very fine
Possible soil type	Sandy	Loamy sand	Clay loam	Silt Clay	Clay

The drainage of the soil (in agricultural perspective) is described according to one of the classes above (FAO, 1990) and was used to assign the USDA hydrologic groups (in runoff generation perspective) based on permeability and infiltration characteristics. The importance of assigning soil hydrological groups is that they are used in SWAT to assign Curve Numbers (CN) for the land use-soil combinations, also known as Hydrologic Response Units (HRUs), which are used in the equation to calculate surface runoff and therefore determine the amount

of water that will infiltrate the soil. Therefore, this indicates that in hydrological modelling using CNs, the CN is sought to be the most sensitive parameter when considering the objective function that evaluates the fit to river flows.

The soil reclassification linked with the SWAT's database for the soil type and subsurface soil layers gave rise to the following layers: Clay Loam: CL-CL (two layers), Sand Clay Loam: SCL-SCL (two layers), Fine Sand Loam: FSL-CL-SCL (three layers) and Loamy Sand: LS-S (two layers). The above soil types covered 73.05%, 25.73%, 0.50% and 0.72% of the catchment area respectively.

Parameters sensitivity and auto-calibration algorithms

The sensitivity analysis method implemented in SWAT 2005 is called the Latin Hypercube One-factor-At-a-Time (LH-OAT) (Morris, 1991). The LH-OAT sensitivity analysis combines the strength of global and local sensitivity (OAT) analysis methods. In the combined LH-OAT sensitivity analysis, the OAT method is repeated for each point sampled in the LH sampling. The details of the method can be found in SWAT 2005 Advanced Workshop (Griensven, 2005). The reference catchment outlet at Ndagalu gauging station (5D1) (Fig. 1) in subbasin 11 was used in the sensitivity analysis for daily average flow at the station and in the autocalibration.

The automatic calibration procedure in SWAT 2005 is based on the Shuffled Complex Evolution Algorithm developed at the University of Arizona (SCE-UA). SCE-UA is a global search algorithm that minimizes a single objective function for up to 16 model parameters (Duan et al., 1992). It combines the direct search method of the simplex procedure with the concept of a controlled random search, a systematic evolution of points in the direction of global improvement, competitive evolution and the concept of complex shuffling. SCE-UA has been widely used in watershed model calibration and other areas of hydrology, such as soil erosion, subsurface hydrology, remote sensing and land surface modelling. It was generally found to be robust, effective and efficient (Griensven, 2005). SWAT has two options for the objective function in the auto-calibration: Sum of Squares Residuals (SSQ) and Sum of Squares of the difference of measured & simulated values after Ranking (SSQR). SSQ is useful for hydrological studies while SSQR is recommended for water quality studies.

The sensitivity analysis was carried out for a SWAT model run and a rank of parameters obtained starting with the most sensitive to the least sensitive. The hierarchy of sensitive parameters were then used for the automatic calibration. In searching for the sensistive parameters especially CN, the method of variation of the parameter was multiplying initial parameter by value (in percentage). This ensures the physical meaning of parameters due to dependence of initial values. For each land use-soil combination (HRUs) and for a SWAT model run, a single or sets of parameters were selected for the auto-calibration using the SSQ. The auto-calibration yielded optimum parameters, which were then used for simulation of river discharge. The estimated river discharge was then compared to observed river discharge using the Nash and Suctliff model efficiency (R^2), Index of Volumetric Fit (IVF) and graphical plot to assess the model performance.

Surface water flow generation in Simiyu using SWAT

The rainfall data used (Fig. 1) is the same as in the previous study (Mulungu and Mkhandi, 2005a,b) and a skewed normal distribution was used in SWAT simulation. The Simiyu River catchment is in a semi-arid area where the runoff generation mechanism is sought to be infiltration excess Hortonian overland flow (Mulungu and Mkhandi, 2005a,b; Pilgrim *et el.*

(1988)). Therefore, in hydrological modelling the parameters that caters for infiltration excess runoff are the most important. To estimate surface runoff, SWAT uses a sub-model developed by United States Soil Conservation Service (SCS). The storm runoff depth for every patch within a catchment is estimated based on runoff Curve Numbers (CN) (USDA, 1972). For the catchment water balance, evapo-transpiration was calculated by Penman-Monteith equation and flow routing in channels calculated by Muskingum equation. In this study, all the possible HRUs were set and used in the simulation for river flow at 5D1 gauging station (Fig. 1).

Results discussion

The results discussion is mainly qualitatively by considering the improved spatial data impacts, SWAT model performance and physical basis of the model parameters.

SWAT has two options for the ranking of sensitivity results: one is based on for each objective function and the other for each output. Below are the results for the objective function thus representing the error in estimating the observed discharge at Ndagalu gauging station.

Table 6: Sensitivity analysis results

Rank	1	2	3	4	5	6	7	8
Parameter	CN2	ALPHA-BF	SURLAG	ESCO	SOL-AWC	CH-K2	SOL-Z	CH-N

Rank	10	11	12	13	14	15	16	17
Parameter	CANMX	SOL-K	SOL-ALB	SLSUBBSN	SLOPE	GWQMN	GW-DELAY	RCHRG-DP

The rank shows the order of decreasing sensitivity of the parameters and the parameter in rank 9 is BIOMIX (Biological mixing efficiency) but it was omitted in the above table since it pertains to water quality and tillage in the agricultural management.

In this study, the auto-calibration was followed by manual calibration to assess the impact of the auto-calibrated parameters on the river flow estimation. The manual calibration revealed that only the CN2 values for PAST, RNGB, RNGE and AGRR among all the land use in Table 2 had sound impact on model performance for flow estimation. The CN2 is SCS runoff Curve Number for moisture condition II. Table 7 presents the auto-calibration results for the most sensitive parameter CN2 for the major HRUs (combination of Table 2 and soil data), which was used in the simulation. Other CN2 values for other HRU and other model parameters (except for the ground water, Table 8) were maintained at their default values. It was observed that in simulations the use of auto-calibrated CN2 values for other HRUs could not improve the model performance and the use of default values resulting in few parameters (sensitive) for CN2 as shown in Table 7. Yapo et al. (1996) and Liew et al. (2005) had similar results on few sensitive parameters, which were obtained in well-calibrated catchments.

Table 7: Auto-calibration results for optimum CN2 parameters used for the simulation

Parameter	**Soil texture**	**Land use – Soil Combination (HRU)**				
	Profile	**FRSD**	**PAST**	**RNGB**	**RNGE**	**AGRR**
CN2	CL-CL		59.25 (79)	63.51 (74)		63.75 (85)
CN2	SCL-SCL		51.75 (69)		51.75 (69)	
Previous CN2	SCL-SCL	51 (66)	61 (69)	50 (61)	65 (69)	74 (78)

The low value of CN2 is associated with less dense vegetation, which is typical case of the semi-arid Simiyu River catchment. The field under the previous refer to the values obtained by manual calibration in the previous study by Mulungu and Mkhandi, 2005a, b. Comparing, this shows that for the same soil texture (SCL-SCL) only two sets of CN2 values for PAST and RNGE was significant for flow estimation. Also, lower values for these land use class were used in this study than in the previous one for this type of less dense vegetation (grassland).

Table 8: Tuned and optimum ground water and routing model parameters 1976-1983

Parameter/ Soil profile	CL-CL	SCL-SCL	FSL-CL-SCL	LS-S	**Previous Profile** SCL-SCL
SOL_K(1)	2.7 (2.7)	32 (32)	78 (78)	450 (450)	900 (32)
SOL_K(2)	1.4 (1.4)	18 (18)	9.9 (9.9)	450 (450)	500 (18)
SOL_K(3)			19 (19)		
REVAPMN	0 (1)	0 (1)	0 (1)	0 (1)	0 (1)
RCHRG_DP	0.9 (0.05)	0.9 (0.05)	0.9 (0.05)	0.9 (0.05)	0.9 (0.05)
GW_REVAP	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)
SURLAG	2 (4)	2 (4)	2 (4)	2 (4)	2 (4)
EPCO	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
ESCO	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
GWQMN	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

The description of parameters in Table 8 is as follows with the default parameter values in the brackets: SOL_K(1), SOL_K(2) and SOL_K(3) is saturated hydraulic conductivity (mm/h) in layer 1, 2 and 3 respectively. REVAPMN is threshold depth of water in the shallow aquifer for “revap” or percolation to the deep aquifer to occur (mm). RCHRG_DP is deep aquifer percolation fraction (-), GW_REVAP is groundwater “revap” coefficient (-) and ALPHA_BF is baseflow alpha factor. SURLAG is surface runoff lag time (days), EPCO is plant uptake compensation factor and ESCO is soil evaporation compensation factor. GWQMN is the threshold depth of water in the shallow aquifer required for return flow to occur (mm).

In this study, most of the ground water parameters (Table 8) were left at their default values as initially estimated by databases, which maintained their physical basis. Therefore, the new datasets used in this study improved the physical meaning of the parameters. The flow estimation results (Table 10, 11 and Fig. 2) were similar to the previous study (values in Table 10 are in square brackets) with both studies having low model performance. This shows that other factors are more important for contribution to the model performance. Table 9 shows the long-term average water balance values for the simulation in the period 1976-1983.

Table 9: Observed and simulated long term average water balances.

Water variable	**Observed (mm) 1976-1983**	**Estimated (mm) 1976-1983**
Total Water Yield (WYLD)	78.66	74.56
Surface Runoff (SURQ)	65.35	67.61
Base flow (GWQ)	13.31	6.95

From Table 9, the estimated long-term average water balance in the simulation period is close to the observations and showed that the water balances fairly matches.

Table 10: Daily model performance efficiencies for the period 1976-1983.

Year(s)	**R^2 (-)**	**Cumulative R^2 (-)**	**Consecutive R^2 (-)**
1976	-0.4403 [-0.1566]		
1977	**0.2376 [0.2464]**	**0.2511 [0.2651]**	
1978	**0.4208 [0.4881]**	**0.3042 [0.3338]**	**0.2943 [0.3210] (1977-1978)**
1979	-0.3578 [-0.4679]	0.1774 [0.1802]	
1980	-0.4831 [-0.4484]	0.1373 [0.1422]	
1981	**0.4749 [0.4787]**	**0.1969 [0.2016]**	
1982	**0.4052 [0.3156]**	**0.2227 [0.2158]**	**0.4439 [0.4061] (1981-1982)**
1983	-0.2583 [-0.4284]	**0.2169 [0.2068]**	0.4054 [0.3595] (1981-1983)

Comparing results in Table 10 for this and the previous study (in square brackets), similar and consistent results shows that the improvement in the land use and soil data had no much impact on better model performance. This shows that other factors other than the detail of spatial data are highly important in the model performance. Model performances in consecutive years were calculated to reduce uncertainty and to get the average performance in the intervals, which had better model performance on yearly evaluation. On average, model performance improvement over the individual years and beginnings of the simulations to a certain year's performances.

Table 11: Daily model performance efficiencies during calibration and validation periods.

Model performance index	**Calibration (1976-1980)**		**Validation (1981-1983)**	
	This study	**Previous study**	**This study**	**Previous study**
Mean of observed flow [Cumecs]	15.65	15.65	13.28	13.28
Index of Volumetric Fit (IVF) [-]	1.43	1.15	1.06	0.84
Model efficiency (R^2) [100%]	13.73	14.22	**40.54**	**36.17**

From Table 11, the model underestimated water volumes (through IVF values) during calibration (1976-1980) and tended to conserve the water volumes (IVF close to 1.0) during validation period (1981-1983). The high values of R^2 in the validation period than in calibration period showed better model fit of the peak flows on the validation period. The poor fit in the calibration period may be attributed by relatively high peak flows observed during this period than in the validation period. A clue of the difference in the peak flows can be reflected in mean flows during calibration and validation periods.

Figure 2 presents the flow hydrographs at Ndagalu gauging station for the year 1978, showing the observed, this study's estimated flow (current) and previous study's estimated flow (previous).

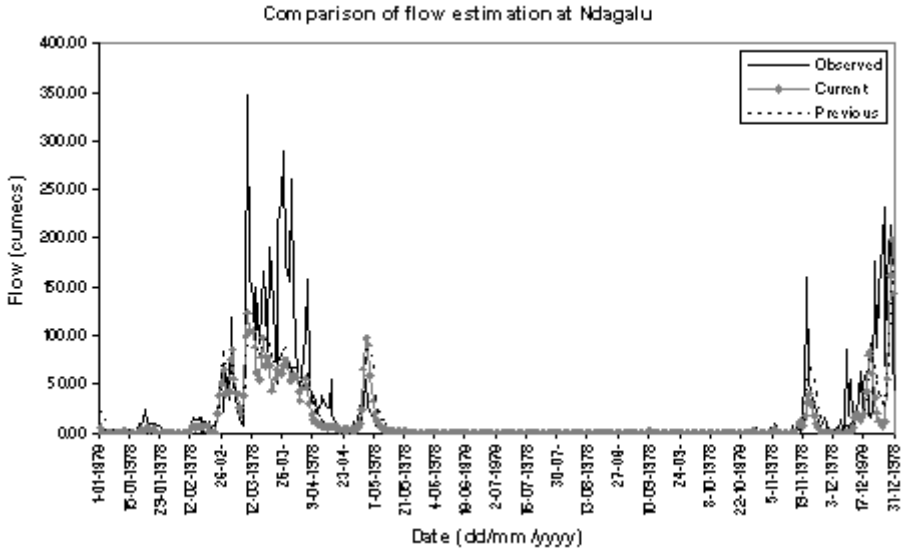


Fig. 2: Comparison of estimated discharges at Ndagalu gauging station (5D1) during 1978

Despite use of more detailed spatial data in this study than in the previous study, the SWAT model fit results (Tables 10-11, Fig. 2) have not improved. It is speculated that the spatial distribution of rainfall is not well captured in this study. Several studies in some catchments support the importance of spatial distribution of rainfall and have indicated that the spatial distribution of rainfall has profound impacts on the spatial distribution of soil moisture and temperature, production of runoff and partitioning of the surface energy balance. They also found that the variability of soils and vegetation generally have a second-order modifying effect on the spatial variability imposed by precipitation (e.g. Kustas and Goodrich, 1994; Schmugge et al., 1994; Jackson et al., 1993; Michaud and Sorooshian, 1994). Therefore, it is recommended that in future study more attention should be on the spatial distribution of rainfall data than the spatial data.

Conclusions

This study is a further step in hydrologic simulation in Simiyu River catchment and has used more detailed DEM, land use and soil data. Comparison with previous study showed that parameters obtained by manual and automatic sensitivity analysis for the surface runoff are different, but their respective calibration results showed more or less the same estimate of river flow at Ndagalu station. This study's parameters had more physical meaning especially for the CN2 and the SOL_K(?) parameters. The low level of model performance showed that other factors than the spatial data are greatly important for improvement of flow estimation by SWAT in Simiyu. As an immediate concern, an analysis and use of distributed rainfall data in the catchment is required so that other pending hydrological modelling problems with SWAT can be attacked with confidence.

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