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Full Length Research Paper

Hydrological modeling approaches for the Kihansi river catchment in south central Tanzania

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This study presents distributed and lumped hydrological modeling approaches for the Kihansi river catchment in south central Tanzania using the Soil and Water Assessment Tool (SWAT). The catchment is source of water for the Lower Kihansi Hydropower Plant (LKHP) that supplies 25% power to the national grid and the bio-diverse gorge eco-system in lower Kihansi Basin. In the distributed modeling sub-watersheds were defined at the existing gauging stations. There are four upper sub-watersheds and ten sub-watersheds located downstream. Three sub-watersheds of the river system were separately modelled in a lumped approach. Subsequent parameterization of physically-based soil parameters, landuse, and management files were defined. Four quantitative and two qualitative evaluation criteria were used to evaluate the prediction performance of SWAT model. Model prediction results using unoptimized parameter sets resulted poor modeling performance. Hence parameter specification and optimization was necessary to ensure correct hydrological processes. Modelling results using optimized parameter sets resulted better prediction of hydrological variables. Finally correction factors were introduced for optimised parameters to facilitate future land cover change studies.

Key words. Hydrology, modeling, SWAT, Kihansi river, calibration, validation.

INTRODUCTION

The great challenge in hydrology today is the develop-ment of models that can give reliable predictions of runoff from catchments, especially from ungaged ones, and yet to be flexible enough to be used to evaluate different management scenarios. Despite different philosophy in development and application, the history of model development ranges from the well-known rational formula (Mulvaney, 1850) to recent distributed physically-mean-ingful mathematical models (Abbot et al., 1986a,b; Arnold et al., 1998). The recent hydrologic models are computer-based and have become important in water resources engineering for hydrologic forecasts and managing water systems (Duan et al., 1994).

Recent applications of hydrologic modeling in tropical data-scarce catchments (Ndomba and Birhanu, 2008; Birhanu et al., 2007; Mulungu and Munishi, 2007; Van Liew et al., 2003) suggest a wide use of the SWAT model (Arnold et al., 1998). Moreover parameters like curve number in SWAT model may be appropriate to reflect the impact of changes in landuse or land management on agricultural watersheds (Van Liew et al., 2003). Account-ing for heterogeneity of environmental variables such as soil types, land uses, topographic features, and weather parameters is essential in order to properly simulate the effect of spatially varying properties (Muleta and Nicklow, 2005). In SWAT model spatial data base of model parameters; that is, landuse, soil and crop management files are developed using physically-based approach and sensitive parameters are identified using the sensitivity analysis based on the Latin Hypercube One factor at a Time (LH-OAT) method (Van Griensven and Srinivasan, 2005) . The LH -OAT method was identified as more stra-tegic, efficient, and effective sampling approach that can significantly reduce computational demand (Muleta and Nicklow, 2005). Parameter optimization is based on the shuffled complex evolution (SCE- UA) method (Duan et al., 1992, 1993) which was more effective and efficient compared to other optimization methods (Duan et al., 1994; Yapo et al., 1996). Therefore this paper focuses on the development of physically-based and distributed hydrological model for the data-scarce Kihansi river catchment in south central Tanzania using the SWAT

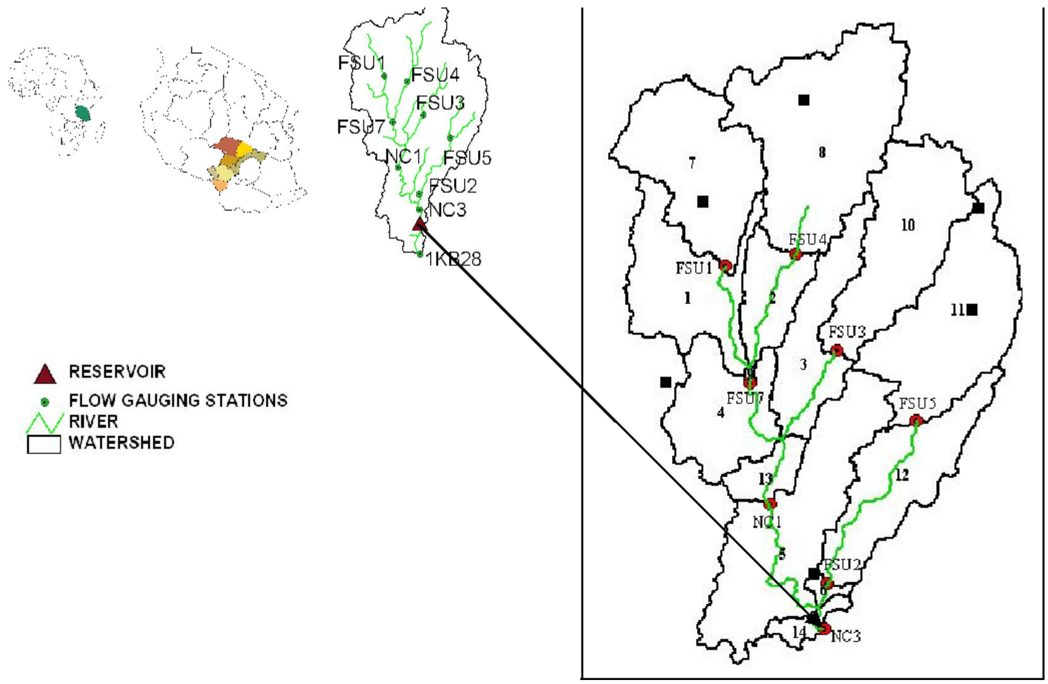

Figure 1. Kihansi river catchment and hydrologic networks including sub-watersheds.

hydrologic model.

METHODOLOGY

The study area

The study area, shown in Figure 1, is a catchment located in the southern part of the Eastern Arc Mountains (EAMs) of Tanzania. The approximate drainage area of the catchment is 581 km^2 and is characterised with mean annual precipitation (MAP) and mean annual runoff (MAR) of 1890 and 793 mm respectively.

There are two water users in the catchment; the gorge eco-system and the Lower Kihansi Hydropower Plant (LKHP) designed for 180 MW run-of-the river type with a possible extension to 300 MW in the future. The LKHP provides a significant proportion of the electricity needs of Tanzania (currently contributes 25% to the national grid). There are 8 gaging stations upstream of the recently built reservoir and coded by their Field Station Unit location (for example, FSU1) and the company who installed the gages (for example Nor-Consult as NC1 and NC2).

The famous endemic Kihansi Spray Toads (*Nectophrynoides Asperginis*) were discovered during the feasibility study of the LKHP in the gorge eco-system. Various water allocation proposals and conservation measures have been suggested to avoid the reduction of power outputs and conserve the ecosystem which is under extinction (World Bank, 2001). However, streamflow reduction and valley-bottom cultivations, associated with land cover changes pose management challenges to the energy-strapped country and the existence of the Kihansi Spray Toad population (Birhanu, 2008).

Data

Information used is time series hydro-meteorological data, spatial data of landuse, soil, Digital Elevation Model (DEM) and definitions of management conditions in the catchment. Daily hydrometeorological data of rainfall, flow, maximum and minimum temperature, relative humidity, wind speed and sunshine hours were collected from various Tanzanian government institutions. These data were checked for systematic errors and representativness. As shown in Table 1, climatic data were found to be of shorter length. Missing rainfall data were filled using cross correlation and inverse distance square method and seasonal mean method was used to fill-in missing flow data.

Soil data were obtained from soil and terrain database for Africa (SOTERAF) (Dijkshoorn, 2003) and other soil research studies in Tanzania (National Soil Service, 1986) . Three main soil types were identified for the study area: nitisols (10%), acrisols (87%) and fluvisols (3%).

Landuse data were based on the 30 x 30 m Landsat Thematic Mapper (Landsat TM) prepared from scenes number P168R66, P169R66 dated on 26/06/1995, 14/08/1994 and 14/08/1994. The data indicated that about 73% of the catchment cover was Bushland with Scattered Cropland (BSC), Natural Forest (14%), and Grassland with Scattered Cropland (12%). The rest is Open Woodland (WO) (Figure 2). The 90 x 90 m resolution DEM for the study area was obtained from the Water Resources Engineering Department (WRED) of the University of Dar es Salaam, Tanzania. The DEM data was archived from the seamless data distribution system, EROS available at (http://seamless.usgs.gov).

Parameter derivation

The methodology adopted in the present study focused on the development and use of SWAT model parameters using physically-based approach. Derived soil data parameters include soil type, horizon number, lower depth (cm), and percentages of sand, silt, clay and rock, organic carbon, colour of the soil and drainage type. These data are direct input to the SWAT model and are also used to estimate the following parameters; moist bulk density (BD), available water capacity (Av), saturated hydraulic conductivity (Ksat), Universal Soil Loss Equation, soil erodibility factor (USLE_K)

Table 1 Time series data used in the study

S. No	Station code	Data Type	Lat (S)	Long (E)	Alt (m)	Start Date	End Date	Length (Years)	% Missing
1	983501	Rainfall	8.25	35.81	1890	09/01/1999	03/05/2004	6	6.63
2	983502		8.28	35.9	1871	12/01/1996	30/04/2005	10	10.09
3	983503		8.3	37.75	1820	22/02/1999	31/03/2005	7	4.26
4	983504		8.33	35.94	1850	02/01/2000	30/04/2005	6	0.16
5	983505		8.32	35.81	1890	01/01/1998	30/04/2005	8	28.88
6	983506		8.38	35.93	1860	02/01/2000	30/04/2005	6	3.34
7	983507		8.4	35.87	1760	01/09/1997	30/04/2005	9	10.59
8	983508		8.42	35.76	1871	01/01/2000	30/04/2004	5	8.03
9	983509		8.52	35.85	1410	12/01/1995	31/03/2005	11	1.03
10	FSU1	Flow	8.34	35.79	1723	01/01/1996	31/12/2004	9	0
11	FSU2		8.52	35.85	1344	01/01/1996	31/12/2004	9	0
12	FSU3		8.4	35.86	1648	07/02/1996	31/12/2004	9	0
13	FSU4		8.35	35.83	1698	07/02/1996	31/12/2004	8	0
14	FSU5		8.44	35.9	1504	12/04/1996	31/12/2004	9	0
15	FSU7		8.41	35.81	1598	25/08/1999	31/05/2003	5	0
16	NC1		8.48	35.82	1520	01/01/1996	31/12/2004	9	0
17	NC3		8.55	35.85	1349	01/01/1994	31/12/2004	21	11.98
18	983506	WS,SR, RH, Temp	8.38	35.93	1860	03/02/2000	28/02/2002	3	0
19	983508		8.42	35.76	1871	29/02/2000	31/12/2001	2	0
20	983509		8.52	35.85	1410	03/02/2000	31/05/2002	3	0

WS (Wind Speed), SR (Solar Radiation), RH (Relative Humidity), Temp (Maximum and Minimum Temperature).

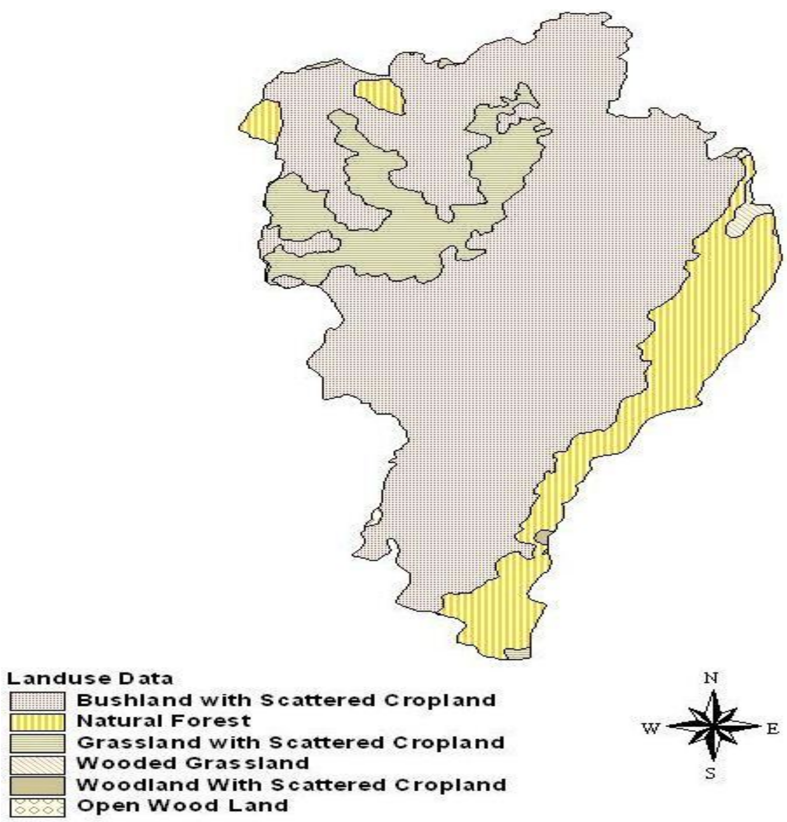

Figure 2. Landuse data for the Kihansi river catchment.

and soil moist albedo (Soil Albedo). From multiple regressions of percent sand, silt and clay using 203 data sets provided in SOTERAF data base, bulk density was estimated using equation (1).

$$BD = 2.26 + (-0.005(S)) + (-0.013(Si)) + (-0.010(C)) \quad [1]$$

Where BD is moist soil bulk density (g/cm^3), S is percentage sand, Si is percentage silt and C is percentage clay. The coefficient of determination (R^2) of the regression relation was 0.37. Comparable estimates were obtained with previous research studies (Jones, 1975).

From the study of Jones (1975) reference was made to determine physical soil parameters and estimate the available water capacity. Accordingly, the amount of water available for plant growth (mm) is the difference between the retained water capacity and the volume of water held at 15 bar suction, which is the theoretical wilting point, and given as:

$$A_v = \theta_v(0.05) - \theta_v(15) \quad [2]$$

Where A_v is the amount of water available for plant growth, $\theta_v(0.05)$ the retained water capacity, and $\theta_v(15)$ is the wilting point. Regression equations were developed (Hall et al*.,* 1977) to calculate the retained water capacity and the wilting point

$$\theta_v(0.05) = 47.00 + 0.25(C) + 0.10(Z) + 1.12(X) - 16.52(D_b) \quad [3]$$

$$\theta_v(15) = 2.94 + 0.83(C) - 0.0054(C)^2 \quad [4]$$

Where C is percent clay (<2 m), Z is percent silt (2 – 60 m), X is percent organic carbon and D_b is bulk density. In the study, saturated hydraulic conductivity (Ksat) was determined for the given texture class in different horizons using transfer functions provided by Nemes et al. (2001). The function is a prediction of the Mualem-van Genuchten parameters (Hollis et al., 2006) for the individual soil horizons. The parameter Ks provided in equation (5) was transformed as $K_S^* = \ln(K_{Sat})$. In the equation the organic matter content was estimated to be 1.72* organic carbon.

$$K_S^* = 7.755 + 0.0352*S + 0.93*topsoil - 0.967*D^2 - 0.000484*C^2 - 0.000322*S^2 + 0.0748*OM^{-1} - 0.643*\ln(S) - 0.01398*D*C - 0.1673*D*OM + 0.02986*topsoil*C - 0.03305*topsoil*S \quad [5]$$

where C is percent clay, S is percent silt, OM is organic material content, D is bulk density; topsoil and subsoil were qualitative variables having the value of 1or 0 respectively.

The USLE_K was estimated based on equations presented in the SWAT theoretical manual. Neitsch et al. (2002) gives equations describing the derivations of USLE_K. For moist soil albedo, equation (6) (NRCS, 2008) was used to approximate the values

$$SoilAlbedo = 0.069 * (ColorValue) - 0.114 \quad [6]$$

Table 2 shows the soil data for the SWAT model input in the Kihansi river catchment. Regarding land cover parameters, few, but known and basic parameters were customized based on previous research findings in the tropical catchments while keeping most parameter settings as presented in the SWAT manual (Neitsch et al., 2002). These are the Leaf Area Index (LAI), Root Depth (RD), Canopy Height (CH), Biomass and Potential Heat Unit (PHU). Estimates of LAI for various plantations were archived from the world data base research (Scurlock et al., 2001). Canadell et al. (1996) presented thorough listings of rooting depths for various forests and combinations of forests with grass land covers. Similarly, a range of canopy height and initial estimate of total biomass was presented for various types of forests world wide (Cannell, 1982). The PHU for crop growth was computed from the relationship of average temperature (Tav) and base temperature (Tbase) presented in the SWAT theoretical manual (Neitsch et al*.,* 2002). Apart from the definition of soil and landuse parameters, four management operations were scheduled, these are: planting/beginning of growing season, harvest only operation, harvest and kill operation and kill/end of growing season operation.

Model setup, simulation options and efficiency criterion

Water balance is the driving force behind everything that happens in the watershed (Neitsch et al., 2002) and SWAT uses equation 7 to simulate the water balance.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad [7]$$

where SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day *i* (mm H_2O), *t* is the time (days), R_{day} is the amount of precipitation on day *i* (mm H_2O), Q_{surf} is the amount of surface runoff on day *i* (mm H_2O), E_a is the amount of evapotranspiration on day *i* (mm H_2O), w_{seep} is the amount of water entering the vadose zone from the soil profile on day *i* (mm H_2O), and Q_{gw} is the amount of return flow on day *i* (mm H_2O). Equations describing the computation of each of the water balance component of equation 7 are presented in the SWAT user manual (Neitsch et al., 2002).

To indicate distributed modeling using SWAT model, the catchment was discretised into 14 sub-watersheds as shown in Figure 1. Similarly, the catchment was separately modelled in a lumped approach at three watersheds to evaluate performance efficiency of flow predictions. These are FSU2-L (119 km^2), NC1-L (378 km^2) and NC3-L (581 km^2). Eight years of data (1997 - 2004) were available for calibration and validation. At the outlet of the catchment, that is, two-third of the data was used for model calibration and the remaining data for validation. Sensitive parameters were identified based on sum of squares (SSQ) objective function (Van Griensven and Srinivasan, 2005). Model performance was assessed using four quantitative and two qualitative evaluation criteria (Table 3). These are computation of (1) deviation of stream flow volume (Dv), (2) the Nash and Sutcliffe coefficient of efficiency (NCE) (Nash and Sutcliffe, 1970), and (3) prediction efficiency (coefficient of determination, R^2), (4) index of volumetric fit (IVF), and visual inspection of (5) hydrographs and (6) flow duration curves. The importance of these evaluation criteria were briefly explained in the works of Van Liew et al.(2003)

RESULTS AND DISCUSSION

Poor prediction efficiencies were observed with the use of catchment characteristics. In this case predicted flows were tending to be higher with poor seasonal distributions. For bigger watersheds (NC1 and NC3) however, the percentage deviation (Dv), the prediction efficiency (Pe (R^2), and the long-term water balance (IVF) were found to be promising prior optimization as shown in Table 4. Similarly, a mixture of variations in model predic-

Table 2. Soil parameters and data

Soil Parameters	Type of soil											
	Eutric Fluvisols						Haplic Acrisols		Umbric Nitisols			
Horizon Number	1	2	3	4	5	6	1	2	1	2	3	4
Bottom Depth	150	300	500	600	950	1200	240	680	150	500	1000	1500
Depth of Each Layer	150	150	200	100	350	250	240	440	150	350	500	500
Sand (%)	16	20	24	5	60	45	83	72	39	26	22	19
Silt (%)	43	23	35	34	23	37	6	5	17	14	12	14
Clay (%)	41	57	41	60	17	18	11	23	44	60	66	67
BD (gm/cm^3)	1.2	1.3	1.2	1.2	1.4	1.3	1.5	1.5	1.3	1.3	1.3	1.3
Total Carbon (g/Kg)	17	9	3	6	2	2	14	9				
Carbon (% soil Wt)	1.7	0.9	0.3	0.6	0.2	0.2	1.4	0.9	4.5	0	0	0
Organic Matter	2.92	1.55	0.52	1.03	0.34	0.4	2.41	1.55	7.74	0	0	0
USLE_K	0.15	0.13	0.16	0.24	0.17	0.18	0.05	0.1	0.1	0.12	0.11	0.12
Ksat* (cm/day)	3.53	1.13	4.01	3.54	4.39	4.11	4.65	3.38	2.86	1.53	1.19	1.1
Ks(cm/day)	34	3.1	57.1	34.4	80.4	61	104.5	29.5	17.4	8.47	8.16	8.16
SOL_AWC	0.16	0.11	0.13	0.13	0.15	0.18	0.15	0.11	0.14	0.1	0.1	0.1
Albedo	0.09	0.16	0.16	0.16	0.23	0.23	0.09	0.23	0.16	0.16	0.16	0.16

Depths are in mm, BD refers to Bulk Density, SOL_AWC is in (mm H_2O/mm Soil).

Table 3. Equations of model prediction efficiency measures

S. No	Measure of prediction efficiency	Equation	Target Values (%)
1	Deviation of stream flow volume (D_v)	$D_v = (V_{obs} - V_{sim})(100)/V_{obs}$	0
2	Nash and Sutcliffe coefficient of efficiency (NCE)	$NCE = 1 - [(Q_{obs} - Q_{sim})^2 / (Q_{obs} - Q_{mean})^2]$	100
3	Coefficient of determination (R^2)	$r = \frac{(Q_{obs} - Q_{obsav})(Q_{sim} - Q_{simav})}{\sqrt{(Q_{obs} - Q_{obsav})^2 \quad (Q_{sim} - Q_{simav})^2}}$	100
4	Index of volumetric fit (IVF)	$IVF = \frac{Q_{sim}}{Q_{obs}}(100)$	100

Where V_{obs} and V_{sim} are total observed and simulated streamflow volumes in m^3, respectively. Q_{obs} and Q_{sim} are daily observed and simulated streamflow, respectively. Q_{mean} is the mean observed flow during calibration period. Q_{obsav} and Q_{simav} are average observed and simulated streamflow, respectively during evaluation period.

tion performances was observed between distributed and lumped modeling approaches implying no conclusive differences in prediction efficiencies. However, higher Pe (R^2) (>90%) indicate middle flows were better simulated in lumped modeling approach. The poor prediction efficiency observed with the use of catchment characteristics indicates the need to increase the spatial and temporal scale of the data used. For example the climatic data are of short record as shown in Table 1 and mean seasonal climatic data were used for the entire simulation period. Similarly the soil data base derived from available data (as presented in “Model setup, simulation options and efficiency criterion”) is based on developed transfer function which might not well predict soil parameters. This is observed in poor coefficient of determination result for bulk density. Despite these deficiencies the SWAT model fairly predicted the hydrologic variables reasonably for bigger sub-watersheds prior optimization and it is promising to be a suitable hydrological model even in data-scarce regions.

Table 4. Model performances using physically- based parameter settings

	FSU1	FSU2	FSU3	FSU4	FSU5	FSU7	NC1	NC3	FSU2-L	NC1-L	NC3-L
CN2	69	55	78	78	55	69	69	78	55	78	78
SURLAG	4	4	4	4	4	4	4	4	4	4	4
RCHRG_DP	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
SOL_K	43.5	0.8	7.2	7.2	0.8	43.5	43.5	7.2	0.8	0.8	0.8
GWQMN	1	1	1	1	1	1	1	1	1	1	1
SOL_Z	240	150	150	150	150	240	240	150	150	150	150
SOL_AWC	0.15	0.1	0.14	0.14	0.1	0.15	0.15	0.14	0.14	0.14	0.14
GW_DELAY	31	31	31	31	31	31	31	31	31	31	31
CANMX	0	0	0	0	0	0	0	0	0	0	0
BIOMIX	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
GW_REVAP	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
ALPHA_BF	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048	0.048
ESCO	0	0	0	0	0	0	0	0	0	0	0
SLOPE	0.112	0.20	0.21	0.16	0.21	0.11	0.11	0.19	0.20	0.16	0.175
CNn	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014	0.014
CH_K2	0	0	0	0	0	0	0	0	0	0	0
SLSUBBSN	36.585	15.24	15.244	24.39	15.244	36.6	36.6	18.29	15.244	24.39	18.293
REVAPMN	1	1	1	1	1	1	1	1	1	1	1
SOL_ALB	0.09	0.16	0.16	0.16	0.16	0.09	0.09	0.16	0.16	0.16	0.16
EPCO	0	0	0	0	0	0	0	0	0	0	0
BLAI	4	5	4	4	5	4	4	4	5	4	4
Prediction Efficiency											
Dv (%)	34	-51	-14	-101	-28	-17	3.8	-8.4	-79	-48	5
Pe (R^2) (%)	4	32	14	14	31	18	26	39	93	89	95.5
IVF (%)	66	151	114	201	128	117	96	108	180	147	95
NCE (%)	-925	-1081	-3448	-8300	-457	-2105	-637	-746	-704	-2029	-349

High computational efficiency was required to perform sensitivity analysis and autocalibration for each of the subwatersheds. Based on available resources, specification and optimization of sensitive model parameters were made (Table 5) that governs response from the surface water, subsurface water and the basin.

In parameter estimation stage, it is important to determine if spatially distributed predictions are satisfactory so that model results from subbasins can be determined with reasonable confidence (Muleta and Nicklow, 2005). After identifying sensitive parameters the model was calibrated using the auto-calibration option by following multi-step procedure recommended by Neitsch et al. (2002) and Van Liew et al. (2003). The values of the parameters used in multi-step calibration procedure were within the range suggested in the SWAT user manual (Neitsch et al., 2002).The upper subwatersheds (FSU1, FSU3, FSU4, and FSU5) were calibrated first, and the parameters in these subwatersheds were then held constant while the lower nested subbasins were calibrated. This approach to calibration was the most reasonable option for relating model parameters to specific soil and landuse conditions in the study area. At the outlet of the catchment (NC3) the model was capable of capturing 61% of the variance in calibration (1997-2001) and 37% in validation (2002-2004) using the NCE (Figure 3) . This is considered as '*satisfactory simulation*' (Motovilov et al., 1999). Results of model prediction performance at other subwatersheds are presented in Table 5. The improvement in performance efficiencies of sub-watersheds FSU2, FSU7, and NC1 were partly associated to parameters of the upper subwatersheds at FSU1, FSU3, FSU4 and FSU5 and the nested subbasinsin between. In this case to get better simulation at downstream subwatersheds model parameters at the nested subbasins were fine tuned manually and better simulation at all subwatersheds and outlet of the catchment were obtained.

Similar to unoptimized parameter setting, no marked difference was observed in prediction efficiencies between distributed and lumped modeling systems at the outlet of three tested watersheds (FSU2-L, NC1-L and NC3-L). The importance of distributed modeling was justified by using the optimised sets of parameters of a lumped model at NC3-L to each sub-watershed in distributed modeling system. In this case poor prediction effi-

Table 5. SWAT model optimized parameters and the prediction efficiency for the period 1997 -2004

	FSU1	FSU2	FSU3	FSU4	FSU5	FSU7	NC1	NC3	FSU2-L	NC1-L	NC3-L
CN2	75.44	77.5	80.13	68.4	75.94	78	78	78	71.447	86.775	91.025
CF	1.09	1.41	1.03	0.88	1.38	1.13	1.13	1	1.3	1.11	1.17
SURLAG	0.005	0.01	0.006	0.004	0.01	0.006	0.006	0.006	0.013	0.013	0.022
CF	0.00125	0.0025	0.0015	0.001	0.0025	0.0015	0.0015	0.0015	0.0033	0.0033	0.0055
RCHRG_DP	0.68	1	0.917	1	1	0.05	0.05	0.05	1	0.952	0.948
CF	13.6	20	18.34	20	20	1	1	1	20	19.04	18.96
SOL_K	22.64	10.2	2.42	7.114	9.88	0.8	0.65	0.8	10.965	14.65	4.29
CF	0.52	12.75	0.34	0.99	12.35	0.018	0.015	0.11	13.7	18.31	5.36
GWQMN	2938	0.18	1	1	1	1	1	1	1	152.19	4986
CF	2938	0.18	1	1	1	1	1	1	1	152.19	4986
Prediction Efficiency											
Dv (%)	11.1	6.6	0.36	96.3	0.88	13	-2.9	-5.3	0	-0.11	16.3
Pe (R^2) (%)	69.6	89	91.7	93.4	91.2	85	97.5	50	90.6	95	86.6
IVF (%)	89	93	99.6	96.3	99.1	87	103	105	100	100	84
NCE (%)	11	62.6	56.1	33	56.4	14	48	60.4	63.33	21.1	41

CF is a correction factor introduced for future landuse change.

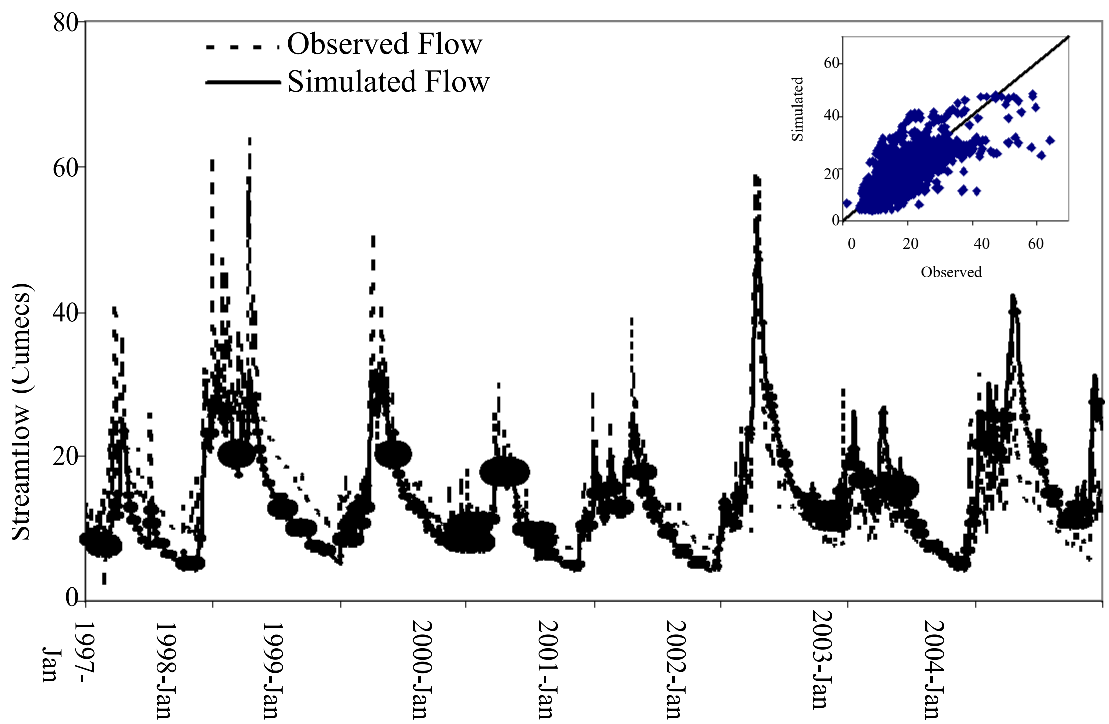

Figure 3- Observed and simulated streamflow hydrographs.

ciencies were observed and flows were over- predicted as shown in Table 6 indicating loss of accurate prediction of hydrologic parameters in a lumped modeling approach. Using optimised parameter sets the timing of runoff events was well predicted and low flows were reasonably simulated as shown in Figures 3 and 5. However, in most simulation periods the hydrograph peaks were under-estimated. This is partly attributable to the way that curve

Table 6. Prediction efficiency of lumped optimised parameter sets in a distributed system for the period 1997 -2004.

	FSU1	FSU2	FSU3	FSU4	FSU5	FSU7	NC1	NC3	FSU2-L	NC1-L	NC3-L
Dv (%)	11.1	6.6	0.36	96.3	0.88	13	-2.9	-5.3	0	-0.11	16.3
Pe (R^2) (%)	69.6	89	91.7	93.4	91.2	85	97.5	50	90.6	95	86.6
IVF (%)	89	93	99.6	96.3	99.1	87	103	105	100	100	84
NCE (%)	11	62.6	56.1	33	56.4	14	48	60.4	63.33	21.1	41

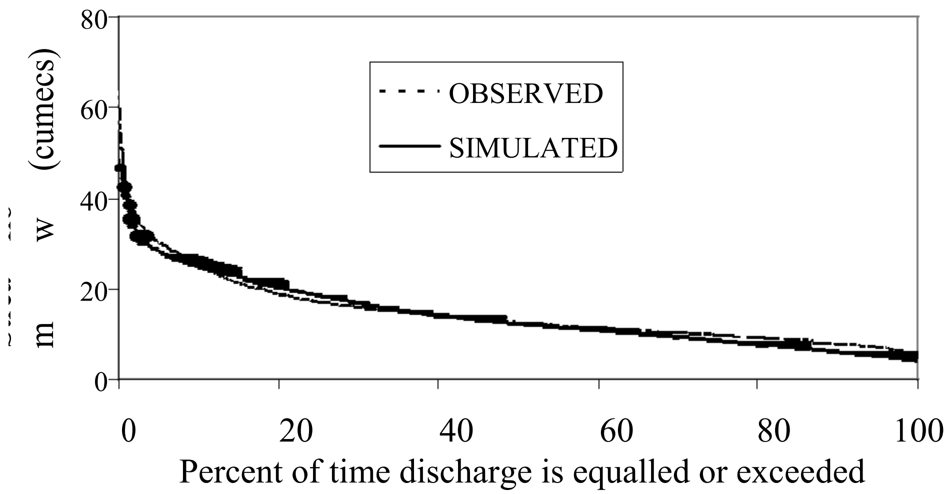

Figure. 4- Daily 1-day FDCs at NC3 for the period 1997- 2004.

number is updated based on changes in soil moisture (Van Liew et al., 2003). In SWAT, the curve number value is updated based on the available water content of the entire soil profile. However, it is probably more appropriate to update the curve number values in accordance with soil water content of the topmost soil layer, which could more closely reflect the process of surface saturation during heavy rainfall events (Kannan, et al., 2007). Simulation results indicated that 85% (664 mm) of the annual water yield (773 mm) was contributed from the ground water flow indicating strong base flow component in the catchment

The long term (1997-2004) simulation result (14.25 cumecs) indicates reasonable water balance with the observed average annual flow (14.71cumecs). As shown in Figure 4 the daily 1-day flow duration curves (FDC) of the observed and simulated flow indicate reasonable prediction of middle flows.

SWAT being a deterministic model, the parameters are constant with time for a catchment. However for catchments experiencing high population pressure and subject to scarce-data condition like the case of Kihansi river catchment, it is important to introduce correction factors (CF) to optimize model parameters for correct hydrological processes with time. The CF values presented in Table 5 are calculated as the ratio of optimized parameter value (Table 5) to unoptimized parameter value (Table 4). Any future landuse change in the catchment should necessitate the use of the correction factors presented in Table 5.

CONCLUSIONS AND RECOMMENDATIONS

The present study demonstrates hydrological model prediction efficiencies of a physically- based distributed and lumped hydrological systems using SWAT model. Model prediction efficiencies were found to be poor with the use of catchment characteristics. Parameter specification and estimation were important to identify sensitive parameters ensuring correct representations of hydrologic processes. The prediction efficiency of the model is improved with increasing the spatial and temporal scale of the data used. A marked improvement in flow prediction was observed in distributed modeling and correction factors were introduced for optimized parameters in future simulations involving land cover changes. Here it is recommended that the approach used in the present study need to be tested widely in bigger catchments to enable better understanding of the methodology and hydrological processes of catchments in data-scarce conditions for efficient management of environmental

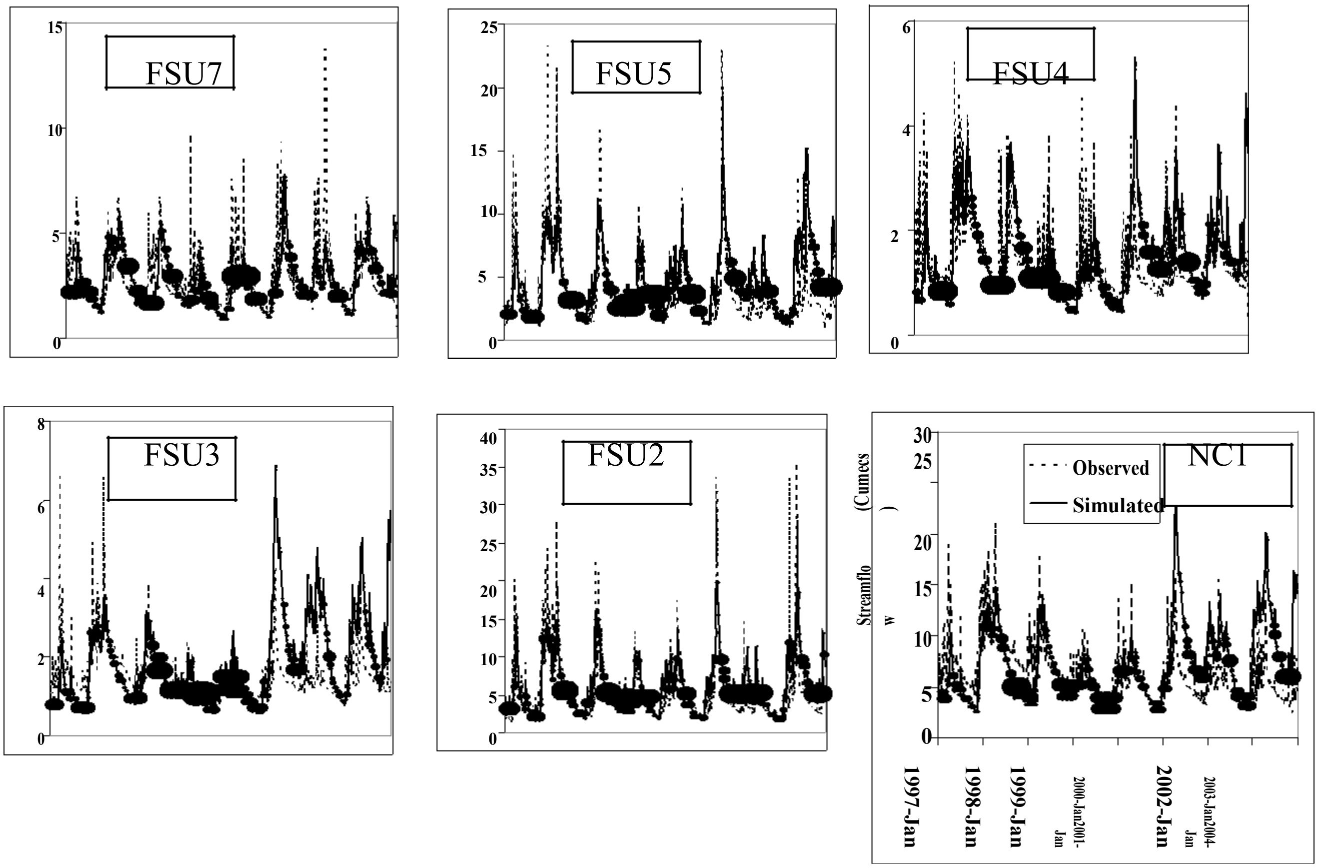

Figure 5. Observed and simulated streamflow hydrographs at gauging stations located inside the catchment.

changes.

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