Effects of Different Retention Parameter Estimation Methods on the Prediction of Surface Runoff Using the SCS Curve Number Method

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Abstract Quantifying different hydrological components is an initial step for sustainable water resources planning and management. One rising concern is the conflict between the environment, hydropower and agriculture mainly in lowland areas where a large share of the base flows need to be abstracted. The Soil and Water Assessment Tool (SWAT) model was used to understand the hydrological processes of the Upper Awash River Basin with the emphasis on analyzing the different options for surface runoff generation using the Soil Conservation Service (SCS) Curve Number (CN) method. In this study, SWAT was applied incorporating two methods for estimating the retention parameter (S) for the SCS-CN method. The first allowed S to vary with soil profile moisture content (SM method) and the second allowed S to vary with accumulated plant evapotranspiration (PT method). Hydrograph comparison indicated that the PT method was better in simulating peak flows while the SM method was better in simulating the low flows. While the predicted stream flow hydrographs showed an agreement between the two methods, the simulated annual water balance indicated a disagreement in quantifying the different hydrological components. After evapotranspiration, base flow was the dominant component simulated in the SM method whereas surface runoff was the foremost in the PT method simulation. The analysis indicated that care must be taken when selecting an appropriate tool for quantifying hydrologic system to be used for decision making especially for un-gauged catchments where validation of model results is not possible.

Keywords Sustainable water use · Water balance components · SWAT · Retention parameter · Awash river basin

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1 Introduction

Prediction regarding the amount and reliability of stream flow is a vital step to achieve a sustainable water resource management (SWRM) system. The need for efficient and effective water resources management systems continues to be vital as water demand increases for hydropower and irrigation. Hydrological models provide a means of quantitative extrapolation or prediction that can be considered helpful in decision-making. Such models provide a tool to better understand and predict stream flows that can, in turn, be used to forecast future impacts associated with land-use and climate changes. Still, even though hydrological modeling has made much progress in recent decades, there remains a challenge in satisfying the data requirement of the more advanced models. The data required to setup a hydrological model (e.g., topographic, hydraulic and meteorological data) is one of the main constraints when choosing a model to apply for a specific area.

Consider Ethiopia. Ethiopia is known for its enormous water resources potential (ECA 1999). The topography of the country is rugged with clearly defined water courses, which concentrate significant flooding to the lowland flat parts of the country. For example, the Awash River basin is located in the Rift Valley and has been a subject of large-scale flooding for several years. The impacts of flooding so far include both the tragic human life loss and extensive property damages. One clear goal of SWRM in this region is to mitigate the impact of these flooding events. This area is also considered to be at a leading position in the development process through hydropower production and irrigation projects aimed at increasing agricultural productivity. Ethiopia, however, has limited weather and hydrological data (World Water Assessment 2004) for use to support development and manage water resources. There is clearly a need for implementing hydrological models in this region that can estimate surface runoff characteristics and hydrologic partitioning under such limited data conditions.

SWAT is one of the models that are widely used for analyzing the different components of hydrology in large river basins (Arnold et al. 1998). It is a semi-distributed and long-term yield watershed model (Neitsch et al. 2005). SWAT, like all models, requires data to produce reliable predictions in ungauged settings. While the parameterization of the model is based largely on USA watersheds, it has been validated for many watersheds where representative data are available (Arnold et al. 1998; Shi et al. 2011). Since measuring the required parameters for SWAT in the field and laboratory is a difficult task, the usual approach, especially for developing countries, is to estimate the initial values from regional databases (e.g. FAO 2002). The existence of such databases makes SWAT an attractive choice for modeling in data-limited settings. As such, there have been several applications of the SWAT model in data-limited conditions like those that exist in Ethiopian watersheds (Chekol 2006; Setegn et al. 2009a, b).

Even with such databases available, there are clear difficulties in applying SWAT in datalimited settings due to the implicit process representation made when assigning certain parameters. For example, the amount of water storage available in the soil profile (the maximum storage) or S, which is the main driver in the calculation of surface runoff in SWAT due to its reliance on the commonly used SCS-CN method, should represent the realworld situation and relevant hydrological processes occurring in the watershed being modeled. This can be difficult because of the various implicit assumptions made in implementing the base-case SCS-CN approach (e.g. Steenhuis et al. 1995; Lyon et al. 2004) like setting initial abstraction (I_a) equal to 0.2S with S defined as a constant value derived from land-use and soil characteristics. Hawkins (1979) showed that using 0.2S for I_a did not result in good runoff prediction unless S was dependent on rainfall amounts. More recently, studies have demonstrated drawbacks to this fixed linear relationship and attempted to obtain acceptable values through experimental approaches (e.g. Mishra et al. 2006; Shi et al. 2009). However, such experimentation often needs a significant amount of observed data and, for situations with large areas and scarce resources, such approaches may not be necessary.

This study focuses on analyzing two different methods for estimating S for the SCS-CN method implemented in SWAT. The first such approach allows for S to vary with the soil profile moisture content (hereafter called SM). The second option is to let S vary with the accumulated plant evapotranspiration and relies more on antecedent climate condition (hereafter called PT). The objective of this study is to assess the outcomes of the two retention parameter estimating methods for specific sub-watersheds in the Awash River basin of Ethiopia. Specifically, we seek to demonstrate that the selection of parameters directly influences the process representation in the model and that care needs to be taken when selecting the type of retention parameter to implement. This can lead to significantly different characterizations of the hydrologic system and has great potential influence on the development of SWRM. This is novel because it explicitly demonstrates the connection between retention parameter estimation methods and the potentials for unsustainable water resource management. This is significant since this and many parameters in SWAT are often autocalibrated or adopted ad hoc without consideration of real-world implications.

2 Methods

2.1 Study Area and Input Data

The Awash River originates at an elevation of about 3,000 m a.s.l. in the central part of Ethiopia (Fig. 1). It follows the southeast direction for a short distance and turns to the northeast direction along the Great Rift Valley. It flows for about 1,200 km before joining Lake Abe at the border of Djibouti Democratic Republic. The basin covers a total area of about 113,000 km² that includes Ethiopia's capital city, Addis Abeba. This study focuses on the uppermost part of the basin with area coverage of about 7,630 km² (Fig. 1). The basin is located between latitude 9° 18' N and 8° 17' N and longitude 37° 57' E and 39° 4' E with an outlet at Hombole gauging station. The main streams draining the upper Awash River Basin are the Holeta, Berga, Akaki and Melka-Kuntire.

Several datasets were brought together to implement SWAT (Table 1). Digital elevation models (DEM) with 30 m resolution were available from the Earth Remote Sensing Data Analysis Center of Japan (ERSDAC 2009). Land-use and soil maps were collected from previous work (Chekol 2006, personal communication). The climatological data available for this study were daily precipitation, maximum and minimum temperature obtained from the National Meteorological Agency of Ethiopia for the period of 1994–2000. The precipitation data were from eight measurement stations, of which six are located inside the watershed and two are nearby. The temperature data were from two stations, of which one is located inside the watershed (Addis Abeba) and the other nearby (Debre-Zeit). The simulation in SWAT was based on 5 year data, 1996–2000. Among these one year was the driest, 1997, and two years were the wettest, 1996 and 1998; while the rest were moderately wet years in relation to each other. Daily river discharge values were collected from the Ministry of Water Resources of Ethiopia. The available discharge data were obtained from four gauging stations inside the Upper Awash watershed (Holeta, Berga, Akaki and Melka-kuntire) and one station at the outlet (Hombole).

The climate of upper Awash is humid to sub-humid in the highlands with an average annual temperature of 16-17 °C and semi-arid in the low lands with an average annual temperature of



Fig. 1 Location of the study area

19–20 °C. The area is characterized by two rainy seasons. The dominant one is from June to September. The other is between January to May that is usually smaller in total rainfall amount and occurs erratically. The average annual rainfall in the highlands is about 1,200 mm and in the lowlands about 900 mm.

2.2 Description of the Base SWAT Model

SWAT developed by Arnold et al. (1998) is a continuous time hydrological model that allows for a simulation of different physical processes in a watershed. The spatial unit for rainfall-runoff calculations in SWAT is the Hydrologic Response Unit (HRU), which is a lumped

Table 1	Summary	of the physical	characteristics	of the five s	ub-watersheds	and wate	ersheds used	d for	the study
Among t	these Akak	ci and Hombole	were studied i	in depth					

Characteristics	Holeta	Berga	Akaki	Melka Kuntire	Hombole
Size (km ²)	131.1	216.8	884.3	4,501.0	7,626.3
Dominant slope (%)/Areal coverage (%)	>15/42.6	>15/36.5	8-15/33.4	2-5/30.8	2-5/28.9
Average elevation (m a.s.l.)	2,544	2,652	2,371	2,048	2,018
Dominant soil type/depth (mm)	Luvisols/1,800	Luvisols/1,800	Vertisols/2,422	Vertisols/2,422	Vertisols/2,422
Dominant land use	Corn	Durum Wheat	Durum Wheat	Eragrostis Teff	Eragrostis Teff

land area within a sub-watershed comprised of unique land-cover, soil, slope, and management combinations. The hydrological components (like surface flow, lateral flow, groundwater flow and evapotranspiration) are calculated for each HRU through a water balance. The cumulative total over a sub-watershed then gives the hydrological 'balance' and estimates the main stream flow for that sub-watershed. The overall watershed hydrologic balance including stream flow at the outlet of the whole watershed is then calculated from the contribution of the upstream sub-watersheds. The model incorporates three different methods for estimation of potential evapotranspiration with varying data requirements. In this study, Hargreaves' method, which needs only air temperature data, was used. Further description of the different components of SWAT model is available in Neitsch et al. (2005).

A key component central to SWAT is the CN, which is a similarity parameter ranging from 0 to 100 that represents soil, land-use and antecedent soil water conditions for a given landscape position. The standard approach in SWAT uses CNs for various soils and land-cover conditions (stored in SCS tables) that are based on average antecedent soil moisture conditions (condition II). This method uses two equations to estimate runoff:

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)}$$
(1)

$$S = 25.4 \left(\frac{1000}{CN} - 10 \right)$$
 (2)

Eq. (1) relates runoff to rainfall and retention parameter where Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), and S is the retention parameter (mm). Note this formulation inherently assumes that initial abstraction (I_a) is equal to 0.2S. Eq. (2) defines S as a function of CN. Since there are shortcomings to assuming static values of S (e.g. Hawkins 1979; Steenhuis et al. 1995) which are reflected directly in the definition of I_a in the base formulation, alternative approaches have been put forward to allow for the temporal evolution of S based on watershed condition.

2.2.1 Defining the Retention Parameter (S)

The spatial variability of S accounts for the changes in soil, land-use, management and slope while the temporal variability accounts for the changes in soil-water-content. SWAT incorporates two different methods for calculating S:

3 Soil Moisture Method (SM)

This method allows S to vary with soil profile water content and characterized by field capacity, wilting point and saturation water content. The CN values are calculated on a daily base using the estimated S values in relation with the initial soil-water-content for the day as:

$$S = S_{max} \left[1 - \frac{SW}{[SW + \exp(w_1 - w_2 \cdot SW)]} \right]$$
(3)

where, S_{max} is the maximum value that S can achieve on any given day (mm) calculated by solving Eq. (2) using moisture condition I (CN1), SW is the soil-water-content of the entire

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profile excluding the amount of water held in the profile at wilting point (mm), and w_1 and w_2 are shape coefficients.

The shape coefficients are calculated from the simultaneous solution of Eq. (4) and (5) by using the following three assumptions:

- S_{max} for dry moisture condition, CN1, corresponds to wilting point (WP) soil profile water content,
- S₃ for wet moisture condition, CN3, corresponds to field capacity (FC) soil profile water content,
- The soil has CN=99 (S=2.54) when completely saturated (SAT),

$$w_1 = ln \left[\frac{FC}{1 - S_3 \cdot S_{max}^{-1}} - FC \right] + w_2 \cdot FC$$
(4)

$$w_{2} = \frac{ln \left[\frac{FC}{1 - S_{3} \cdot S_{max}^{-1}} - FC\right] - ln \left[\frac{SAT}{1 - 2 \cdot 54 \cdot S_{max}^{-1}} - SAT\right]}{(SAT - FC)}$$
(5)

3.1 Plant Evapotranspiration Method (PT)

This method allows S to vary with the accumulated plant evapotranspiration, which minimizes the impact depending on soil storage and gives emphasis on antecedent climate. S as a function of PT is calculated as:

$$S = S_{prev} + E_0 * \exp\left(\frac{-cncoef * S_{prev}}{S_{max}}\right) - R_{day} + Q_{surf}$$
(6)

where S_{prev} is the retention parameter for the previous day (mm), E_o is the potential evapotranspiration for the day (mm/day), S_{max} is the maximum value that S can achieve on any given day (mm) calculated by solving Eq. (2) using moisture condition I (CN1) and cncoef is a weighting coefficient used to calculate the retention coefficient for the daily CN calculations dependent on plant ET (range from 0 to 2). In a recent study, it is described as a depletion coefficient (Kannan et al. 2008). The initial value of S is defined as:

$$S = 0.9 * S_{max} \tag{7}$$

The effect of these two S estimation methods were analyzed initially based on the comparison of the separate model simulation results from their initial parameterization with the observed discharge from the five gauging stations across the Awash region. With the help of this analysis two watersheds, Akaki and Hombole, were selected for further calibration of the separate model setups and finally for validation of the models.

3.2 Model Calibration and Validation

The calibration of the model parameters was undertaken in different steps based on observed data from the period 1996–1998 with a prior 2 year warm-up period 1994–1995. Manual calibration was the first step to obtain some level of agreement with the observed flow. Then, the auto-calibration was done based on the most sensitive parameters from previous study

(Tessema et al. 2014, in press) using both the SM and PT methods for defining S for Akaki and Hombole watersheds using Parameter Solution (ParaSol) method (van Griensven and Meixner 2007) that is incorporated in SWAT.

ParaSol is a multi-objective uncertainty method that is efficient in optimizing a model and providing parameter uncertainty estimates (van Griensven and Meixner 2007). It calculates objective functions (OF) based on the simulated and observed time series, aggregates the OFs into a Global Optimization Criterion (GOC). The optimization was done by adapting the Shuffled Complex Evolution Approach for effective and efficient global minimization method (SCA-UA). This algorithm samples over the entire parameter space with a focus of solutions near the optimum/optima. The OF used in this study was the Sum of the Squares of the residuals (SSQ) with an objective of minimizing the differences between the simulated and measured time series.

The validation of the model was performed to test if the calibrated parameter set would behave consistently for the watershed using different observed datasets for different periods. In this study, the only observed data used for model validation was the measured stream flow datasets for 2 years, 1999–2000.

3.3 Model Performance Evaluation

The performance of the model was evaluated by comparing the simulated flow hydrograph with the observed hydrograph using three model goodness-of-fit statistics methods recommended by Moriasi et al. (2007). Model performance was assessed using both the calibration and validation periods. The first performance statistic was the Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe 1970) which is a commonly used method related to the objective function of the calibration (SSQ) in this study. The second performance statistics considered was the coefficient of determination (\mathbb{R}^2) to characterize the amount of variance in the observed data explained by the model results. The third statistic, Percent bias (PBIAS), was selected as it measures the average trend of the simulated data to be larger or smaller than their observed equivalent in the preferred time step. The ideal value should be zero; however, the lower the values the more precise are the model simulations. Negative value indicates a bias toward underestimation whereas a positive value indicates an overestimation.

The performance of the model can be interpreted based on predefined or recommended ranges. For the NSE in this study, these are: (1) NSE values greater than 0.75 show good model efficiency, (2) NSE between 0.36 and 0.75 shows satisfactory performance, and (3) value less than 0.36 is considered to be unsatisfactory (Moriasi et al. 2007). Similarly, PBIAS values greater than and equal to twenty five percent (± 25 %) are considered to be satisfactory (Moriasi et al. 2007).

4 Results and Discussion

4.1 Analysis of the Model Simulations

4.1.1 Effect of the Retention Parameter Estimation Methods

For Akaki sub-watershed, the SM method over predicted the flows in the dry and small rain season (Jan-May) and under predicted the flows in the wet season (Fig. 2 (top)). The PT method dampened out the input small rainfall signal (Jan-May) resulting in a best fit with the



Fig. 2 Hydrographs that compare observed and simulated stream flow using the SM method (left) and the PT method (right) at Akaki sub-watershed (top), Hombole watershed (middle) for the year 1996 and Holeta sub-watershed (bottom) for the calibration period (1996–1998)

observed stream flow at the outlet of the sub-watershed. In comparison to the SM method, the PT method better predicted peak flows during the wet season.

Hombole and Melka-Kuntire watersheds, which are larger in size and have gentler slopes, reacted in a similar manner (Fig. 2 (middle)). The SM method over predicted the flows in all seasons with an exception of few peak flows during the wet season. The PT method better fitted the flows in dry and small rain season, but showed an extensive over estimation during the main rain season. The apparent improvements in these watersheds were on the falling limb and base flow recession, which were overestimated by the SM method.

Holeta and Berga are the smaller and steeper sub-watersheds that showed identical reactions (Fig. 2 (bottom)). The SM method over predicted the flows in all seasons with an exception of few peak flows during the wet season for the year 1997 and 1998 while it underestimated the flow almost for all seasons in the year 1996. Whereas the change to the PT method decreased the overestimated flows in the dry and small rain season, but increased the over estimation of the flow in the main rain season including some of the peak flows in the year 1996. These catchments, however, seem to respond only to the surface runoff that comes from the heavy rain during the wet season and underestimated the fraction of water contributed by the base flow during that time.

4.1.2 Seasonal Variation of the Antecedent Moisture Condition

The analysis of the daily CNs and the initial soil moisture conditions on the dominant HRU's showed that with both methods allowed the soil-water-content to vary significantly following the season according to the rainfall pattern (Fig. 3). In the case of the CN calculated by the SM method, the variation was somewhat minimal. This means that the seasonal variation of the antecedent moisture condition was not reasonably represented across the area. This could be due to the assumption made in the calculation of the shape coefficients (w_1 and w_2 , in Eq. (4) & (5)), which states that the maximum amount (CN=99) corresponds to the saturation soil content. Analysis (not shown here) on the soil-water-content showed that the saturation level



Fig. 3 Comparison of daily initial soil-water-content and CN of the dominant HRU's for the year 1996 in Hombole (top two) and Holeta (bottom two) watershed from the SM and PT method simulations

was almost never reached. Hence, the daily CNs were between the dry condition (CN1) and wet condition (CN3) and, thus, miss the peak flows that correspond to the maximum CN values. On the other hand the daily CNs from the PT method reflected the seasonal variation with high CN values in wet season and low values in dry season (Fig. 3). These variations help in controlling the influence and predictions associated with small rainfall signals from being overestimated in the basin response and also gives a better prediction for the peak flows during the wet season.

In the case of the smaller watersheds, Holeta and Berga, the analysis showed that the percolation (since the base flow and lateral flow is also minimized substantially, the effect here is on the total infiltration) was minimized when using the PT method. This might be due to the maximum CNs that corresponds to the minimum S (as S approaches zero) in wet season. Once S reached such a point, it then takes some time to increase again due to the dependency on the previous values, so the larger CNs were persistent even in dry times. In smaller sub-watersheds, where the total flow and storage capacity is low, this situation would result in a quick drying up of the aquifers in the times of no or small recharge. This is due to the fact that the amount of water entering the soil profile is calculated as the difference between the amount of rainfall and the amount of surface runoff (Neitsch et al. 2005). The greater part of the rain that falls afterwards would be calculated as surface runoff before it gets the chance to infiltrate. Another possible explanation could be an overestimation of the field capacity that reduces the availability of water for further percolation to the shallow aquifer from which the base flow originates.

4.2 Model Calibration and Validation

For the PT method, the manual calibration of the cncoef parameter showed that the change in its value was directly proportional with the surface runoff and inversely proportional with the subsurface runoff. This result is similar to the study discussed by Kannan et al. (2008). The increasing of the parameter value also increased the mean of the total flow with an average proportion of about 2.5 mm for each 0.1 increment of cncoef. The previously discussed base flow fraction accounting problem on the two smaller sub-watersheds was also tested. Improvement was achieved by changing cncoef to 0.25 for Holeta sub-watershed. The calibrated optimal values, based on the comparison of the base flow fraction between the observed and simulated flow, were 1.05 and 0.6 for Akaki and Hombole, respectively.

The final calibration (Akaki and Hombole only) results indicated that the PT method was better estimating peak flow while the SM method performed better in simulating the low flows (Fig. 4). These results are in accordance with the analysis of the seasonal variation of the antecedent moisture condition (subsection 3.1.2). This might be due to the ability of the PT method to capture the higher daily CN that is responsible for the peak flows. For Akaki sub-watershed, the peak flows were represented better with the PT method that was confirmed by the model performance metrics (Table 2). For Hombole watershed, the peak flows were overestimated in the relatively drier years (1997 and 2000) using the SM method. Using the classification of Moriasi et al. (2007), the model performance was satisfactory for the Akaki and good for the Hombole watershed independent of the method considered.

Validation for years 1999 and 2000 indicated that the simulated hydrographs are in good agreement with the observed flows (Fig. 4). However, for Akaki sub-watershed the underestimation of the peak flows is significant for the 1999 rainy season. The performance measures show from satisfactory to good simulations in all cases (Table 2).



Fig. 4 Comparison of the daily observed hydrographs from Akaki (top) and Hombole (bottom) watersheds with the two simulated flows from using the SM and PT methods during the calibration (1996–1998) and validation (1999–2000) periods

Performance evaluators		Akaki sub-watershed (Annual Mean in m ³ /s for: calibration=13.15 validation=12.97)				Hombole watershed (Annual Mean in m ³ /s for: calibration=52.95 validation=39.99)			
		Daily		Monthly		Daily		Monthly	
		SM	РТ	SM	РТ	SM	РТ	SM	РТ
Mean (m ³ /s)	Calibration	11.98	13.19	11.89	13.08	59.32	52.07	58.79	51.62
	Validation	10.09	10.84	9.99	10.75	46.16	41.13	45.64	40.7
NSE	Calibration	0.49	0.53	0.80	0.84	0.80	0.83	0.94	0.96
	Validation	0.50	0.44	0.77	0.75	0.73	0.79	0.87	0.93
R^2	Calibration	0.50	0.53	0.83	0.85	0.82	0.83	0.95	0.97
	Validation	0.55	0.46	0.84	0.78	0.76	0.79	0.91	0.93
PBIAS	Calibration	-8.87	0.3	-8.65	0.56	12.02	-1.68	12.01	-1.64
	Validation	-23.08	-17.39	-22.97	-17.12	14.31	1.86	14.14	1.78

 Table 2
 Model Performance statistics for prediction of stream flow in Akaki and Hombole watersheds during the calibration and validation periods

4.3 Water Balance of the Upper Awash River Basin

The major water balance component for Hombole was evapotranspiration at 67 and 69 % (expressed as % of total rainfall) in the PT and SM simulations, respectively (Fig. 5). For this specific watershed, the major difference between the methods is on the accounting of surface runoff and base flow on annual basis. The PT method resulted in a 24 % and 2 % of surface runoff and base flow (from shallow aquifer), respectively. The SM method resulted in a 3.3 % and 20.5 % of surface runoff and base flow, respectively. These results were compared with previous works, Moreda (1999) and Chekol (2006). According to Moreda (1999), using a 10 day and a monthly lumped conceptual rainfall-runoff model, the dominant flow is the inter flow (lateral flow) with 13 % as compared to the base flow that accounts 2 %. The study explained that due to the simulation time scale, the short intensive storms are likely smoothed (averaged) and surface runoff was not generated. On the other hand, the study by Chekol (2006) that applied SM method in SWAT model indicates the base flow as the important component of the total discharge with a 53 % of total water yield. According to the study, the base flow is 9.8 % from a 100 % rainfall input while surface runoff is 6.8 %. The comparison indicates that the SM method consistently simulate the base flow as a dominant contributor on annual basis (both in the current study and in Chekol (2006)), while the PT method is in accordance with the discussed result from Moreda (1999). Hence, the large differences in the discussed results should be taken as an incentive for further investigation that also includes the geological characteristics of the catchments.

Based on the annual water balance, the sensitivity of the cncoef parameter was also checked in the calibrated model. The result indicated the possibilities of adjusting the surface runoff and base flow components with a single parameter calibration. Changing the parameter to 0.5 from the calibrated 0.6 shifts some of the surface runoff contribution to the base flow while changing to 0.7 is vice versa (Fig. 5). Similar result is also discussed in Kannan et al. (2008).



Fig. 5 Simulated water balance components from using the SM method and the PT method (with different cncoef values; 0.5, 0.6 and 0.7) during the calibration period (1996–1998)

4.4 Implications of These Results for Management in Awash

A similar underestimation of the large runoff events when adopting the SM method as demonstrated in this current study has also been reported by King et al. (1999) and Shi et al. (2009). The assumption of average moisture value might work in acceptable range for humid climates with minimum seasonal variation. King et al. (1999) compared the SCS-CN method that depends on the soil-water-content with a modified Green-and-Ampt infiltration method on Goodwin Creek Watershed in the USA. The paper describes that precipitation for this area is generally greatest during winter with a minimum average monthly value of 83 mm in September. According to the work, the CN method underestimates annual surface runoff throughout the year while keeping the seasonal trend. But in the case of this study area, which is characterized by highly seasonal variation in rainfall (from 4.4 mm in December to 275 mm in July), it failed to capture the temporal variation of the antecedent moisture condition of the soil. On the contrary, the simulation result from the modified Green and Ampt infiltration method appeared to match the results of this study, which is under-simulated during the rainy season and over-simulated during the small rain season.

According to Shi et al. (2009), changing the initial abstraction coefficient from 0.2 to 0.05 improved the estimation of large runoff but still overestimates the small events, with the area

having similar seasonal trend like the current study. On the other hand, Jacobs et al. (2003) demonstrated that using remotely sensed soil moisture data, when combined to the CN equation with the SM method, can improve predictions.

The SM method is reported to predict excessive runoff in shallow soils and soils with low storage (Neitsch et al. 2005; Kannan et al. 2008). According to Kannan et al. (2008) the calibrated model using the PT method performs better than the SM method in the areas of low storage soils and shallow soils. The result of this study is also in accordance, which shows that the PT method improves the prediction of stream flow in the areas characterized by a relatively medium to low storage. The significant factor that was observed from the analysis is the capability of the methods in mimicking the seasonal variation of the rainfall and the retention capacity of the soils that in turn govern the surface runoff estimation. The quality of climate data and its representativeness to the catchment is vital for this method since the core of this method was to depend more on antecedent climate condition rather than the soil storage.

The key difference between the SM and the PT method was on the calculation of the water balance of the watershed. They oppose each other on the allocation of a significant amount of water either to surface runoff or to base flow. The SM method estimated lower surface runoff contribution than the groundwater while the PT method estimated higher surface runoff contribution than the groundwater. However, prediction and allocation of reliable water resource components are vital steps to achieve SWRM. Particularly in this area, where the development of hydropower plants and irrigation canals are active, unsustainable ways of constructing water infrastructure and utilizing water lead to considerable impacts. Altering the regime of stream flows, flooding risk to the downstream and reducing or blocking of water to the ecosystem are concerns (Ngigi et al. 2008). Furthermore, according to a study made on irrigation in Africa (FAO 2005), the main concern on water use is the conflict between the environment and agriculture particularly in lowland rural areas, where total base flows are diverted for irrigation without releasing water for ecological conservation. Hence, further studies on similar watersheds are necessary to validate the outcomes of this study and help to categorize the characteristics of a catchment that could be modeled with a good performance and in a reliable way using the different methods for a SWRM.

5 Conclusions

The model-based water balance investigation taken up in this study showed a disagreement between the two different methods for estimating S used in SWAT on the estimation of the contribution from the base flow. The SM method estimated lower surface runoff contribution than the groundwater while the PT method estimated the other way around. One noticeable advantage of the PT method was its single parameter (cncoef), which made parameterization relatively easier particularly for adjusting the contribution of base flow and surface runoff to total streamflow. However, since the only measurement used for the calibration of the model was streamflow data these results should further be analyzed with additional measurements of variables, in this case soil moisture data. Overall, the present study indicated that proper care must be taken in selecting an appropriate tool for quantifying the different water balance components, which would be used for decision making, especially for un-gauged catchments where validation of model results is not possible. In addition, further studies are necessary to find reliable methods to model the characteristics of a catchment for planning and managing water use, such as hydropower and irrigation, in a sustainable water management system.

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