Evaluation of SWAT Manual Calibration and Input Parameter Sensitivity in the Little River Watershed

G. W. Feyereisen, T. C. Strickland, D. D. Bosch, D. G. Sullivan

Abstract. *The watershed-scale effects of agricultural conservation practices are not well understood. A baseline calibration and an input parameter sensitivity analysis were conducted for simulation of watershed-scale hydrology in the Little River Experimental Watershed (LREW) in the Coastal Plain near Tifton, Georgia. The Soil and Water Assessment Tool (SWAT) was manually calibrated to simulate the hydrologic budget components measured for the 16.9 km^2 subwatershed K of the LREW from 1995 to 2004. A local sensitivity analysis was performed on 16 input variables. The sum of squares of the differences between observed and simulated annual averages for baseflow, stormflow, evapotranspiration, and deep percolation was 19 mm^2; average annual precipitation was 1136 mm. The monthly Nash-Sutcliffe model efficiency (NSE) for total water yield (TWYLD) was 0.79 for the ten-year period. Daily NSE for TWYLD was 0.42. The monthly NSE for three years with above-average rainfall was 0.89, while monthly NSE was 0.59 for seven years with below annual average rainfall, indicating that SWAT's predictive capabilities are less well-suited for drier conditions. Monthly average TWYLD for the high-flow winter to early spring season was underpredicted, while the low-flow late summer to autumn TWYLD was overpredicted. Results were negatively influenced when seasonal tropical storms occurred during a dry year. The most sensitive parameters for TWYLD were curve number for crop land (CN2(crop)), soil available water content (SOL_AWC), and soil evaporation compensation factor (ESCO). The most sensitive parameters for stormflow were CN2(crop), curve number for forested land (CN2(forest)), soil bulk density (SOL_BD), and SOL_AWC. The most sensitive parameters for baseflow were CN2(crop), CN2(forest), ESCO, and SOL_AWC. Identification of the sensitive SWAT parameters in the LREW provides modelers in the Coastal Plain physiographic region with focus for SWAT calibration.*

Keywords. *Calibration, Hydrologic modeling, Sensitivity, Streamflow.*

The objective of the USDA-ARS Conservation Effects Assessment Project (CEAP) is to assess on a nationwide basis the benefits of soil and water conservation programs in support of policy decision and implementation (USDA-ARS, 2005). The project consists of two major components: a national assessment and a watershed-scale evaluation (Mausbach and Dedrick, 2004). The purpose of the national assessment is to estimate the environmental benefits of USDA conservation programs nationally. Conservation benefits will be quantified each year, given the suite of practices implemented, and compared with program expenditures. The purpose of the watershed-scale assessment is to complement the national assessment by providing analysis of conservation benefits at a smaller scale. Understanding gained by studying conservation practices at a small catchment or field scale will be incorporated into the methods used for the national assessment.

A key component of the approach adopted by the USDA to carry out the watershed-scale evaluation is to use historic hydrologic and land management record data from 12 ARS benchmark watersheds to calibrate and validate the watershed-scale hydrologic simulation models Soil Water Assessment Tool (SWAT) (Arnold et al., 1998) and Annualized Agricultural Nonpoint-Source Pollution (AnnAGNPS) (Bingner and Theurer, 2001). The validated models will in turn be employed to evaluate at the watershed scale the environmental benefits of conservation practices. Four of the USDA-ARS's key objectives supporting CEAP are to provide detailed databases that delineate reasonable ranges for key model input parameters, to provide best available parameters for calibrating the models to "representative" regional conditions, to provide regional estimates of model output uncertainty, and to evaluate the potential variations in output uncertainty as affected by the spatial and temporal scale of input parameters versus the desired scales of assessment.

The focus of this article is the calibration of SWAT and the evaluation of SWAT input parameter sensitivity on water yield and stormflow for subwatershed K (SW-K) of the Little River Experimental Watershed (LREW) near Tifton, Georgia. The LREW is one of the original 12 ARS benchmark watersheds identified in CEAP.

Several authors have previously addressed input sensitivity and output uncertainty for SWAT. However, prior sensitivity analyses yielded mixed results. Differences in approaches and differences in regions indicate a wide range in the most sensitive parameters, suggesting that some site-specific sensitivity analysis may be required. Lenhart et al. (2002) used

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two approaches to develop sensitivity indices for 44 SWAT input parameters. The authors developed a simple artificial catchment, utilizing soil and climate information from a low mountain range area in central Germany. The most sensitive parameters were found to be the soil physical properties, two plant-specific parameters, slope length, slope steepness, and curve number. In another study based on the same artificial catchment representation, Huisman et al. (2004) concluded that plant parameter uncertainty had a much larger effect on an adapted version of SWAT (SWAT-G; Eckhardt et al., 2002) model output uncertainty than did soil property changes due to land use change from cropland to pasture. Huisman et al. (2004) cited Eckhardt et al. (2003), who identified that a relatively large range of values was possible for the plant input parameters.

A sensitivity analysis can provide a better understanding of which particular input parameters have greater effect on model output. Monte Carlo simulation (MCS) is a technique that quantifies the input parameters' influence on the model output. Sohrabi et al. (2002) used MCS to estimate uncertainty in SWAT flow, sediment, and nutrient loading outputs, given a mean, range, and distribution for 33 input parameters, for the Piedmont physiographic region of Maryland. The authors concluded that the modeled flow estimate was decreased by 64%, sediment load estimate was increased by 8%, and nutrient load estimates remained unchanged when input parameter uncertainty was included in the modeling process, as compared to using a fixed, mean value for each input parameter.

In order to reduce the SWAT output uncertainty for a specific study area in upstate New York, Benaman and Shoemaker (2004) developed a methodology for reducing input parameter ranges prior to employing MCS analysis. They performed a sensitivity analysis for input parameters throughout the entire range of values at regular intervals. When the difference in model output of the sensitivity analysis and model output of the base case exceeded a threshold value considered to be the limit for a reasonable outcome, the end of the range for the input parameter was established. They reported a reduction in model output uncertainty of an order of magnitude after applying the methodology.

Prior research has examined application of the SWAT model to the LREW (Bosch et al., 2004; Van Liew et al., 2005; Van Liew et al., 2007). The focus of Bosch et al. (2004) was to compare the effects of high spatial resolution and low, default spatial resolution land use and soil input data on SWAT hydrologic outputs. Extensive calibration to improve daily model efficiencies and to reduce the differences between modeled and observed values for water budget components was not performed. Default input parameters were used, except for three parameters affecting the characteristics of the alluvial aquifer and one heat unit parameter for pine tree land use. The modeling was performed on SW-J, adjacent to SW-K (fig. 1), where the SEWRL has detailed land use and land coverage data. Coupled with county-level soil maps, the detail level of the input information for the Bosch et al. (2004) study was high. The simulations were executed with the SWAT 2000 version within BASINS 3.0. Van Liew et al. (2005) used both an automated calibration procedure, with eleven parameters and three different objective functions, and a six-parameter manual calibration procedure to develop input parameter sets for SW-F, an area of 114.8 km^2, and SW-B, an area of 334.2 km^2 (fig. 1). Low-resolution land

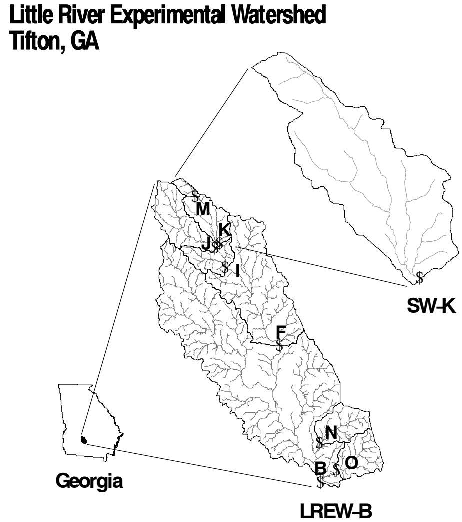

Figure 1. Location of Little River experimental watershed and subwatershed K.

use and soils coverages were used for this study. The four calibrated input parameter sets differed from one another, and between three and nine of the eleven parameters for SW-F differed from the parameters for SW-B, which entirely encompasses SW-F. This is critical because it suggests that calibration of the model must be done at the planned scale of assessment and that transfer of a calibrated parameter set to another spatial scale yields less than optimal results. This result, if true, would have implications regarding the utility of SWAT in developing agricultural land management policy.

The autocalibration in the Van Liew et al. (2005) study that yielded the best daily NSE underestimated average annual streamflow by 29% and adjusted parameters outside of reasonable ranges; for example, CN2 was decreased by 48%. The authors stated that caution needs to be exercised when using the procedure so as to limit parameters to reasonable values. The 2003 version of SWAT that included a multi-objective, automated calibration procedure was used in their study.

Prior sensitivity analysis results have been mixed, indicating that different parameters are more sensitive for some regions than for others. Analysis is needed of SWAT hydrologic parameter sensitivity within the Coastal Plain, with its flat to gently rolling topography, sandy soils, and riparian-buffered, low-gradient streams. Results from research throughout the U.S. indicate a wide variability in optimum parameter sets, further indicating a need for guidance that can be applied in specific regions.

The primary goal of the current research was to establish a sensitivity analysis that could provide guidance for SWAT hydrologic parameter selection in the southeastern U.S. An emphasis of the work was to match modeled hydrologic components of baseflow, stormflow, and ET to observed values in preparation for chemistry modeling. An accurate separation of flow is necessary for effective chemistry modeling because the fate and transport of various nutrients and pesticides are linked to mechanisms and reactions occurring both at the soil surface and in the root zone. A key component of the sensitivity analysis was establishing a base parameter set around which to perform the sensitivity analysis. Subwatershed K was selected for the investigation because of its extensive stream chemistry record, and subsequent nutrient and pesticide modeling research is planned. In addition, detailed, high-resolution land cover land use GIS coverages are available for SW-K, but not for the larger subwatersheds.

The objectives of this article are to: (1) establish SWAT hydrologic calibration results for subwatershed K of the LREW utilizing high-resolution input data, while maintaining parameter values within realistic ranges and preserving an average annual water balance over the period of study for the major components of the hydrologic cycle, and (2) analyze the sensitivity in key SWAT hydrologic input parameters for subwatershed K.

Methods

Watershed Description

The research was conducted using data collected on the Little River Experimental Watershed (LREW) (Sheridan et al., 1982; Sheridan, 1997). The LREW is a 334 km^2 basin at the headwaters of the Little River in Turner, Worth, and Tift counties in southwestern Georgia (fig. 1). The watershed outlet, station B, is approximately 5 km west of the Coastal Plain Research Station near Tifton, Georgia. Eight stream gauges have been placed within the watershed to create nested subwatersheds. Precipitation, flow, and water quality records have been collected on the LREW since the late 1960s (Sheridan, 1997).

The calibration and sensitivity analysis were performed on subwatershed K (SW-K), which is located at the upper end of the LREW (fig. 1). Mixed forest and pines cover approximately 65% of SW-K; land use in the remainder of the 16.9 km^2 subwatershed is primarily row crops, including cotton, peanuts, corn, and fruit and vegetable crops. The agricultural fields are generally small and nested among the forested areas. Riparian zones along the dendritic system of stream channels buffer the stream water from sediment (Sheridan et al., 1999) and chemical runoff (Lowrance et al., 1997) from the fields, and from nitrate-nitrogen leaching from lateral groundwater flow (Lowrance et al., 1984). The soils in SW-K are typically loamy sands with a plinthic layer of low hydraulic conductivity soil underneath the plow layer at a depth of 0.9 to 1.2 m (Rawls and Asmussen, 1973).

Model Description

The Soil Water Assessment Tool (SWAT) model (Arnold et al., 1998) was used to simulate hydrologic processes in SW-K. SWAT is a hydrologic and geochemical process model developed to estimate hydrologic budget, and nutrient and pesticide loadings over long time periods at the watershed scale. SWAT operates on a daily time step. A full description of SWAT can be found in the theoretical documentation by Neitsch et al. (2002b), which is also available on line. The SWAT model has undergone extensive testing throughout the world, and examples of model application are widespread (Bingner, 1996; Smithers and Engel, 1996; Srinivasan et al., 1997; Peterson and Hamlett, 1998; Spruill et al., 2000; Kirsch et al., 2002). The version of SWAT used for the investigation was AVSWATX-2003 (February 2005), which has been developed with a GIS interface.

Sensitivity Analysis

The method followed for analysis of input parameter sensitivity was proposed by Haan et al. (1995) and restated by Haan and Skaggs (2003a). Objective functions of interest were determined, the most influential parameters were identified, and a sensitivity analysis was performed. The most sensitive parameters were selected for further study.

Objective Functions

The base values of the input parameters for the sensitivity analysis were obtained by manually calibrating SWAT to obtain the closest match of simulated water budget components to observed values for the ten-year period 1995-2004 for SW-K, while maximizing the agreement between the observed and predicted total water yield (TWYLD) at annual, monthly, and daily intervals. Two measures of goodness of fit were used to optimize the set of parameter values: the sum of squared differences of the annual averages of the various components of the water budget (SSD_{WBC}), and the Nash and Sutcliffe (1970) model efficiency (NSE) calculated for TWYLD. The sum of squared differences (SSD_{WBC}) was calculated as:

$$SSD_{WBC} = \sum_{i=1}^{4} \left(\overline{O}_{WBC_i} - \overline{S}_{WBC_i} \right)^2 \quad (1)$$

where $\overline{O}_{WBC_i}$ is the observed ten-year average of the annual values for the ith water budget component, and $\overline{S}_{WBC_i}$ is the simulated value for the same component.

The four water budget components examined were baseflow, stormflow, ET, and deep percolation. A smaller value for SSD_{WBC} indicates a simulation outcome that more closely matches the measured values of the water budget components; a perfect match of simulated and measured water budget component values would result in an SSD_{WBC} of 0. For comparison purposes, if the simulated components of the average annual water budget each deviated from the observed values for the 1995-2004 period for SW-K by 5% or 10%, the resulting SSD_{WBC} values would be 1775 or 7031 mm^2, respectively.

The values for the observed water budget components were based primarily on stream gauge measurements, which quantify total streamflow, or TWYLD. Observed stormflow, the portion of the hydrograph characterized by its rapid response to rainfall and normally attributed to surface runoff, was calculated as 30% of the total streamflow based on prior work in the watershed (Shirmohammadi et al., 1984). The remaining 70% of the TWYLD was assumed to be baseflow. Groundwater percolation into the deep aquifer was estimated as 1% of precipitation based on research conducted at the Coastal Plain Experiment Station in Tifton, Georgia (Rawls and Asmussen, 1973). Observed evapotranspiration was calculated as the difference between precipitation and the sum of deep groundwater percolation and TWYLD. Although storage could affect the water balance for any given year, the assumption was made that storage would have minimal effect on the average annual water balance over the ten-year study period.

In our modeling effort, we also compared the average monthly observed and simulated TWYLDs for drier years and wetter years with the following sum of squared differences (SSD_{mo}):

$$SSD_{mo} = \sum_{i=1}^{12} \left(\overline{O}_{mo_i} - \overline{S}_{mo_i} \right)^2 \quad (2)$$

where $\overline{O}_{moi}$ is the observed ten-year average of the monthly TWYLD the *i*th month, and $\overline{S}_{moi}$ is the simulated value for the same month. We calculated an average relative error, $\overline{RE}$, by the following formula:

$$\overline{RE} = \frac{\sum_{i=1}^{12} \frac{\left|\overline{O}_{moi} - \overline{S}_{moi}\right|}{\overline{O}_{moi}}}{12} \cdot 100\% \quad (3)$$

where $\overline{O}_{moi}$, $\overline{S}_{moi}$, and i are as defined for SSD_{mo}.

The Nash-Sutcliffe model efficiency was calculated as:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \quad (4)$$

where O_i is the observed, gauged water yield for time period i, S_i is the simulated value for the same period, $\overline{O}$ is the mean gauged water yield per time period, and n is the number of time periods. Nash Sutcliffe model efficiencies were calculated on an annual, monthly, and daily basis. Model efficiency represents the proportion of the flow variance accounted for by the model. The maximum NSE value possible is 1.0 and occurs if simulated values perfectly match observed values. The lower the NSE value, the less the goodness of fit between the simulated and observed time series. Negative values of NSE are possible and indicate that the mean observed output fits the data better than the simulated values.

Precipitation Over Study Period

In order to provide context and understanding for interpretation of the study results, the precipitation pattern for the LREW SW-K for 1995-2004 is charted in figure 2, which shows the departure of annual precipitation from the 37-year mean for each of the ten years of the study. The average annual precipitation over the ten-year period was 8% (93 mm) below the 37-year mean annual precipitation of 1229 mm. In five of the ten years, the annual precipitation was at least 15% less than the long-term mean.

GIS Data

The digital elevation model (DEM) data used in the study consisted of a 30 m grid and was obtained from the Georgia GIS Clearinghouse (http://gis.state.ga.us/Clearinghouse/clearinghouse.shtml). During the stream definition process,

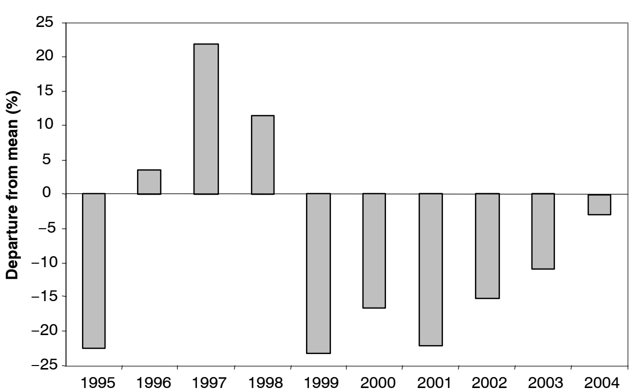

Figure 2. Annual precipitation departure from 37-year mean of 1229 mm.

the stream channels were aligned to match a stream coverage digitized from 1972-1977 USGS 1:24000-scale topographic quadrangle maps with a burn-in option available within SWAT. The stream threshold area was set at 40 ha. The land use coverage consisted of agricultural field boundaries that were digitized using 1993 digital ortho-photos; the data table was filled from information collected during actual land use field surveys in 2004. Areas that were neither field nor water were classified as forest. County-level Soil Survey Geographic (SSURGO) soils data, also obtained from the Georgia GIS Clearinghouse, were used for the soil data layer. Land use and soil class threshold settings were 10% and 18%, respectively, during the creation of SWAT hydrologic response units (HRUs).

Input Parameter Selection

Guidance for identifying input parameters for the calibration and sensitivity analysis was provided by prior research within the LREW by Bosch et al. (2004) and Van Liew et al. (2005, 2007). Bosch et al. (2004) evaluated SWAT on subwatershed J (SW-J) in the LREW, which is adjacent to SW-K (fig. 1). They used three parameters to reflect initial simulation conditions and to improve streamflow predictions: the initial depth of water in the shallow aquifer (SHALLST), the time required for water leaving the bottom of the root zone to reach the shallow aquifer (GW_DELAY), and the initial water storage in the vadose zone (FFCB).

Van Liew et al. (2007) found that the following parameters, grouped by their association with either surface, subsurface, or basin response, influenced the calibration of the SWAT model for five USDA-ARS experimental watersheds including the Little River watershed:

Surface response: Runoff curve number (CN2), soil evaporation compensation factor (ESCO), and available soil water capacity (SOL_AWC).

Subsurface response: Groundwater ”revap” coefficient (GW_REVAP), depth of water in the shallow aquifer for ”revap” to occur (REVAPMN), depth of water in the shallow aquifer required for return flow to occur to the stream (GWQMN), baseflow recession constant (ALPHA_BF), time for water leaving the bottom of the root zone to reach the shallow aquifer (GW_DELAY), and deep aquifer percolation fraction (RCHRG_DP).

Basin response: Channel hydraulic conductivity (CH_K2), and stormflow lag time (SURLAG).

In addition to the 14 parameters obtained from the previous studies, two additional soil property parameters were incorporated into the sensitivity analysis portion of this study: soil bulk density (SOL_BD) and saturated hydraulic conductivity (SOL_K). Soil bulk densities and hydraulic conductivities tend to vary in the field; the purpose of including them in the sensitivity analysis was to determine whether deviations from default book values effect noticeable changes to model hydrologic outputs and therefore warrant closer investigation.

Table 1 provides a description of the 16 parameters included in the manual calibration and sensitivity analysis: CN2 (forest land use), CN2 (crop land use), ESCO, SOL_AWC, SHALLST, GW_DELAY, FFBC, GW_REVAP, REVAPMN, GWQMN, ALPHA_BF, RCHRG_DP, CH_K2, and SURLAG, SOL_BD, and SOL_K.

Table 1. SWAT input parameters chosen for sensitivity analysis and results for water yield, stormflow, and baseflow.

Parameter	Description	Units	SWAT Default Value	P[a]	ΔP (%)	S_r Values: Water Yield	Storm Flow	Base Flow
Surface response								
CN2(forest)	SCS curve number, antecedent moisture condition II, for forested land use	n/a	55.0	50.0	±25	0.03	1.20	-0.47
CN2(crop)	SCS curve number, antecedent moisture condition II, for crop land use	n/a	77.0	76.0	+18.8/ -25	0.74	4.22	-0.73
ESCO	Soil evaporation compensation factor	fraction	0.95	0.74	±25	0.38	0.26	0.44
SOL_AWC	Available soil water capacity	mm mm^{-1}	0.09-0.19[b]	0.10-0.20[b]	±8.6	-0.45	-0.53	-0.42
SOL_BD	Soil bulk density	g cm^{-3}	1.40-1.73[b]	1.40-1.73[b]	±6.2	-0.04	-0.94	0.34
Subsurface response								
SHALLST	Initial depth of water in the shallow aquifer	mm	0.5	800	±25	0.00	0.00	0.00
GW_DELAY	Time required for water leaving the bottom of the root zone to reach the shallow aquifer	days	31	1	±25	0.00	0.00	0.00
FFBC	Initial water storage in the vadose zone	fraction	0.0	0.95	+0.05/ -0.24[c]	0.07	0.04	0.08
GW_REVAP	Rate of transfer from shallow aquifer to root zone	n/a	0.02	0.02	+0.05[c]	0.00	0.00	0.00
REVAPMN	Threshold water depth in shallow aquifer for percolation to deep aquifer to occur	mm	1.0	500	-125[c]	0.00	0.00	0.00
GWQMN	Threshold water depth in shallow aquifer for return to reach to occur	mm	0	0	+15[c]	0.00	0.00	0.00
ALPHA_BF	Baseflow alpha factor, lower number means a slower response	days	0.048	0.039	±25	0.01	0.00	0.02
RCHRG_DP	Deep aquifer percolation fraction	fraction	0.05	0.05	±25	-0.02	0.00	-0.03
SOL_K	Saturated hydraulic conductivity	mm h^{-1}	8 - 500[b]	8 - 500[b]	±25	0.01	0.00	0.01
Basin response								
SURLAG	Surface lag coefficient; controls fraction of water entering reach in one day	n/a	4.0	1.0	±25	0.00	0.00	0.00
CH_K2	Effective hydraulic conductivity in main channel alluvium	mm h^{-1}	0.0	0.0	+150[c]	0.00	0.00	0.00

[a] Calibrated parameter base value.
[b] Range of values for all layers of the nine soil groups represented in the HRUs.
[c] Units are the same as for *P*.

Calibration and Sensitivity Analysis

The manual calibration method outlined in the SWAT Version 2000 user's manual (Neitsch et al., 2002a) was used to minimize SSD_{WBC} and maximize NSE. The SWAT default parameter values were adjusted as follows. First, the surface flow component of average annual TWYLD was balanced by adjusting the NRCS runoff curve numbers for forested and cropped land use. An effort was made to keep the curve numbers close to standard table values. Next, SOL_AWC, GW_REVAP, REVAPMN, and GWQMN were adjusted to match the simulated baseflow and baseflow calculated from stream measurements. Once the proportion of surface flow to subsurface flow was established, the model ET output was matched to observed ET by adjusting values for ESCO. With the major components of the modeled water balance nearly corresponding to the observed values, SSD_{WBC} was minimized. These additional parameters were adjusted to maximize the monthly NSE: SHALLST, SURLAG, and ALPHA_BF. Readjustment of a parameter was frequently necessary after the value of a subsequent parameter was reset. Final adjustments were made to attempt to maximize the daily NSE. The calibrated parameters became the base values about which the parameter sensitivity coefficients were calculated.

The sensitivity coefficient (*S*) represents the ratio of the rate of change of the output function versus the rate of change of the input parameter under study:

$$S = \frac{\delta O}{\delta P} \tag{5}$$

where *O* is the model output, and *P* represents an input parameter. The relative sensitivity (S_r) is approximated as follows (Haan, 2002):

$$S_r \cong \left[\left(O_{P+\Delta P} - O_{P-\Delta P}\right)/O_P\right]/\left(2\Delta P/P\right) \tag{6}$$

where S_r is relative sensitivity; $O_{P+\Delta P}$ and $O_{P-\Delta P}$ are model outputs with the input parameter being studied set at a value equal to the initial, calibrated value, also known as the base value, plus or minus a specified percentage (often taken to be in the range of 10% to 25%); O_P is the model output with input parameters set at base values; ΔP represents the prescribed absolute change in the value of the input parameter; and *P* is the initial value of the input parameter. The relative sensitivity is unitless and therefore can be utilized to compare sensitivities among parameters (Haan, 2002). For this study, relative input parameter sensitivities were determined for the model outputs of TWYLD, stormflow, and baseflow. Thus, O_P represented the model outputs for average annual TWYLD, average annual stormflow, and average annual baseflow. ΔP was taken to be 25% of *P*, except in a few cases for which a change of 25% would have resulted in a meaningless parameter value or a value outside the limits set within SWAT.

Table 2. Water budget components, 1995-2004; SSD = 18.8 mm^2.

Component	Observed (mm)	Simulated (mm)	Ratio of Simulated to Observed
Total water yield	317.4	316.2	0.996
Baseflow	222.2	222.6	1.002
Stormflow	95.2	93.6	0.983
ET	807.0	803.0	0.995
Deep percolation	11.4	11.4	1.000
Total	1135.8	1130.6	--

The purpose of sensitivity analysis is to identify the parameters that have the greatest influence on model results (Hamby, 1994). The division of parameters into various degrees of sensitivity is subjective. For example, Haan and Skaggs (2003a) considered hydrologic parameters with absolute values for S_r of greater than 0.15 and nitrogen cycle parameters with absolute values for S_r of greater than 0.20 (Haan and Skaggs, 2003b) sensitive and warranting additional uncertainty analysis. Lenhart et al. (2002) ranked sensitivity coefficients into four classes: small to negligible ($0.00 \le |S_r| < 0.05$), medium ($0.05 \le |S_r| < 0.20$), high ($0.20 \le |S_r| < 1.00$), and very high ($|S_r| > 1.00$). We identified sensitive parameters as having an absolute value for S_r of greater than 0.10 for either TWYLD, stormflow, or baseflow. Once the sensitive parameters were identified, additional model runs were executed with each of the sensitive input parameters being set to values near or at the limit of the range expected for that parameter.

The method of sensitivity analysis described above is laborious but simple to carry out and requires consideration of its potential shortcomings. The method does not account for interactions among parameters. The size of ΔP and the base value of P within the potential range of values can influence the results; a percentage change of a small value for P results in a smaller ΔP. Lenhart et al. (2002) compared two approaches to sensitivity analysis, varying P by a fixed percentage (±10%), and varying P by a percentage (25%) of the potential range of P, given a mean value of P. The latter approach addresses some of the shortcomings of the former approach; however, Lenhart et al. (2002) concluded that the ranking of parameter sensitivity was similar for both methods.

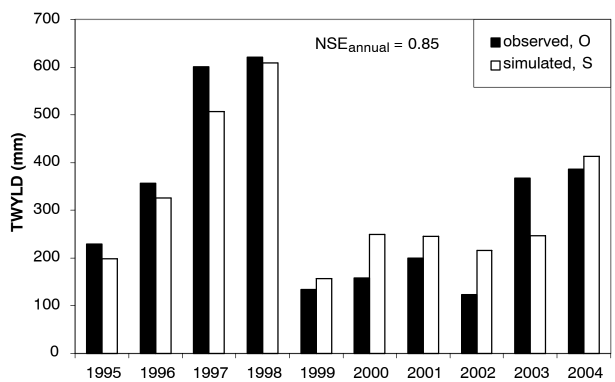

Figure 3. Average annual total water yield by year, 1995-2004.

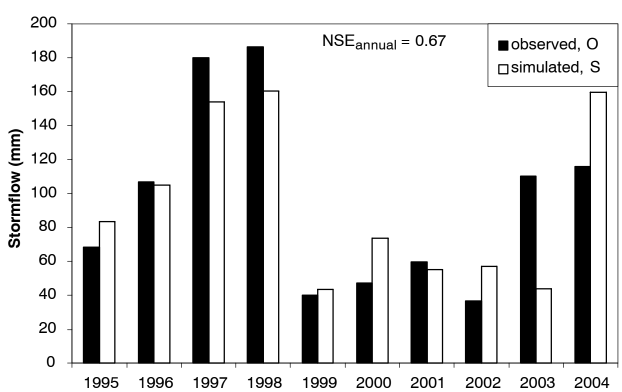

Figure 4. Average annual stormflow by year, 1995-2004.

RESULTS

CALIBRATION

The manually calibrated model parameter values are identified in table 1. The objective of the calibration was to minimize the SSD_{WBC} between the observed and simulated water budget components while maximizing the monthly and daily model efficiencies. The results of the calibration are summarized in the next two sections.

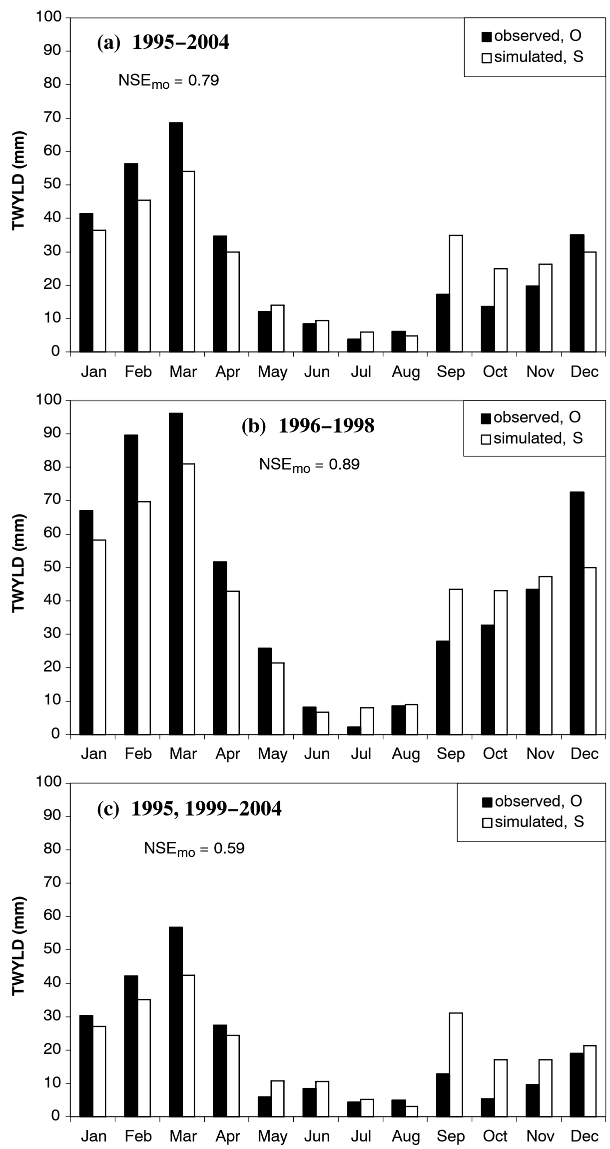

Figure 5. Average monthly total water yield for (a) all years, (b) three years with greater than average annual precipitation, and (c) seven years with less than average annual precipitation.

Table 3. Comparison of SWAT model efficiencies and TWYLD estimates for LREW studies (1997-2002).

	Current Study	Bosch et al. (2004)	Van Liew et al. (2005)	Van Liew et al. (2005)
Little River Experimental Subwatershed	K	J	F	F
Calibration method	Manual	Manual	Manual	SSQauto11
Monthly NSE	0.88	0.80	0.44	0.82
Daily NSE	0.56	-0.03	0.18	0.70
Simulated average annual TWYLD (% of measured)	100	117	100	71

Water Budget

Average annual values for TWYLD, divided between baseflow and stormflow, ET, and deep aquifer recharge, were obtained from SWAT outputs and compared to calculated values based on precipitation and streamflow measurements in SW-K. The results are shown in table 2. The simulated baseflow was calculated as the difference between TWYLD and stormflow, which is the difference between the SWAT output variables WYLD and SURQ. The sum of the simulated budget components is slightly less than the amount of precipitation because transmission and other minor losses accounted for by SWAT are not included in the table.

The annual time series of observed and simulated TWYLD and stormflow for the 1995-2004 period are charted in figures 3 and 4, respectively. The series follow similar patterns; in eight of the ten years simulated, values for TWYLD

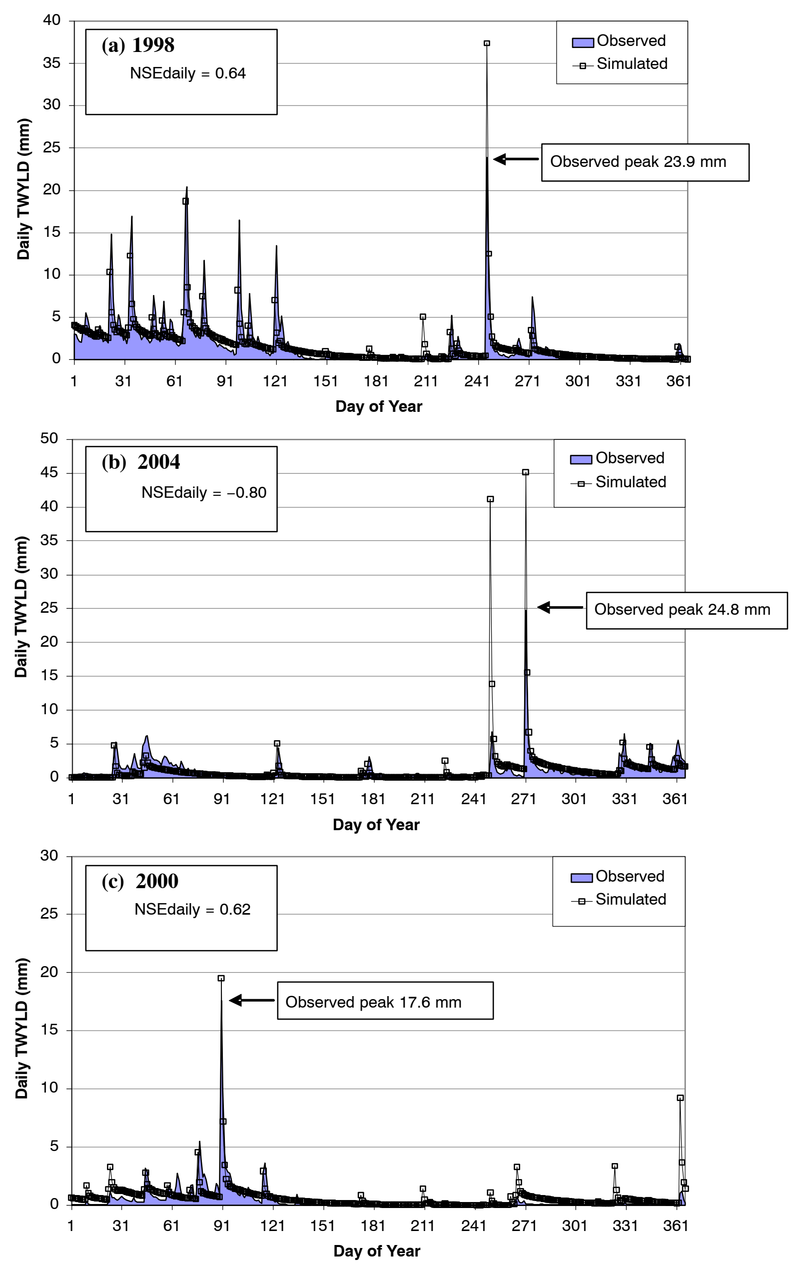

Figure 6. Daily total water yield for (a) 1998, a wet year with highest daily NSE; (b) 2004, a dry year with lowest daily NSE; and (c) 2000, a dry year with highest daily NSE and without autumnal tropical storms.

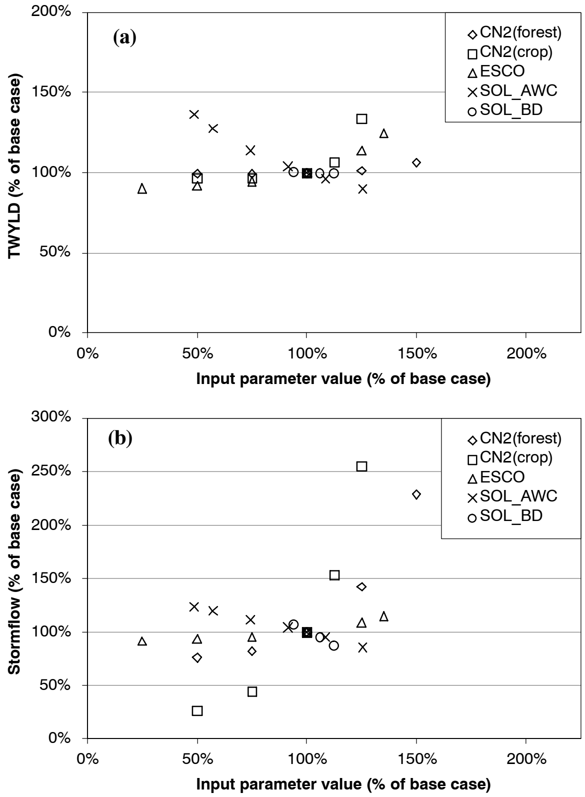

Figure 7. Changes in model (a) TWYLD and (b) stormflow response to changes to the five most sensitive input parameters.

and stormflow were consistent with respect to being above or below the observed value. The ten-year average monthly TWYLDs, observed and simulated, are depicted in figure 5a. The monthly results were separated between years (1996-1998) wherein average annual precipitation was greater than the 37-year mean annual precipitation (fig. 5b) and years (1995, 1999-2004) wherein the average annual precipitation was less than the 37-year mean (fig. 5c).

Goodness of Fit

The annual Nash Sutcliffe efficiencies over the 1995-2004 period for the calibrated model are indicated on the charts in figure 3 for TWYLD and in figure 4 for storm flow. The charts in figure 5 indicate the monthly NSEs for TWYLD for all years and for the dry and wet years. The daily NSE over the ten-year period was 0.42. Table 3 shows the monthly NSE (0.88) and daily NSE (0.56) for the current study over the six-year period from 1997 to 2002. Results from two previous studies over the same time period are shown for comparison purposes. The simulated daily TWYLD is graphed with observed TWYLD for three years of the study in figure 6. The years chosen include 1998, a wet year with an autumnal tropical storm, having a high daily NSE; 2004, a dry year with an autumnal tropical storm, having a low daily NSE; and 2000, a dry year without an autumnal tropical storm, having a high daily NSE.

Sensitivity Analysis

The relative sensitivities of all tested input parameters on annual TWYLD, annual stormflow, and annual baseflow are shown in table 1. The absolute values of S_r of CN2 on the cropped land, ESCO, and SOL_AWC on TWYLD ranged between 0.38 and 0.74. The S_r value of 0.38 for ESCO essentially means that for a 1% change in ESCO there will be a 0.38% change in the model TWYLD output. The S_r values of CN2 for forested and cropped land use and SOL_BD on stormflow were 1.20, 4.22, and −0.94, respectively. The parameters ESCO and SOL_AWC were somewhat sensitive for stormflow, with S_r values of 0.26 and −0.53, respectively. The absolute values of S_r for CN2(crop), CN2(forest), ESCO, SOL_AWC, and SOL_BD for baseflow ranged from 0.34 to 0.73. The annual TWYLD, stormflow, and baseflow were insensitive to changes in the remaining eleven parameters, for which the absolute values of S_r were ≤ 0.08.

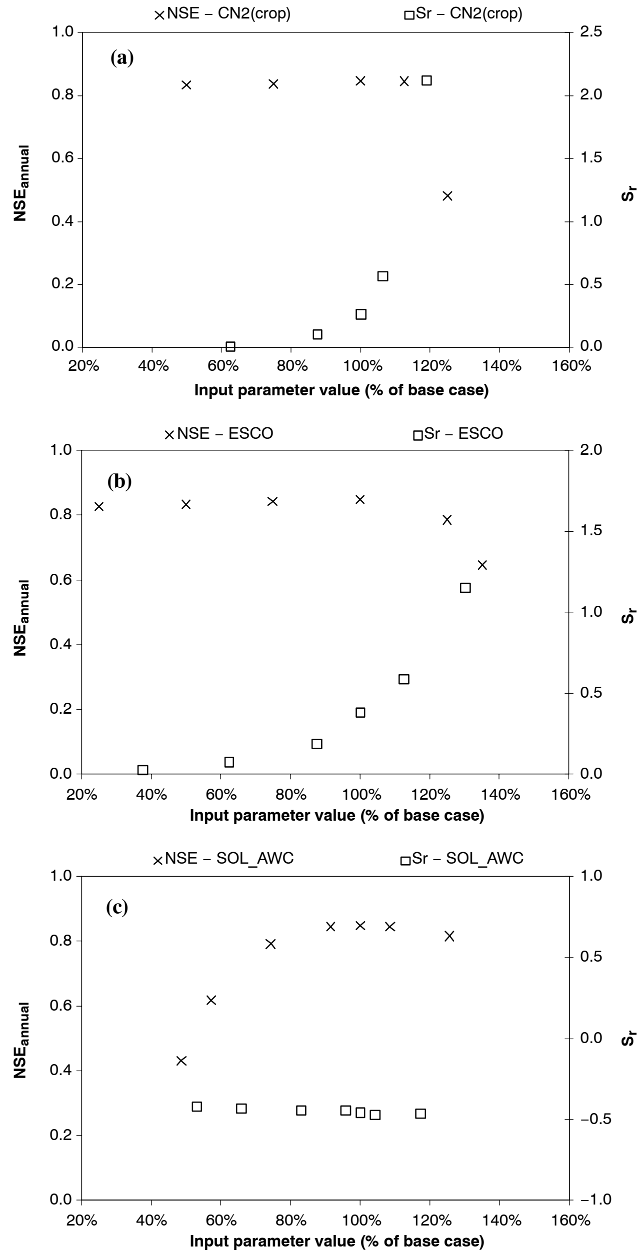

Figure 8. Effects (annual NSE for TWYLD and S_r for TWYLD) of parameter value changes for (a) CN2(crop), (b) ESCO, and (c) SOL_AWC.

The relationships of changes in the values of the five most sensitive input parameters to simulated TWYLD and stormflow are depicted in figures 7a and 7b, respectively. Figure 7a shows that TWYLD is most sensitive to CN2(crop), ESCO,

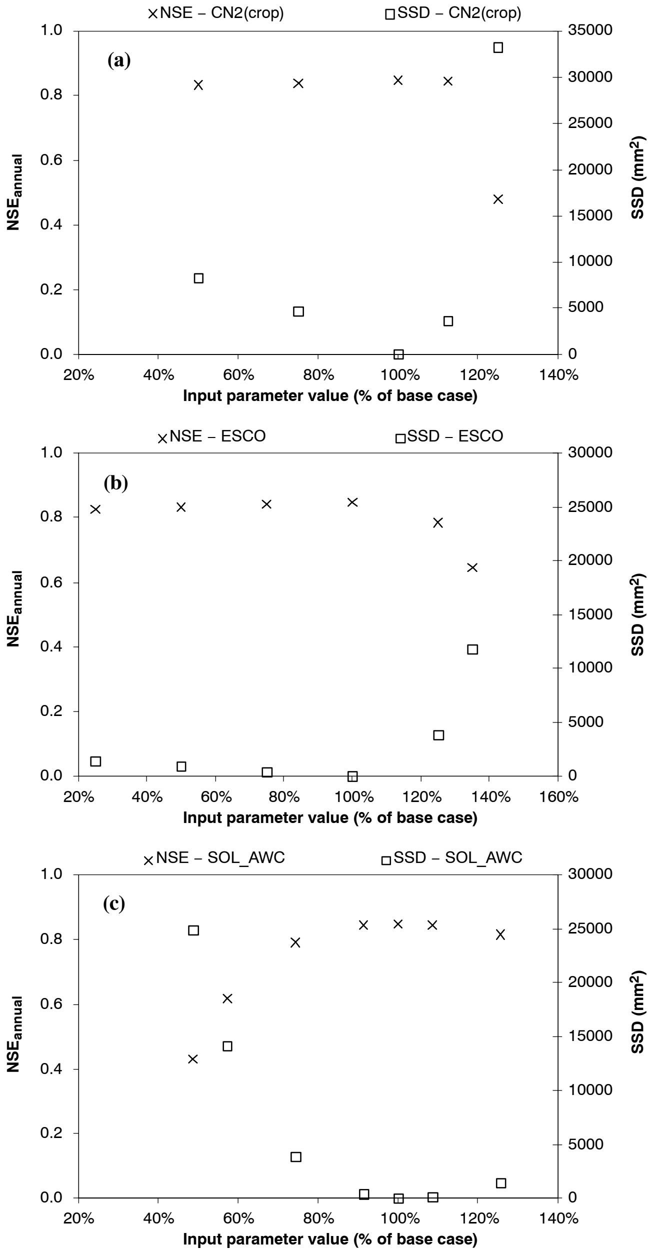

Figure 9. Effects (annual NSE for TWYLD and annual average SSD_{WBC} of baseflow, stormflow, ET, and deep percolation) of parameter value changes for (a) CN2(crop), (b) ESCO, and (c) SOL_AWC.

and SOL_AWC. The slope of the curves represents the relative sensitivity coefficient; thus, the curves indicate how sensitivity changes through the ranges of parameter values. Figure 8 presents additional analysis of CN2(crop), ESCO, and SOL_AWC, showing the interrelationship of S_r for TWYLD and annual NSE over the ranges of the input parameters, and the different responses among the three parameters. The effects of changes to the base parameters on the simulated water budget, as measured by SSD_{WBC}, the sum of the squared differences between the observed and simulated annual averages of the baseflow, stormflow, ET, and deep percolation components of the water balance, are graphed in figure 9. The graphs of annual NSE versus parameter value are also included in figure 9.

Discussion

Calibration

The objective of calibrating SWAT to match the observed annual water balance, within measurement error, was achieved. However, meeting annual averages for hydrology budget components does not indicate the goodness of fit of the simulated hydrograph. Nash-Sutcliffe efficiencies for monthly and daily basis compared well with previous modeling performed within the LREW. Table 3 shows the NSEs for SWAT modeling of SW-J (Bosch et al., 2004), which is adjacent to SW-K, and of LREW SW-F (Van Liew et al., 2005), which contains SW-K. An improvement in daily NSE for TWYLD was also observed during the sensitivity analysis of the current study when CN2(forest) and CN2(crop) were reduced by 25%, with daily NSE for TWYLD for the 1997-2002 period increasing from 0.56 to 0.62 and 0.60, respectively. Estimation of ten-year average annual TWYLD, 315 mm and 307 mm, remained relatively close to the observed value of 317 mm; however, the change to stormflow and baseflow components of the water budget increased SSD_{WBC} from 19 mm^2 to 601 and 4846 mm^2 for the CN2(forest) and CN2(crop) reductions, respectively.

Review of the sensitivity analysis simulation outputs revealed that the 25% reduction of SURLAG, from 1.0 to 0.75, improved daily NSEs from 0.56 to 0.63 for the 1997-2002 period and from 0.42 to 0.53 for the 1995-2004 period. However, unlike the change to CN2, the change to SURLAG reduced SSD_{WBC} by a fraction. Thus, the base case parameter values would have been improved with SURLAG equal to 0.75. This point emphasizes the difficulty in knowing when the optimum parameter settings have been attained when manually calibrating SWAT.

After initial analysis of wetter-than-normal years and drier-than-normal years, we had concluded that the model gives better results in wetter years than in drier years (fig. 5). For example, the monthly NSEs for TWYLD are 0.89 for the three wetter years and 0.59 for the seven drier years from 1995 through 2004. Average daily NSEs for TWYLD were 0.55 for the wetter years and 0.22 for the drier years. Closer investigation of the differences between average monthly observed and simulated TWYLDs for wetter (fig. 5b) and drier (fig. 5c) years indicates that the sum of the squared differences between average monthly observed and simulated TWYLDs, SSD_{mo}, is actually less for the drier years (841 mm^2) than for the wetter years (1741 mm^2), although the average relative error, $\overline{RE}$, for the wetter years (40%) is less than for the drier years (56%). A comparison of the daily observed and simulated streamflows for the wet year with the best daily NSE, 0.64 (fig. 6a), and the dry year with the worst daily NSE, −0.80 (fig. 6b), reveals that the model tended to underpredict streamflow during the wetter portion of the year and overpredict streamflow during the drier autumn months. In particular, large autumn precipitation events, such as those associated with seasonal tropical storms, do not produce as great a streamflow as SWAT predicts, especially in drier years. Following the same pattern, SWAT overpredicted streamflow for a seasonal event following a long dry period in October 2002, which contributed to a negative daily NSE for 2002 (−0.37). During drier years that have no larger events during the normally drier autumn months, the daily NSE values are similar to those for the wetter years (fig. 6c). For example, the daily NSEs for 1999, 2000, and 2001 were 0.56, 0.62, and 0.57 respectively; the annual precipitation departures from normal for these years were −23%, −16%, and −22%, respectively. Thus, after the additional analysis, we have concluded that SWAT's streamflow predictive capabilities are similar in wet years and dry years without seasonal tropical storm events.

The average monthly TWYLD predictions for both wet and dry years are low for the winter and early spring months, during which time Sheridan (1997) found that 54% of precipitation became streamflow, and high for the remainder of the year, when Sheridan (1997) determined that only 12% of precipitation became streamflow. Bosch et al. (2004) noted the same tendency for SWAT to underpredict flows in the wetter winter months and overpredict flows in the summer months, as did Van Liew et al. (2005) for the case when SWAT was manually calibrated. One potential explanation for the repeatable overpredictions and underpredictions could be that the model's adjustment for curve number based upon antecedent moisture conditions does not accurately reflect the seasonal variations in soil water storage in the LREW. Sheridan and Shirmohammadi (1986) concluded that a change in the manner in which antecedent moisture conditions are represented is required to effectively model storm runoff in the LREW. They divided the year into three periods, differentiated by the seasonal characteristics of the primary runoff-producing zones of the watershed: wet, dry, and intermediate antecedent conditions, occurring during winter to early spring, late summer to fall, and the remainder of the year, respectively. By assigning curve numbers of 98 for the wet season, 93 for the intermediate seasons, and 59 for the dry season to the low-lying, level, wet areas, they were able to improve the correlation coefficient (r) of predicted to observed runoff for SW-K from 0.71, for the standard SCS antecedent moisture condition relationships, to 0.91. Although the technique of changing the curve number improved the correlation coefficient, it was an empirical fix that did not address underlying processes.

Another potential explanation for the repeatable overpredictions and underpredictions could be that storage in the stream network riparian zone is not adequately represented in SWAT. Field research indicates that during dry periods, the water table in the riparian zone continues to be lowered by transpiration from the riparian forest (Shirmohammadi et al., 1986). The water table depression results in storage that must be filled prior to streamflow being re-established after precipitation resumes. SWAT tends to model TWYLD poorly during this period of time (fig. 6c), a result that can be expected from using the curve number method. An interim solution to the dry-spell storage issue is to use optional functionality that exists within SWAT to adjust curve number for antecedent soil moisture condition based on a method developed by Williams and LaSeur (1976), which included as a factor the potential evaporation since the previous precipitation event. The optional functionality was not available in the version of SWAT used for the current study. A longer-term solution would be the structuring of SWAT such that HRUs in the riparian zone are spatially referenced as streamside, which would provide opportunity to uniquely parameterize these HRUs so that transpiration, water table drawdown, and storage would more nearly represent field conditions. Work on the longer-term solution is in progress (J. Arnold, personal communication, 4 May 2006).

Finally, storage capacity in surface ponds could be another contributing factor to overprediction of TWYLD during dry periods. The SW-K land use coverage area for water was 1.22% prior to HRU delineation and 0% after HRU delineation. The loss of surface pond storage effects after HRU delineation, aggravated by the use of surface pond water for irrigation in the LREW, could be a substantial factor in underestimating storage after dry periods.

Sensitivity Analysis

The SWAT model TWYLD, stormflow, and baseflow outputs were most influenced by the curve number of the cropped land within SW-K. Even though agricultural land use represented only 30.4% of the area within SW-K after SWAT threshold application, and forest and pines represented the remaining 69.6% of the area, the stormflow S_r for CN2(crop) (4.22) was more than three times that for CN2(forest) (1.20), and the baseflow S_r for CN2(crop) (−0.73) was about 50% higher than for CN2(forest) (−0.47). From these numbers, one can see that a change of 5% to 10% in CN2(crop) values would result in large adjustments to stormflow predictions.

The greater sensitivity to CN2(crop) than to CN2(forest) is caused by the different responses of forested and cropped watersheds to precipitation, reflected in the model by their associated curve numbers and where these values are in the range from 0 to 100. Runoff from forested land is much less than from cropped land for average-sized precipitation events. This is illustrated in surface runoff estimates calculated by the CN method in the *National Engineering Handbook*, Part 630: Hydrology (USDA-NRCS, 2001). For a CN of 76 (calibrated value for crop land), runoff is produced by storms larger than 20 mm (0.8 in.). However, for a CN of 50 (calibrated value for forest land), no surface runoff is produced until a precipitation event is greater than 58 mm (2.3 in.). Given that the frequency of events >20 mm is much greater than the frequency of events >58 mm, the land with a CN of 76 will have a greater influence on surface runoff than the land with a CN of 50 by virtue of the number of events for which surface runoff is calculated. In addition, changes in storm runoff resulting from increasing CN2 by a fixed percentage will be larger for the initial value of 76 because of the functional form of the curve number equation.

With an S_r of 1.20 for stormflow, CN2(forest) still had a sizable influence on model stormflow output. However, annual TWYLD was relatively insensitive to changes in CN2(forest) with an S_r of 0.03. The S_r for baseflow was −0.47, opposite in sign from the stormflow S_r since, with little change to TWYLD, the increase in stormflow became the decrease in baseflow. The S_r for CN2(crop) for annual TWYLD was 0.74, again one of the higher values. For crop land, changing CN2 also changed stormflow, but the magnitude of the stormflow volume increase more than offset the decrease in baseflow volume. Increasing CN2(crop) by 25% resulted in lower ET, while increasing CN2(forest) by 25% had little affect on ET. The ET demands of the forest were not sensitive to CN2(forest), implying sufficient available water in the soil profile for all CN2(forest) values examined.

After curve number, soil available water content (SOL_AWC) was the next most sensitive parameter on TWYLD, stormflow, and baseflow outputs. Increase in SOL_AWC resulted in a decrease to TWYLD, stormflow, and baseflow of approximately the same proportion. The additional soil water holding capacity effected an increase in ET. As with CN2 values, an attempt was made in the calibration process to keep the values for the soil properties close to the standard defaults. The calibrated values for SOL_AWC were +0.01 mm mm^{-1} from the default values for each layer of each soil, and SOL_BD remained unchanged. The weighted average SOL_AWC for Tifton loamy sand, the soil that comprised 73% of the SW-K area after SWAT land use and soil coverage threshold application, was 0.115 mm mm^{-1}. The reasonableness of the calibrated SOL_AWC when compared with field-measured values is a topic for further investigation. Hubbard et al. (1985) measured and published soil properties for three upland soil series of the Georgia Coastal Plain, all of which are found in SW-K. The weighted average SOL_AWC for Tifton soil series published by Hubbard et al. (1985) was 0.057 mm mm^{-1}, half the calibrated value used in this modeling exercise. Other literature values for the Tifton soil indicate a wide range of available water content, 0.04 to 0.22 (Perkins, 1987). Because SOL_AWC is a sensitive parameter, using the lower field value as the model input would result in relatively large TWYLD and stormflow increases, and reduced ET. The use of measured soil property values as model inputs would require a set of calibration values for the remaining parameters different from the set found for this study. It remains to be seen if water budget components could be balanced and similar model efficiencies attained with such a calibration.

Total water yield was insensitive to changes in SOL_BD, but stormflow was sensitive to SOL_BD (S_r = −0.94), and baseflow was somewhat sensitive (S_r = 0.34). The negative S_r indicates that an increase in the parameter results in a decrease in the model output. The directional signs for S_r of SOL_BD for stormflow and baseflow are counterintuitive. During the sensitivity analysis of SOL_BD, only SOL_BD was changed. However, in the real world, changes in SOL_BD would be accompanied by corresponding changes to other parameters such as SOL_AWC and CN2. We suggest that these two more sensitive parameters offset the model's sensitivity to SOL_BD.

Total water yield, stormflow, and baseflow were somewhat sensitive to the soil evaporation compensation factor (ESCO). All three S_r values were positive, indicating that an increase in ESCO results in an increase in the three model outputs. Raising the ESCO value decreases the soil depth to which SWAT can satisfy potential soil evaporative demand (Neitsch et al., 2002a), thus decreasing soil evaporation and ET and increasing TWYLD, stormflow, and baseflow. The soil evaporation compensation factor is a calibration parameter and not a property that can be directly measured.

Figures 7a and 7b graphically depict the TWYLD and stormflow results, respectively, of model runs that included additional values for the sensitive input parameters. Note that S_r was calculated as the slope of the plot of output versus input value for each parameter around the base case (100% of the output value versus 100% of the input value). The plot of input parameter value versus TWYLD output value (fig. 7a) shows that reductions of 50% from base case values to CN2(forest), CN2(crop), and ESCO have little affect on TWYLD. However, increases to CN2(crop) and ESCO beyond the base case values result in substantial changes to TWYLD. Soil available water content was varied throughout the range of published values for the Tifton soil series. The effect on TWYLD of SOL_AWC becomes more pronounced as SOL_AWC is decreased. Although a range of values for SOL_AWC has been published, it is not known what the spatial variability of SOL_AWC is over the watershed and how that variability affects SWAT model outputs.

Figure 7b shows the dramatic impact that changing CN2(crop) has on model stormflow prediction, whether CN2(crop) is increased or decreased from the base case value. Increasing CN2(forest) also increases stormflow, but to a lesser degree than CN2(crop). Stormflow is inversely proportional to SOL_AWC; the two variables exhibit a straight-line relationship throughout the range of values for SOL_AWC. Although SOL_BD was identified as a sensitive parameter for stormflow, the range of potential values for SOL_BD, based on published field measurements (Hubbard et al., 1985; Perkins, 1987) was limited to −6.2% to +12.4% of the base case value. Thus, the range of stormflow outputs based on the range of SOL_BD inputs was limited to +7.2% to −12.1%.

The results illustrated by figure 7a and 7b support the results of the S_r calculations. The relative sensitivity coefficient was calculated as the slope of the plot of output versus input value for each parameter around the base case (100% of the output value versus 100% of the input value). Relative sensitivities with respect to TWYLD were the greatest for CN2(crop) (0.74), ESCO (0.38), and SOL_AWC (−0.45). For the relative sensitivity with respect to stormflow, the greatest sensitivities were observed for the parameters CN2(crop) (4.22) and CN2(forest) (1.20). Figures 7a and 7b show that the slope of the CN2(crop) and CN2(forest) plots increases when the parameters are adjusted to values above 100% of the base case, indicating a higher S_r and an even greater impact on TWYLD and stormflow. Greater negative slopes and more negative S_r values for TWYLD are shown for SOL_AWC as values decrease below 100% of the base case.

The relationships between parameter values and annual NSE and parameter values and S_r for TWYLD for CN2(crop), ESCO, and SOL_AWC are shown in figures 8a, 8b, and 8c, respectively. The figures indicate that the response of annual NSE to changes in S_r differs in magnitude and direction among these three input parameters. For values of CN2(crop) greater than the base case, S_r increases exponentially while annual NSE remains nearly constant until a sharp drop off is observed when CN2 $\geq$ 110% of base case. For values of CN2(crop) less than the base case, S_r gradually declines while annual NSE remains constant. The relative sensitivity index for ESCO increases as a power function throughout the range of the parameter's potential value. The annual NSE remains constant at values of ESCO lower than the base case, and begins to drop off at values of ESCO higher than the base case, although the drop in annual NSE is not as severe as with CN2(crop). In contrast to the previous cases, S_r and the input parameter value for SOL_AWC maintain a straight-line relationship with a relatively flat slope, indicating that the sensitivity of annual TWYLD to SOL_AWC is similar throughout the range of possible values for SOL_AWC. Annual NSE for TWYLD remains constant for SOL_AWC greater than about 90% of the base case value; however, it then drops off from 0.85 to 0.43 as SOL_AWC is reduced to 50% of the base case value. At the lower values of SOL_AWC, surface runoff and consequently TWYLD are substantially higher than observed TWYLD, negatively influencing the NSE. Figures 8a and 8c indicate that changes to CN2(crop) and SOL_AWC parameter values can influence annual NSE by approximately 0.4, whereas changes to ESCO can influence annual NSE by approximately 0.2. Thus, CN2(crop) and SOL_AWC are more critical in maximizing model efficiency during model calibration than is ESCO.

Figures 9a, 9b, and 9c show that the base parameter values were chosen to minimize SSD_{WBC}. Selection of parameter values for CN2(crop) and ESCO greater than base case values results in large SSD_{WBC} values, while selection of SOL_AWC values less than base case values has the same effect. The trends of the annual NSE values for all three parameters follow an inverse pattern of SSD_{WBC}; when SSD_{WBC} is at its lowest point, the annual NSE is maximized.

The range in CN2(crop) values that result in a low SSD_{WBC} is narrow, since CN2 directly influences the surface runoff and baseflow components of the water balance. ESCO adjusts the depth of the soil profile from which SWAT meets soil evaporative demand. As ESCO increases, the depth to which soil evaporative demand can be met decreases, which limits soil evaporation and reduces the simulated value for ET. Figure 9b shows that water balance components changed little for values of ESCO below the base value, but that SSD_{WBC} increased sharply at higher values of ESCO, primarily because the ET component of the water balance changed. The effect of reducing SOL_AWC from the base value is to increasingly raise SSD_{WBC}, as shown in figure 9c. Reducing SOL_AWC results in the soil profile filling sooner, with more runoff, less ET, and increased baseflow, all of which increase SSD_{WBC}.

Conclusion

SWAT was calibrated to match annual averages of the water budget components for the period 1995-2004 for LREW SW-K on the Coastal Plain in south Georgia, with the input parameters CN2, SOL_AWC, and SOL_BD maintained at or close to their standard table or default values. Average monthly TWYLDs were low during the winter to early spring period, typically the season with higher water yields, and high during the late summer to autumn dry season, a result consistent with previous research in the LREW. The most sensitive input parameters on TWYLD model output were the CN2 of agricultural cropland, SOL_AWC, and ESCO. The CN2 for cropland and for forest land use and SOL_AWC were the most sensitive input parameters on stormflow. The ranking of sensitive parameters on baseflow was CN2 for cropland and forest, followed by ESCO and SOL_AWC. Although SOL_BD was sensitive for stormflow and baseflow, the directions of the sensitivity coefficients were counterintuitive. We suggest this was due to interdependency among SOL_BD, SOL_AWC, and CN2 that was not accounted for by perturbing only one parameter at a time. For the 16.9 km^2 SW-K, the TWYLD, stormflow, and baseflow outputs were insensitive to the remaining 11 SWAT input parameters tested. Analysis of the influence of the most sensitive parameters on annual NSE for TWYLD indicated that CN2(crop) and SOL_AWC have more influence than does ESCO. Thus, CN2(crop) and SOL_AWC dominate the SWAT calibration for this Coastal Plain watershed.

Having minimized SSD_{WBC} ensures the accurate separation of baseflow, stormflow, ET, and deep percolation, which is important for subsequent chemistry modeling. In order to maintain an accurate water balance, the calibration and sensitivity analysis results from this study can be useful in bounding reasonable ranges for SWAT hydrologic parameters for similar-sized watersheds in the southeastern U.S. The research indicates that bounding CN2(crop) to ±10% of the base values used in the study will result in an SSD_{WBC} less than 1775 mm^2, an SSD_{WBC} that results when each modeled component of the water balance differs by 5% from the observed values. To meet the same SSD_{WBC} requirement, the SOL_AWC values would need to range from 85% of the base value to the maximum range observed for the soils in the watershed, approximately 125% of base value in this case. This study indicates that ESCO values less than 110% of the base value will result in SSD_{WBC} of less than 1775 mm^2.

Additional study is warranted in order to develop SWAT as a tool for predicting the hydrologic and stream chemistry response of the LREW, and ultimately the southeast Coastal Plain, to changes in climate, land use, and agricultural management practices. Correcting the seasonal flow discrepancies and trimming the high peak predictions after long dry spells would improve the hydrologic modeling efficiency. Better adjustment of curve number for antecedent conditions holds some potential to provide flow correction during dry spells and subsequent improvement in modeling efficiency. Spatial recognition of SWAT HRUs in the riparian areas would provide the opportunity to parameterize and specify management of these HRUs to more accurately model water storage in the riparian zone.

Opportunity exists to incorporate field-measured parameters into the model. Using more field measurements and fewer default values for inputs will provide better opportunity to test the SWAT model's representation of processes in the LREW and on the Coastal Plain. Large plot-scale research being done at the LREW is beginning to show differences in soil properties and runoff characteristics between tillage/management practices. Transferring the information from this research to the larger scale of the subwatersheds or the entire LREW would be progress toward assessing the impacts of conservation practices, a primary objective of CEAP.

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