

IMPROVING DAILY WATER YIELD ESTIMATES IN THE LITTLE RIVER WATERSHED: SWAT ADJUSTMENTS

E. D. White, G. W. Feyereisen, T. L. Veith, D. D. Bosch

ABSTRACT. Researchers are assessing the beneficial effects of conservation practices on water quality with hydrologic models. The assessments depend heavily on accurate simulation of water yield. This study was conducted to improve Soil and Water Assessment Tool (SWAT) hydrologic model daily water yield estimates in the Little River Experimental Watershed (LREW) in south Georgia. The SWAT code was altered to recognize a difference in curve number between growing and dormant seasons, to use an initial abstraction (I_a), of 0.05S rather than 0.2S, and to adjust curve number based on the level of soil saturation in low-lying riparian zones. Refinements were made to two SWAT input parameters, SURLAG and ALPHA_BF, from a previous set of calibration parameters. The combined changes improved the daily Nash-Sutcliffe model efficiency (NSE) from 0.42 to 0.66 for water yield at the outlet of the 16.9 km² subwatershed K of the LREW for the ten-year period 1995 to 2004. Further calibration of the SURLAG coefficient yielded the largest improvement of five alterations, and changing I_a effected the next largest improvement. Over the ten-year investigation period, the model predicted annual average water yield within 1% of measured streamflow, and deviation between observed and simulated values for stormflow was $\leq 2.2\%$. Annual daily NSEs for each of the ten years were improved; for two years affected by seasonal tropical storm events, NSEs were changed from negative to positive values. The results of this study support the adjustment of the I_a ratio in the runoff curve number and suggest that additional changes to SWAT would improve water yield prediction for southern Coastal Plain locations.

Keywords. Calibration, CEAP, Coastal Plain, Curve number, Hydrologic modeling, Initial abstraction, SWAT.

The Farm Security and Rural Investment Act of 2002, known as the 2002 Farm Bill, increased funding for conservation programs nearly 80% over the previous (1996) farm bill. The additional investment in conservation measures heightened the need to quantify water quality, soil quality, and water conservation benefits of conservation practices. To address this issue, the USDA Natural Resources Conservation Service (NRCS) initiated a project, the Conservation Effects Assessment Project (CEAP), with two components: a national assessment of conservation benefits based on modeled estimates; and an appraisal of the benefits of specific practices at the watershed scale based on modeled estimates and analysis of field data (Mausbach and Dedrick, 2004). Twelve research watersheds managed by the USDA Agricultural Research Service (ARS) were chosen as benchmark locations for performing the watershed assessment. The designed approach was to evaluate

environmental benefits of conservation practices by employing two different watershed-scale models that had been calibrated and validated with historic data from the research sites. One of the two complex simulation models chosen was the Soil and Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005; Gassman et al., 2007).

Researchers in the U.S., Europe, Asia, Africa, and Australia have published over 250 peer-reviewed articles using SWAT for watershed hydrology and water quality studies at scales ranging from small experimental stations (<10 km²) to river basins (>100,000 km²) (Gassman et al., 2007). The manner in which SWAT handles hydrology is critical to the model's water quality outcomes, and thus assessment of conservation practices. SWAT calculates the partitioning of precipitation into runoff, surface interception, and infiltration by using the NRCS curve number (CN) method (USDA-NRCS, 2004a). The CN is a dimensionless number between 0 and 100 that relates runoff to precipitation based on vegetative cover, surface treatment, and soil properties. Despite this method's frequent use, it stirs controversy because of its empirical nature and the fact that its use has extended beyond its intended purpose of estimating cumulative runoff depth and peak flow rate. Gassman et al. (2007) provide a concise review of the strengths and uncertainties of using the CN method in SWAT. One particular part of the CN that is difficult to generalize is the amount of rainfall that does not immediately run off during a precipitation event. This quantity, known as the initial abstraction (I_a), is expressed as a portion of the available storage capacity (S) in the watershed. Historically, I_a has been established as 0.2 times S ; however, researchers have suggested that results can be improved by using a smaller fraction of S (Woodward et al., 2003; Bryant et al., 2006).

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Another CN issue currently being addressed by the SWAT modeling community is the manner in which the model does or does not reflect variable source area hydrology. Easton et al. (2007) redefined the CN to estimate variable source area contribution to runoff and incorporated their concepts into a modified version of SWAT, known as SWAT-VSA.

Meeting the CEAP goals involved development of watershed assessment models tailored to specific regions in the nation. The Little River Experimental Watershed (LREW), located in south Georgia and representative of the southeastern Coastal Plain physiographic province, was chosen as one of the CEAP benchmark watersheds. Prior hydrologic modeling studies focusing on the entire LREW or one of its nested subwatersheds have shown that SWAT tends to overpredict streamflow during drier, low-flow periods, especially in response to late summer or autumn tropical storms (Bosch et al., 2004; Van Liew et al., 2005; Feyereisen et al., 2007; Van Liew et al., 2007). Researchers using SWAT for studies in other geographic regions have observed the same seasonal trend: underprediction of streamflow or runoff during wet periods and overprediction during drier periods (King et al., 1999; Arnold et al., 2000; Anand et al., 2007; Green et al., 2007). Because biogeochemical processes affecting surface and subsurface water quality are complex, an accurate assessment of chemistry and pollutant load needs to be supported by an accurate accounting of water in the atmosphere-soil-water system (Skaggs, 1999). More precise model estimation of water movement reduces the uncertainty of estimating the effects of conservation practices on water quality.

Previous studies in the LREW provided clues that informed our research approach. Although Feyereisen et al. (2007) calibrated SWAT for subwatershed K, they found in a subsequent sensitivity analysis of 16 model input parameters that at least one parameter had not been optimized. Feyereisen et al. (2008), following the procedure of Yoo et al. (1993), calculated CNs from plot runoff data for a typical cotton-peanut rotation on a soil-landscape typical of the LREW and reported higher CNs during the dormant season than the growing season. Plot runoff was estimated using the NRCS CN method (USDA-NRCS, 2004b) and either one annual CN or two separate CNs for the growing and dormant seasons for each of two tillage types: conventional and conservation strip. The CNs were not adjusted for antecedent moisture conditions when calculating runoff from each storm in the test period record. Although the CNs for the two seasons were significantly different from one another, the researchers found that there were only slight improvements in runoff estimates when using separate growing and dormant season CNs. In this study using SWAT, we hypothesized that incorporating seasonal CNs into SWAT would improve runoff estimates over those in the previous LREW SWAT study (Feyereisen et al., 2007). We anticipated improvement because SWAT adjusts CN daily based upon soil moisture.

Sheridan and Shirmohammadi (1986) improved CN method storm event runoff volume estimates for LREW subwatersheds K and O by using CN values corresponding to typical seasonal antecedent moisture conditions (AMC) in low-lying, runoff-producing, near-stream alluvial soils. By assigning CNs to the alluvial soils corresponding to historically relatively dry conditions during late summer and fall (AMC-I), normal conditions during late spring and early summer (AMC-II), and relatively wet conditions during the winter and early spring (AMC-III), they improved the aver-

age runoff estimate for 37 storms for LREW subwatershed K from 11.4 to 19.3 mm (measured = 20.1 mm) and improved the correlation coefficient (r) of predicted to measured values from 0.81 to 0.91.

The objective of this study was to improve SWAT's representation of processes governing total water yield (TWLD) for the LREW subwatershed K by: (1) differentiating CN for growing and dormant seasons; (2) assigning CNs to runoff-generating lowlands based on season and soil moisture condition; (3) re-calibrating SURLAG and ALPHA_BF, input parameters identified in a previous study as needing further calibration; and (4) adjusting I_a in the CN method to reflect the findings of other researchers.

METHODS

In this analysis, we investigated methods of improving SWAT's daily streamflow prediction for the 16.9 km² subwatershed K (LRK) of the LREW. Our research approach was to improve daily water yield estimates by adjusting curve number (CN) seasonally; using a different initial abstraction (I_a), that is, the rainfall amount in the NRCS CN method above which runoff begins; changing CN in the low-lying riparian soils based upon soil moisture; refining SWAT input parameter calibration values; and making other simple modifications to SWAT input parameters or coding.

WATERSHED DESCRIPTION

The LREW is a 334 km² watershed located in south-central Georgia in Turner, Worth, and Tift counties (fig. 1). The USDA-ARS has monitored weather and streamflow data on this watershed since the 1960s (Bosch and Sheridan, 2007). Streamflow data are collected from eight nested subwatersheds within LREW, one of which, LRK, was chosen for this study. Hydrologic response from LRK was examined for the period from 1 January 1995 through 31 December 2004 because detailed land use coverages were available for this period. Located near the headwaters of the Little River, LRK supports a variety of land uses. Approximately 66% of the 16.9 km² LRK is covered with riparian and upland forests. The riparian forest cover consists of a mix of hardwoods and evergreens along the dendritic stream system and provides buffering of sediment, agricultural runoff, and nitrate-nitrogen in subsurface flow (Lowrance et al., 1984; Hubbard et al., 1990; Lowrance et al., 1997). The remainder of LRK is comprised of cotton and peanut fields, 21.6% and 9%, respectively, as well as pasture, corn, orchard, and other agricultural fields. Fifty-four percent of the upland area of LRK contains Tifton soil series, a loamy sand, while other soil types, primarily loamy sands and sandy loams, are found in the lower riparian zones near the stream system. Land use characteristics were gathered from a 2004 survey, while elevation and soil data were acquired from the Georgia GIS Clearinghouse (Feyereisen et al., 2007). A detailed description of the process followed to incorporate the land use data into SWAT is given by Bosch et al. (2004).

MODEL DESCRIPTION

The Soil and Water Assessment Tool (SWAT) hydrologic model was developed by the ARS to simulate the following major groups of processes: hydrology, nutrient and pesticide

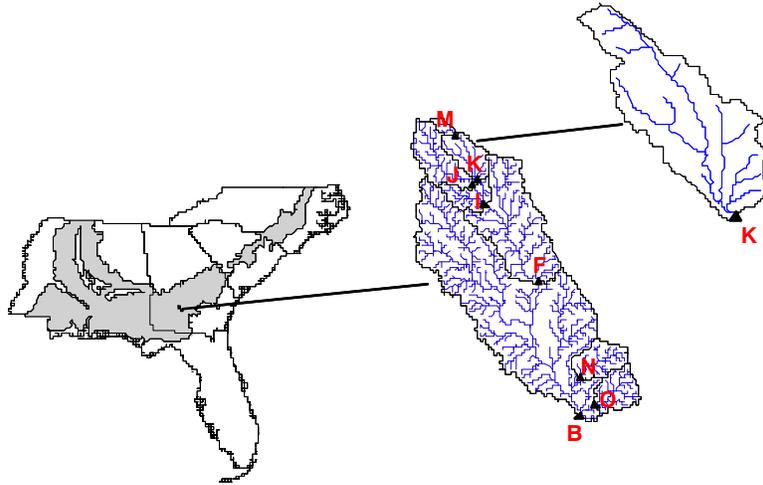


Figure 1. Location of LREW and LRK on the Coastal Plain (shaded gray) in south-central Georgia.

cycling, erosion, plant growth, management practices, and main channel and water body dynamics. The version of SWAT used for evaluating this project's objectives was SWAT2003. Land use/coverage, weather, soil, and geographic data were input into SWAT using the integrated ArcView GIS interface (AVSWAT-X) (Di Luzio et al., 2004). The study watershed was divided into 24 subbasins; within each subbasin the GIS interface aggregated parcels of land with identical properties (land use, soil type, and management) into hydrologic response units (HRUs). SWAT was then used to simulate the hydrologic processes throughout the watershed. Within each HRU, SWAT uses the NRCS curve number method (USDA-NRCS, 2004b) to partition daily precipitation volume into infiltration and surface runoff. SWAT modifies CN on a daily basis as a function of antecedent soil moisture content. CN can vary between the values assigned for wilting point and field capacity for a given soil type and cropping condition. CN is also adjusted based upon the field slope.

Infiltrated precipitation is redistributed as lateral flow, shallow and deep groundwater recharge, plant uptake, and soil evaporation; surface runoff is routed into streams, ponds, and reservoirs within the HRUs' respective subbasins. Transport processes are then performed to determine the movement of nutrients, pesticides, and sediment. Finally, the surface water and any infiltrated water determined by SWAT to return to surface waters as baseflow is routed from subbasins to the watershed outlet. The routing portion consists of both channel and reservoir routing and transport of nutrients, pesticides, and sediments associated with these two segments of routing (Neitsch et al., 2002).

SWAT INPUT PARAMETERS AND PROCESS MODIFICATIONS

SWAT input data for the LREW has been developed from previous calibration studies (Bosch et al., 2004; Van Liew et al., 2005; Feyereisen et al., 2007). Base values used for the current study were taken from the Feyereisen et al. (2007) calibration of LRK. Some of these input parameters to SWAT were varied from their base values in an attempt to improve upon the baseline calibration and increase the overall model prediction accuracy. A description of the changes made to each of these adjusted parameters follows.

Seasonal Curve Number Adjustment

Rainfall-runoff data from monitored field plots have indicated that CN for antecedent runoff condition II (CN2) can vary as much as five CN units between growing and dormant seasons for typical crops on the Southeast Coastal Plain (Feyereisen et al., 2008). To incorporate this observation into the SWAT model of LRK, CN2 was adjusted within the program code for land uses corresponding to an agricultural crop other than hay, orchard, or upland forest. Thus, CN2 values for the following non-crop or perennial plants were not adjusted: orchard, hay, forests, wetlands, pastures, ranges, grasses, alfalfa, clovers, and any type of tree. Once the HRU was identified as having agricultural plant coverage, SWAT was programmed to adjust CN2 2.5 units higher or lower depending upon the day of year. During the growing season (1 May to 1 Nov.), CN2 was lowered 2.5 units. During the remainder of the year (the dormant season), CN2 was increased 2.5 units.

Initial Abstraction

The NRCS CN method (USDA-NRCS, 2004b) estimates the amount of direct runoff from precipitation with a minimal number of inputs:

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S} \quad (1)$$

where Q is the direct runoff, P is precipitation, I_a is the initial abstraction, and S is the maximum potential retention (all units are inches of H_2O). By convention, I_a is assumed to equal $0.2S$, and S is transformed into CN (USDA-NRCS, 2004b):

$$CN = \frac{1000}{S + 10} \quad (2)$$

where the CN for each land use can be determined from reference tables (USDA-NRCS, 2004a). The NRCS has suggested in the *National Engineering Handbook* (USDA-NRCS, 2004b) that $I_a = 0.2S$ may not be the optimal assumption. Through comprehensive analysis of 28,301 rainfall-runoff events on 307 watersheds in 23 states, Woodward et al. (2003) determined that $0.05S$ fit the observed data better than $0.20S$. Additionally, after analyzing 58 rainfall-runoff events in the Ridge and Valley Province of east-central Pennsylvania, Bryant et al. (2006) suggested that I_a needs to be variable,

that is, $<0.2S$ for smaller precipitation events and $>0.2S$ for larger precipitation events. Given the geographical breadth and volume of data of the Woodward et al. (2003) analysis and support of the Bryant et al. (2006) findings, we changed I_a in the SWAT code to $0.05S$ to determine if SWAT hydrologic model accuracy would improve as a result.

SWAT uses USDA-NRCS CN values for various land uses, which are calculated from rainfall-runoff pairs using the assumption that $I_a = 0.2S$ (USDA-NRCS, 2004b). Therefore, all CN inputs into the SWAT model were adjusted to a value corresponding to what they would have been had the new assumption, $I_a = 0.05S$, been used. The conversion from the original CN ($CN_{0.20}$) to the adjusted CN ($CN_{0.05}$) was done by incorporating equation 3 into the SWAT code (Woodward et al., 2003):

$$CN_{0.05} = \frac{100}{1.879 \times \left(\frac{100}{CN_{0.20}} - 1 \right)^{1.15} + 1} \quad (3)$$

Riparian Zone Curve Number Modifications

To adjust for the varying alluvial storage of the LREW (Sheridan and Shirmohammadi, 1986; Shirmohammadi et al., 1986), areas described as alluvium were identified in the SWAT code. The two alluvial soils in the LREW, Kinston and Alapaha (Sheridan and Shirmohammadi, 1986), are in the forested lowlands that cover approximately 21% of LREW. The hypothesis that these riparian zones contribute much of the surface runoff during wet seasons when the alluvial soil profile is close to saturation was tested by adjusting CN2 of these riparian HRUs. Shirmohammadi et al. (1986) described the relative wetness of the soil profile in the LREW via a ratio (α) of saturated alluvial depth (SAD) to total alluvial depth (TAD):

$$\alpha = \frac{SAD}{TAD} \quad (4)$$

For our study, relative wetness was captured similarly by incorporating a variable, *ratioX*, into the SWAT code:

$$ratioX = \frac{sol_st(X)}{sol_awc(X) \times sol_z(X)} \quad (5)$$

where X is the soil layer, $sol_st(X)$ is the amount of water (mm H₂O) in the x th soil layer on the day of simulation, $sol_awc(X)$ is the amount of water that the x th soil layer is capable of storing (mm H₂O/mm soil), and $sol_z(X)$ is the depth of the x th soil layer. The value of *ratioX* was calculated for each soil layer in each riparian HRU having alluvial soils. It is important to note that $sol_st(X)$ is the stored water beyond the depth corresponding to the permanent wilting point. For example, if the soil moisture storage of the layer at wilting point is 2 mm H₂O, and the soil layer contains a daily value of 6 mm H₂O, then the corresponding $sol_st(X)$ will be 4 mm H₂O. Similarly, the product of $sol_awc(X)$ and $sol_z(X)$ represents the available storage capacity between wilting point and field capacity of the soil layer. Using *ratioX* provides a ratio similar to α that compares daily water depth in each soil layer to the theoretical maximum water depth the layer can store.

The final step towards using *ratioX* as an indicator for changing CN2 was to determine appropriate values of *ratioX* to represent wet and dry antecedent moisture conditions. Examination of *ratioX* values calculated daily over the

ten-year simulation period (1995-2004) revealed that alluvial riparian zone HRUs did not contribute much surface runoff until the *ratioX* value for the top soil layer reached 0.80. Under these same conditions, the *ratioX* value for the second soil layer was typically 0.30. Both values are very similar to the values reported by Shirmohammadi et al. (1986) for α under “wet” and “medium wet” conditions for LRK and another LREW subwatershed, LRI. The alluvial properties of LRI and LRK are similar to each other (effective alluvial depths of 1.81 and 1.87 m, respectively) and calculated values of α were similar as well. “Wet conditions” in LRI were defined by an α of 0.83 and in LRK by an α of 0.77 (Shirmohammadi et al., 1986). The mean of these two values, 0.80, is the same value chosen for *ratioX*. Similarly, a “medium wet” condition corresponded to α of 0.35 in LRK (Shirmohammadi et al., 1986), close to the value of 0.30 determined for *ratioX*. Based upon the similarities between *ratioX* values and α , wet conditions in the riparian zones were assumed to occur when the top layer’s *ratioX* value reached or exceeded 0.80 and the second layer’s *ratioX* value exceeded 0.30.

We used *ratioX* to determine the moisture condition of the soil profile and adjusted CN2 of the riparian zone HRUs to reflect those moisture conditions as follows. The base CN2 value (before modification) was 55, which was assigned to the riparian zones as a result of the forested riparian zones being in “good” hydrologic condition with soils in the B hydrologic soil group (USDA-NRCS, 2004a). To implement the observations made from previous studies, the base CN2 value was adjusted to simulate the wet and dry conditions. Rather than choose CN values at random, the modified CN values were taken from CN tables corresponding to wooded land use for a variety of hydrologic conditions. The first adjustment made was to use CN values for woods in “fair” hydrologic condition, which results in a CN range from 36 to 79, depending on soil hydrologic condition. These extreme CN values were then used as values for the dry and wet seasons, respectively. Along these same lines, another adjustment was made to the riparian zones for the dry and wet seasons. This second adjustment assumed that during the dry season there was a “good” hydrologic condition, and during the wet season there was a “poor” hydrologic condition. This then resulted in a range of CN values from 30 to 83. While the dry season values differ slightly from previous studies, the two values used for the wet season, 79 and 83, correspond to values used previously for the riparian zones in LRK (Sheridan and Shirmohammadi, 1986). Once adjusted for wet and dry seasons, these new CN values were used by SWAT to determine the daily variation in CN as a function of the HRUs’ antecedent moisture conditions.

In addition to matching previous research results from LRK, these riparian modifications also help SWAT to determine the spatial distribution of runoff-producing areas. Previous research has led to the idea of variable source areas, the concept that surface runoff is generated mainly from only a given portion of a watershed. Typically, this runoff-producing area is in the lowland portion of a watershed, which due to the large upstream contributing area and changes in topography will remain saturated for longer periods of time (Easton et al., 2007; Schneiderman et al., 2007; Lyon et al., 2004). Thus, by increasing the CN for these lowland riparian areas during the wet season, the spatial identification of runoff-producing areas is better modeled.

PARAMETER CALIBRATION

Surface Runoff Lag (SURLAG)

The surface runoff lag coefficient (SURLAG) is an input parameter incorporated into SWAT to increase accuracy of runoff predictions for large watersheds by adding a temporary storage factor to the watershed model; as SURLAG decreases, temporary available storage increases (Neitsch et al., 2002). Previous studies have shown that for streamflow, SURLAG can be a relatively sensitive parameter (van Griensven et al., 2006) or a relatively insensitive parameter (Feyereisen et al., 2007). The two watersheds used for the van Griensven et al. (2006) analysis were much larger than the LRK watershed in the other study: 932 km² and 3240 km² versus 17 km², respectively. After creating the manually calibrated baseline of LRK in SWAT, Feyereisen et al. (2007) performed sensitivity analysis of 16 parameters, including SURLAG. The results showed that water yield was virtually unaffected by perturbing the value of SURLAG, but that modeling efficiency was affected. The researchers indicated that adjusting SURLAG to something less than the baseline value of 1 could improve model efficiency. SURLAG was methodically varied across the range of 0 to 1 using the bisection method. At each adjustment SWAT was rerun and the Nash and Sutcliffe (1970) model efficiency (NSE) was recalculated. This process was repeated until the maximum NSE for this SURLAG value range was located.

Baseflow Recession Constant (ALPHA_BF)

The SWAT input parameter alpha baseflow (ALPHA_BF) is a baseflow recession constant that describes how quickly groundwater is affected by recharge (Neitsch et al., 2002). Van Griensven et al. (2006) identified ALPHA_BF as “slightly important” with respect to streamflow sensitivity, yet having an “important” effect on stream sediment and nutrient estimates. As with SURLAG, Feyereisen et al. (2007) determined that ALPHA_BF was an insensitive parameter to streamflow estimate for LRK, but that it may influence modeling efficiency. During the previous manual calibration and sensitivity analysis of that study, it was found that an ALPHA_BF of 0.039 was more accurate than using the baseline value of 0.035. Thus, this parameter was adjusted between 0.035 and 0.050 at intervals of 0.005, and the impact on TWLD was determined using goodness-of-fit characteristics.

GOODNESS-OF-FIT CHARACTERISTICS

Model simulations must be compared to observed data in some manner in order to assess prediction accuracy of the model. As discussed by Moriasi et al. (2007), there are numerous methods commonly used to evaluate hydrologic model efficacy. One of the more frequently applied techniques in the literature is the NSE (Nash and Sutcliffe, 1970), defined by equation 6:

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (6)$$

where O_i is the observed water yield for time step i , S_i is the simulated water yield for time step i , \bar{O} is the mean of the observed data over the entire period of simulation, and n is

the number of time periods. Nash-Sutcliffe efficiencies vary from one to $-\infty$, where a value of one indicates that the simulated model water yield matches the observed data perfectly.

The squared terms in equation 6 heavily influence NSE values to the presence of outliers in the simulated water yield values. While visual inspection of the hydrographs may confirm that measured and predicted values match the majority of the time, the presence of one extreme overprediction by SWAT (as occurs in LREW by the presence of tropical storms) can negatively skew the computed NSE value. To correct for this sensitivity to extreme values, Legates and McCabe (1999) suggested using the absolute difference in values (eq. 7) rather than the squared differences:

$$NSE^1 = 1 - \frac{\sum_{i=1}^n |O_i - S_i|}{\sum_{i=1}^n |O_i - \bar{O}|} \quad (7)$$

where NSE^1 is the Nash-Sutcliffe efficiency based on unsquared absolute difference values, and O_i , S_i , \bar{O} , i , and n are as previously defined.

The third goodness-of-fit characteristic considered was percent bias (PBIAS):

$$PBIAS = 100 \times \left(\frac{\sum_{i=1}^n (O_i - S_i)}{\sum_{i=1}^n O_i} \right) \quad (8)$$

where O_i , S_i , i , and n are as previously defined. Percent bias quantifies the model's tendency to overpredict or underpredict values, on average, over the entire modeling period. When a model underpredicts streamflow, a positive bias results; when a model overpredicts streamflow, a negative PBIAS occurs. PBIAS is zero when the model favors neither underprediction nor overprediction.

NSE is widely reported for hydrologic models and provides a quick overview of a model's accuracy. The model's PBIAS towards underprediction or overprediction is also useful because it indicates the overall trend of the model's predictions. These two characteristics provide a concise summary of the conclusions that can be drawn from an examination of the output hydrographs for the entire modeling period. NSE indicates how close the predicted values are to the observed, and PBIAS indicates whether the predictions on average were too high, too low, or evenly distributed between the two. NSE^1 was included because it is less sensitive to outliers, and large tropical storms produced outlier events during the timeframe of our study.

AVERAGE ANNUAL WATER BALANCE

In addition to the goodness-of-fit characteristics, an average annual water balance was used as an indicator of model accuracy. The simulated and observed average annual water balances were compared by calculating the relative error (eq. 9) between the two, which is often referred to as the deviation of runoff volume (D_v) (Martinez and Rango, 1986; ASCE, 1993; Gitau et al., 2006; Moriasi et al., 2007):

$$D_v = \frac{S_k - O_k}{O_k} \times 100\% \quad (9)$$

where S and O represent simulated and observed data averages, respectively. The subscript k stands for the component of the annual water balance being compared: stormflow; baseflow; evapotranspiration; deep percolation; or total water balance, which is defined as the sum of the four previous components. The deviations of volume for stormflow (D_{vSF}) and total water balance (D_{vBAL}) were included in model assessment to quantify model output differences from corresponding observational data for various components of the hydrological cycle.

ADJUSTMENT FOR UNCERTAINTY IN OBSERVED DATA

The goodness-of-fit characteristics described are useful in quantitatively describing the performance of a model, but the observed data used for comparison in these equations are assumed to be error free, which is very rarely the case. As discussed in depth by Harmel et al. (2006), it is known that error exists in all data and can be of relatively large magnitude. Therefore, while useful in demonstrating relative improvements in model accuracy, the aforementioned characteristics can be improved upon by including observed data uncertainties. Harmel and Smith (2007) propose two modifications to goodness-of-fit characteristics to account for what Harmel et al. (2006) termed probable error range (PER). One of these modifications was implemented on the SWAT simulation results of the LREW.

The PER is determined by equation 10:

$$PER = \sqrt{\sum_{j=1}^n E_j^2} \quad (10)$$

where E_j represents the amount of error introduced to the observed data from the j th potential source, and n is the total number of potential sources. For example, in total water yield measurements, error can be introduced by improper installation of a weir, an inaccuracy in a stage-discharge relationship, an unstable streambed, or data recorder imprecision. Specific values for E_j are given by Harmel et al. (2006) and were used to predict three different error ranges: best case, worst case, and intermediate case scenarios. These error ranges were then used to determine an uncertainty range (UR) above and below each observed datum for the three scenarios, as shown in equation 11:

$$UR_i = O_i \pm \frac{PER \times O_i}{100} \quad (11)$$

Harmel and Smith (2007) suggest that a more realistic description of model accuracy would be to quantify how far the simulated result is from the outer limit of the uncertainty range, as compared to the difference between the observed and simulated values. A graphical representation of this modification is given in figure 2 (adapted from Harmel and Smith, 2007). In practice, the numerator of goodness-of-fit characteristics ($O_i - S_i$) is set to zero when S_i falls within UR_i (fig. 2, case 2). When S_i is above or below UR_i , (fig. 2, cases 1 and 3, respectively) ($O_i - S_i$) is changed to S_i subtracted from the upper or lower limit to UR_i , respectively.

When including an uncertainty range for observed data, model NSE values can increase in proportion to the size of the

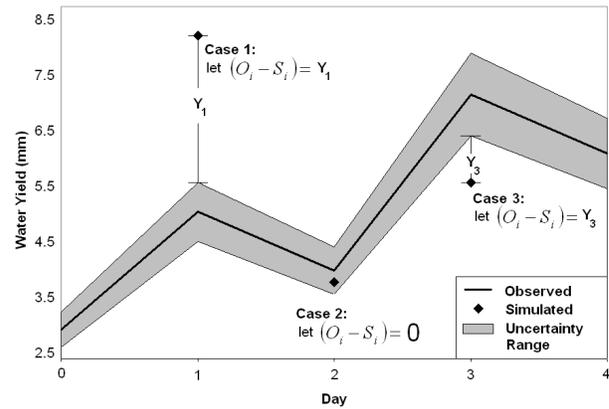


Figure 2. Graphical representation of a hypothetical uncertainty range (UR) associated with observed data and the modifications to “goodness-of-fit” parameters as suggested by Harmel and Smith (2007).

Table 1. Three scenarios for error in observed data; error ranges and PER calculated from Harmel et al. (2006).

Error Source	Best Case	Intermediate	Worst Case
Stage-discharge relationship	±5%	±8%	±10%
Data recorder	±2%	±2%	±2%
Streambed condition	±0%	±0%	±10%
Probable error range (PER)	±5.39%	±8.25%	±14.28%

uncertainty range. By assuming a broader range of possible values for the observed data, a broader range of simulation values is considered acceptable. Therefore, if error in observed data is assumed to be minimal, the model is held to the strictest performance requirements. Three scenarios were examined for the inclusion of error in observed data: best case, worst case, and an intermediate case scenario based on Harmel et al. (2006) (table 1). The best case assumed that the observed data were as accurate as possible (placing the tightest restrictions on NSE calculations), the worst case assumed that the observed data were least accurate, and the intermediate case calculated errors between these two assumptions. Of the error sources and uncertainty ranges reported by Harmel et al. (2006), three were determined to be relevant to the recorded streamflow from LRK. The first source of error was the stage-discharge relationship at the weir. An uncertainty range for a “pre-calibrated flow control structure” ranges from 5% to 10%, depending upon the frequency at which the recorded flows are double-checked with a flowmeter. The other two error sources were determined to be the data recorder and the stability of the streambed. A 2% error range was assumed to be present due to the use of a float recorder, and a stable or unstable streambed would introduce 0% or 10% error, respectively (Harmel et al., 2006).

VISUAL ASSESSMENT

The “goodness-of-fit” characteristics discussed provide valuable information regarding the accuracy of models, but they do not tell the whole story regarding the SWAT model’s predictive proficiency. Visual comparisons of observed hydrographs are needed in addition to quantitative statistics (ASCE, 1993). Predicted and observed daily TWYLD for each year of the study period were graphed, event peaks and durations were compared, and overprediction and underprediction tendencies were evaluated.

MODIFICATION METHODOLOGY

The ten-year period 1995 to 2004 was simulated for the described SWAT parameter and process modifications using baseline calibration input parameters. Goodness-of-fit characteristics were calculated at each modification step. The volume deviations (D_v) of the simulated annual water balance components were also examined after each simulation to ensure that the division of water among baseflow, surface runoff, ET, and deep percolation was not compromised for a higher predictive capability at the daily time step. The first modification made to the SWAT code was the seasonal adjustment of CN2 for cropped land. The next code modifications made were $I_a = 0.05S$ and riparian zone CN adjustments based on *ratioX*. Finally, the two input parameters, SURLAG and ALPHA_BF, were individually changed by manual adjustment, as discussed previously. SWAT's sensitivity to each of the changes (seasonal CN adjustment, $I_a = 0.05S$, *ratioX*, SURLAG, and ALPHA_BF) was determined by running the model separately for each single adjustment. Once all individual changes were modeled, a final simulation, named "combined changes," was performed with all of the modifications included. Finally, to provide perspective on the influence of measurement uncertainty on model results, goodness-of-fit characteristics were recalculated incorporating the uncertainty range associated with the observed hydrologic data.

RESULTS AND DISCUSSION

Statistical measures of modeling accuracy for the baseline calibration, each individual adjustment, and the combined changes are summarized in table 2. Results for each adjustment are discussed in the following sections.

SEASONAL CURVE NUMBER ADJUSTMENT

Adjusting CN for growing and dormant seasons resulted in modest improvements in the water yield predictions (table 2). Results of the current study showed a slight improvement for daily NSE, from 0.42 to 0.44, but a slight decline for PBIAS from 0.38% to 0.52% (table 2). The stormflow estimate of the annual water balance more nearly matched the observed value ($D_{vSF} = 0.22\%$, table 2) than all but one of the other modifications. Thus, the daily water yield and stormflow estimates were both slightly improved when unique CNs were used for growing and dormant seasons.

Table 2. SWAT accuracy for water yield simulations in LREW subwatershed K (1995-2004).

Modifications	NSE _{daily}	PBIAS (%)	D_{vBAL} ^[a] (%)	D_{vSF} ^[b] (%)
Baseline calibration	0.42	0.38	-0.46	-1.70
Seasonally adjusted CN2	0.44	0.52	-0.46	0.22
$I_a = 0.05S$	0.52	0.01	-0.48	-2.22
Riparian CN2 Adjust #1: Fair condition	0.45	0.14	-0.44	-0.75
Riparian CN2 Adjust #2: Poor condition	0.46	0.00	-0.43	0.02
SURLAG = 0.460	0.62	0.52	-0.47	-1.76
ALPHA_BF = 0.045	0.42	0.23	-0.41	-1.70
Combined changes	0.66	-0.17	-0.42	-0.91
Ideal values	1.00	0	0	0

^[a] D_{vBAL} = volume deviation for total water balance.

^[b] D_{vSF} = volume deviation for stormflow.

INITIAL ABSTRACTION ADJUSTMENT

Re-evaluation of USDA-NRCS's assumption that I_a equals one-fifth of the potential storage of a watershed was the second most effective modification made. By incorporating the assumption that $I_a = 0.05S$, the model daily NSE increased to 0.52, just above the threshold of 0.50 suggested by Moriasi et al. (2007) for an "adequate" hydrologic model calibration for a monthly time step. Given that lower performance ratings are generally warranted for shorter time steps, the daily NSE of 0.52 is well within the "adequate" category. PBIAS was reduced to 0.01% after changing I_a , very close to the 0% PBIAS obtained from the Riparian CN2 Adjust #2 modification. While daily NSE and PBIAS values improved substantially from the baseline, annual stormflow deviation (D_{vSF}) was greater for the I_a modification than for any other modification, increasing by 0.52% from the baseline deviation. The discrepancy between an improved NSE and slightly less accurate D_{vSF} may be resolved by finding a uniquely fit I_a for LRK.

Another potential avenue for improvement in modeling with the CN method is to use the suggestion of Bryant et al. (2006) to vary I_a as a function of storm size. Their suggestion to decrease I_a for smaller storms conceivably addresses SWAT's tendency to underpredict low flows because with a lower I_a , more runoff will be estimated. Conversely, their suggestion to use a higher I_a for larger storms will decrease runoff prediction by the CN method, which addresses SWAT's tendency to overpredict runoff due to large storms. The seasonal CN differences identified by Feyereisen et al. (2007) were based on the $I_a = 0.2S$ assumption. Perhaps focusing on a seasonal I_a rather than on a seasonal CN would yield better results. However, while the aforementioned approaches provide promising possibilities for hydrologic modeling improvement, they were beyond the scope of this project, which was to examine the effectiveness of using 0.05 rather than 0.20. To those ends, the suggestions made by Woodward et al. (2003) did indeed provide a more accurate hydrologic model.

RIPARIAN ZONE MODIFICATION

Adjustments made to the riparian zone CNs provided slightly more accurate results than the baseline calibration. Riparian CN2 Adjust #1, in which CNs for woods in fair hydrologic condition were used, resulted in an 0.03 increase from the baseline of daily NSE values for the ten-year period (table 2). PBIAS was reduced by 0.24%, while stormflow deviation (D_{vSF}) between predicted and observed volumes improved by 0.95%. D_{vBAL} was essentially unchanged. Riparian CN2 Adjust #2, which based CN2 values on a "poor hydrologic condition" rating, resulted in an even better predictor of the hydrologic processes in LREW LRK. The stormflow prediction was essentially identical to the observed annual average, with $D_{vSF} = 0.02\%$. The daily NSE value also improved by 0.04, from 0.42 to 0.46. The PBIAS for this modification improved as well, to 0%, indicating that the simulated and measured average water yields are equal. D_{vBAL} was again essentially the same.

While modest improvements were made to the daily NSE of the model for both of these two riparian zone modifications, Adjust #2 resulted in a more accurate prediction of annual stormflow. These improvements provide both better predictive capabilities of the model and a simple mechanism to account for fluctuating storage due to

lowland alluviums, which otherwise are not incorporated into the SWAT model. Although the riparian CN adjustments are not directly based on daily observed data, they improve the spatial portion of the SWAT hydrology component by causing stormflow to be generated from more realistic locales within LRK. This adjustment begins to address the issue of the CN method's inability to differentiate between the various streamflow generating processes. By increasing the CN for lowlands during wet periods, more surface runoff from these zones was predicted by SWAT. Increasing flow from the wet lowlands results in a model that not only addresses the theoretical discussion of the CN method's inability to predict saturation-excess runoff (Garen and Moore, 2005), but also the observed hydrologic characteristics of these alluvial lowlands (Sheridan and Shirmohammadi, 1986; Shirmohammadi et al., 1986).

SURLAG CALIBRATION

Modification of the SURLAG parameter led to the best value of NSE for LRK. By using a value of 0.460 for SURLAG with the baseline parameter set, rather than the baseline calibrated value of 1.0, the daily NSE value increased to 0.62. Decreasing SURLAG from the baseline calibration value of 1.0 reduces the delay of surface runoff to the main channel, resulting in more accurate daily prediction of streamflow. For LRK, the SURLAG retention parameter serves as an artificial method to account for otherwise unaccounted-for available storage, such as small irrigation ponds located throughout the subwatershed and the variable alluvial storage previously discussed. While the daily NSE values improved by 0.20 from the baseline with the SURLAG adjustment, the other statistics were virtually unchanged; PBIAS increased by 0.14%, and $D_{v,SF}$ dropped from -1.70% to -1.76%. The improved daily NSE indicates that by retaining the surface runoff for a shorter period of time, SWAT is more accurate at predicting the timing and magnitude of peak flows.

ALPHA_BF ALTERATION

Altering ALPHA_BF had the least impact on the SWAT model results for LRK. Adjustment within the range of 0.035 to 0.055 had a negligible effect on the model accuracy. The median of this range, 0.045, led to a slightly better PBIAS (0.23% versus 0.38%), but no changes to NSE. Additionally, changes to ALPHA_BF made no change to the calculated stormflow or evapotranspiration components of the annual water budget, but they did change the baseflow component by increasing the amount of deep percolation ($D_{v,BAL}$ improved from -0.46 to -0.41). Thus, the total water yield component (total water yield = baseflow + stormflow) was slightly improved.

COMBINED CHANGES EFFECTS

The magnitude of improvements to SWAT accuracy varied considerably for the range of code and parameter modifications made. While all individual changes improved some aspect of the hydrologic model, the improvements were not additive when incorporated into a single modification. The five modifications included in the final simulation, termed "combined changes" in table 2, were the seasonally adjusted CN2, $I_a = 0.05S$, Riparian CN2 Adjust #2, SURLAG = 0.460, and ALPHA_BF = 0.045. The resultant

daily NSE value for the combined changes calibration was 0.66 (table 2), which falls above the threshold for "very good" values suggested for the NSE (Moriassi et al., 2007). The estimated water yield for the combined changes simulation (shown by PBIAS) was slightly below the observed value, indicating that the model was consistent with respect to representing the water yield component of the hydrologic cycle. The volume deviation measures for total water balance and stormflow ($D_{v,BAL}$ and $D_{v,SF}$, respectively) decreased slightly from the baseline, suggesting that the combined changes simulation more accurately represented daily fluctuations in the water balance than did the baseline simulation.

The improvements made to daily NSE of the SWAT model of LRK for each year of the simulation can be observed in figure 3. When calculated for individual year, the daily NSE values for the combined changes simulation ranged from 0.10 to 0.78, a marked improvement over the baseline calibration NSE values of -0.80 to 0.64. These NSE values, along with the ten-year value of 0.66, compare favorably to values obtained for other watersheds using SWAT. Gassman et al. (2007) provide a thorough review of over 60 SWAT modeling studies where NSE values were reported for daily streamflow. The range for these reported NSE values was from -102 to 0.99, with many studies having a drainage area roughly the size of the LREW reporting values from approximately 0.2 to 0.7. While there is a lot of variation in the reported values and the drainage area for each of these models, it is clear from examining the review by Gassman et al. (2007) that the current LRK SWAT model returns relatively accurate results.

Improvements to average annual water budget components were not as dramatic as the NSE changes because the baseline calibration returned accurate predictions for water budget component volumes (table 3). Care was taken in the baseline calibration to partition baseflow and stormflow to match values determined by prior research in the LREW (Shirmohammadi et al., 1984). This was done to facilitate future water quality modeling, for which correct representation of surface and subsurface processes is important. However, the combined changes simulation more accurately predicted the stormflow component, as evidenced by the $D_{v,SF}$ value. This finding demonstrates that the study objective of improved TWYLD predictions was met. Thus, the combined changes simulation maintained and enhanced the baseline calibration support for future water quality modeling. Average annual model estimates were slightly off for the combined changes simulation for ET, a water budget component that is difficult to measure and is thus an "observed estimate."

VISUAL ASSESSMENT

The hydrograph for the most accurate year (1995) of the ten-year simulation indicated that the combined changes simulation better predicted peak flows than the baseline calibration (fig. 4). However, it is evident from the hydrograph that SWAT still underpredicted water yield for the wet part of the year (fig. 4, DOY 10 to 40). During the historically dry part of the year when late summer tropical storms tend to occur, the modifications to SWAT improved results compared to the baseline calibration (fig. 5). Overpredictions for the first days of two tropical storms occurring on 13 October (DOY 286) and 11 November (DOY

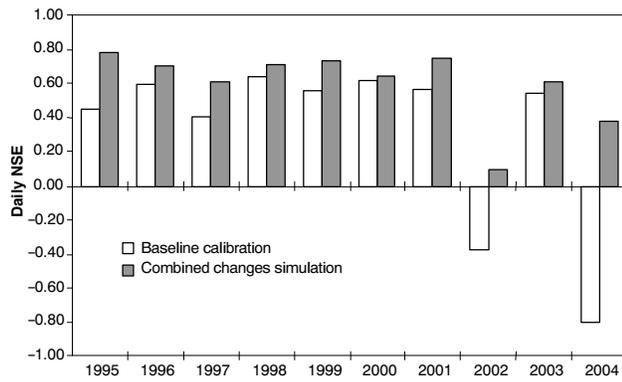


Figure 3. Improvement in daily NSE values from baseline calibration to combined changes simulation, 1995-2004.

315) in 2002 were much less than for the baseline calibration; however, SWAT still predicted nearly 5 mm of total water yield for 13 October when virtually no streamflow was observed in LRK.

The treatment of ET needs to be investigated as a contributor to the seasonal under- and overpredictions in SWAT. Anand et al. (2007) found that SWAT simulated high ET requirements soon after crop planting, which would lead to predictions of lower soil moisture and runoff during the spring. If the converse case holds, then simulated ET

Table 3. Average annual water budget and deviation (D_v) from observed (1995-2004).

Budget Component	Obs. (mm)	Baseline Calibration		Combined Changes Simulation	
		(mm)	D_v (%)	(mm)	D_v (%)
Total water yield ^[a]	317.40	316.23	-0.37	318.11	0.22
Baseflow	222.18	222.63	0.20	222.80	0.28
Stormflow	95.22	93.60	-1.70	95.30	0.08
Evapotranspiration	807.00	803.00	-0.50	801.60	-0.67
Deep percolation	11.40	11.37	-0.26	11.35	-0.44
Total water balance	1135.80	1130.60	-0.46	1131.10	-0.42

[a] Total water yield = baseflow + stormflow.

requirements may be too low during the late summer to autumn dry period, resulting in wetter-than-actual soil moisture and a consequent overprediction of runoff. Since these modeling patterns have been noted in numerous SWAT studies, additional research focusing on the issue is needed.

OBSERVED DATA UNCERTAINTY AND ALTERNATE NSE

Once the combined changes simulation was complete, two variations of the Nash-Sutcliffe efficiency were examined (table 4). The traditional variation, NSE (eq. 6), was used with the acknowledgement that the observed data used for comparison were not error-free, while NSE¹ (eq. 7)

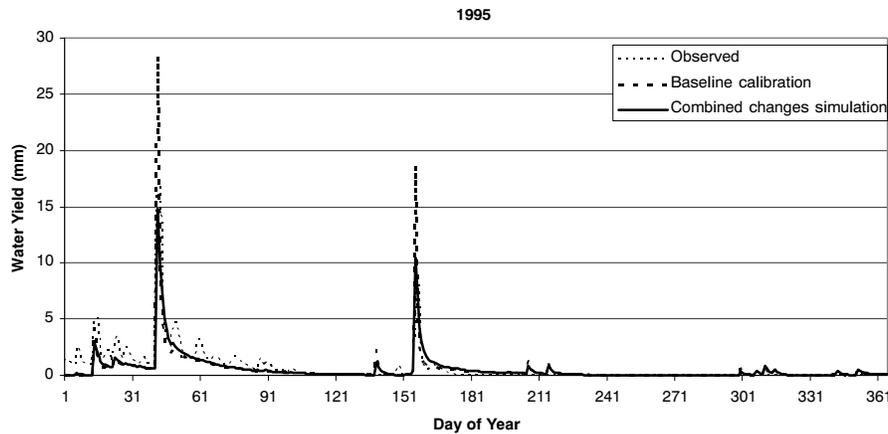


Figure 4. Daily total water yield for 1995, the year with the highest daily NSE value: 0.45 for baseline calibration and 0.78 for the combined changes simulation.

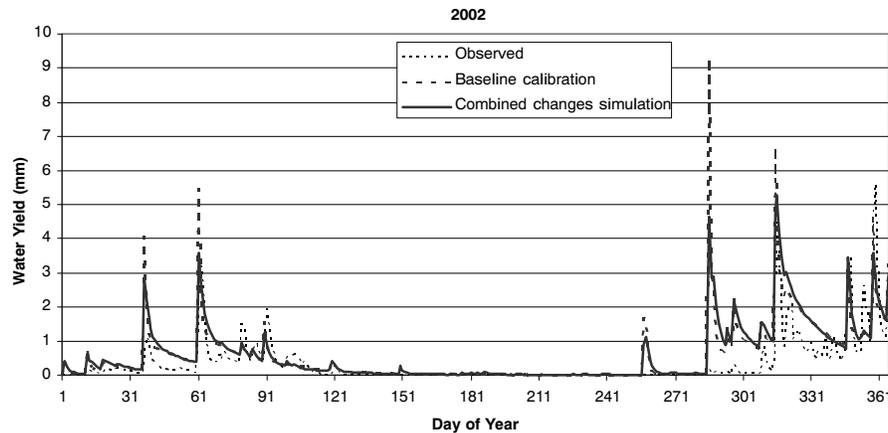


Figure 5. Daily total water yield for 2002, the year with lowest daily NSE value: -0.37 for baseline calibration and 0.10 for the combined changes simulation.

Table 4. Daily NSE values determined by various alternative calculations for two SWAT simulations.

	Baseline	Combined Changes
Baseline NSE	0.42	0.66
NSE ¹ [a]	0.48	0.52
NSE with PER ^[b] = ±5.39% ^[c]	0.48	0.71
NSE with PER = ±8.25% ^[c]	0.51	0.74
NSE with PER = ±14.28% ^[c]	0.57	0.78

[a] From Legates and McCabe (1999), using equation 7.

[b] PER = probable error range.

[c] From Harmel and Smith (2007), using equation 6.

was used to provide a statistic that was not as susceptible to singular large errors. The NSE¹ value was 0.06 units higher than the traditional NSE calculation for the baseline calibration, but 0.14 units lower for the combined changes simulation. By using the absolute value of the differences rather than the square of the differences between observed and simulated, NSE¹ will be less than NSE if the majority of differences are less than one unit (in this case, mm), and vice versa. The lower value for the combined changes simulation indicates that large errors from a few extreme events had less of an effect on model accuracy than numerous slight differences in predictions of average flow; the opposite conclusion can be drawn from the higher value calculated for the baseline calibration.

As expected, daily NSE values were highest for the worst case scenario and lower for the other two scenarios (table 4). All scenarios that included uncertainty of observed data improved NSE values, with larger changes occurring as the uncertainty range increased. The amount of uncertainty assumed in observed data should be kept to a minimum to result in tougher model performance requirements; however, it is important to include some uncertainty to acknowledge that the data used for calibration are not completely error-free.

Throughout all of the modifications that led to an increase in model accuracy on the daily time step, the monthly and yearly predictions (not shown) were not adversely affected. In fact, the monthly NSE increased from 0.78 to 0.80 after the combined changes were made, and the yearly NSE remained at 0.85. A final indicator of the improvements made to the SWAT model of LRK was the daily NSE values calculated for only a portion of the ten-year simulation. In a past modeling study of LREW (Feyereisen et al., 2007), it was reported that model accuracy was greater for the six-year period from 1997 through 2002 than for the ten-year period from 1995 through 2004. In that study, the daily NSE for the baseline calibration was 0.56 for 1997-2002, 0.14 higher than the ten-year NSE of 0.42. The daily NSE values for the combined changes simulation were 0.69 for 1997-2002 and 0.66 for 1995-2004, a difference of only 0.03. The narrowing of the difference in daily NSE values over these two time periods indicates that the modified SWAT model estimates water yield more consistently throughout years that exhibit widely varying meteorological and hydrological conditions.

CONCLUSION

Several simple modifications to the hydrologic component of SWAT were found to notably improve SWAT-simulated water yield predictions from LREW LRK, a 16.9 km² southeastern Coastal Plain watershed with alluvial

riparian buffers. More closely calibrating the SWAT surface runoff lag coefficient (SURLAG) improved total water yield predictions the most, while changing the I_a ratio assumption of $I_a = 0.2S$ to $I_a = 0.05S$ also increased accuracy. Altering cropland CNs for growing and dormant seasons and incorporating the CN into a function to account for riparian soil moisture resulted in modest improvements in the water yield predictions. Further calibrating the baseflow coefficient (ALPHA_BF) had no impact on model accuracy. Improvements in model statistics and visually assessed hydrograph characteristics support the conclusion that the combined modifications made to SWAT better represent the model processes governing TWYLD prediction.

Existing literature has indicated that SWAT typically overpredicts water yield in dry seasons and underpredicts it during wet seasons. The changes made in this study reduced the tendency of SWAT to overpredict total water yield but did not appear to address the underpredictions. While most peaks that were overpredicted were simulated more accurately with the adjusted parameters, extremely large rain events (i.e., tropical storms) during the typically dry autumn still led to SWAT predicting streamflow when no flow was observed. SURLAG calibration appeared to greatly improve the overprediction trend of SWAT, but perhaps cancelled out any improvements during the wet season made by the other modifications. More research should be conducted to determine what parameters and calculations in the SWAT model are responsible for the model's trend towards underpredicting water yield for wet seasons in this physiographic region.

The SWAT modifications used in this study are potentially applicable to watersheds of various sizes in other physiographic provinces. Further research should be conducted to determine if the changes made to SWAT's treatment of hydrologic processes in the current project are applicable and effective in improving modeling for watersheds across a range of climates, soil types, land uses, and topographies. In addition, the results of this study support the findings of others that the $I_a = 0.2S$ assumption made in the CN method can be improved upon and offer a lead-in to future research focused on increasing model performance by identifying a different expression for I_a .

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