Identifying Critical Source Areas of Sediment, Nitrogen and Phosphorus: A Modeling Approach

by

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A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
December 13, 2010

Keywords: Critical Source Areas, SWAT,
GWLF, Sediment, TN, TP

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Abstract

Impairment in the quality of water due to nutrients and sediments originating from watersheds is a serious problem in the USA and the world. Identification of critical source areas (CSAs), which contribute most of the pollutants, is important for cost-effective implementation of best management practices. Watershed models are widely used for this purpose. In this work, we looked into two key issues related to CSA identification. First is whether model choice and model complexity effects CSAs. Second is whether an uncalibrated model can identify CSAs correctly.

A complex model- Soil and Water Assessment Tool (SWAT), and a simple model- Generalized Watershed Loading Function (GWLF) was used in this study to identify the CSAs in the Saugahatchee Creek watershed in east central Alabama. The objective of this study was to explore the effect of model choice and model complexity in location of CSAs. Models were calibrated and validated for flow, sediment, TN and TP on a monthly time scale. Performance of SWAT model was slightly better for predicting sediment, TP and TN. CSAs were identified at sub-watershed scale for sediment, TP and TN. It was found that although a simple model (GWLF) is certainly useful in watershed modeling and identification of CSAs, it may not capture all the CSAs. In the study watershed, SWAT and GWLF identified mostly the same areas as CSAs. However, GWLF failed to capture some CSAs.

We also studied the effects of model calibration on location of CSAs. SWAT was applied to two watersheds with differing characteristics. CSAs were identified at HRU level (Hydrologic Response Unit) based on loadings per unit area. Results revealed that identified CSAs and their location for sediment, TP and TN were similar with calibrated and uncalibrated models in both watersheds. The study thus concluded that calibration of model based on data at the watershed outlet has little effect on location of CSAs. SWAT can thus be used with no calibration for identifying the CSAs in watersheds lacking sufficient data for model calibration.

Acknowledgments

I would like to take this opportunity to extend my sincere gratitude to my advisor Dr. Latif Kalin for his consistent guidance and encouragement throughout this study. This research would have not been possible without his contribution. I would also like to thank my committee members Dr. Puneet Srivastava and Dr. Chris Anderson for their regular assistance and direction throughout this study. I would also like acknowledge my friend Ruoyu Wang for his help during this research. Thanks are due to Auburn University's Water Resources Center for funding this project. Finally, I would like to recognize my family for their unremitting love, support and encouragement in all my endeavors.

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Introduction

Non point source (NPS) pollution, also known as diffuse pollution, occurs when precipitation runs over land, picks up pollutants, and finally deposits them into water bodies. Any pollutant picked up on its journey can become an integral part of the NPS pollution (EPA, 2010). In contrast to point sources of water pollution, such as industrial and municipal treatment plants, NPS are numerous and their contributions are difficult to quantify and regulate. Agriculture, forestry, grazing, septic systems, urban runoff, and construction are potential sources of NPS pollution (EPA, 2010). Agricultural operations have been identified as the primary sources of nutrients in the U.S. water bodies (USGS, 1999). Runoff from urban areas is the largest source of water quality impairments to surveyed estuaries in the U.S (Angle et al., 1986). The most common NPS pollutants are sediment and nutrients. For example, in the Chesapeake Bay, one of the world's largest estuaries, NPSs contribute approximately 67% of total nitrogen (TN) and 39% of total phosphorus (TP) reaching the bay (Angle et al., 1986; Chu et al 2004).

Pollutant loadings especially sediment and nutrients are related to basin characteristics. Land use/cover has a strong relationship with pollutant loadings such as nitrate (Basnyat et al., 1999). Sediment and nutrients from agriculture and urban areas are usually considered as major NPS to aquatic ecosystems and are known to have major impacts on water quality. Excessive amount of nutrients such as Nitrogen (N) and phosphorus (P) can cause problems such eutrophication, oxygen deficiency, fish kills, and loss of biodiversity, among others. It can also make the water unsuitable for drinking, industry, agriculture and recreational purposes (Carpenter et al, 1998). Urban areas have the potential to generate large quantities of NPS pollution from storm water discharge (Carpenter et al, 1998; Basnyat et al, 1999).

Considering the significant role of NPSs in water quality issues, several regulations have been enacted to address NPSs of sediment, TP, TN and other chemicals. Clean Water Act (CWA) has been established in 1972 to restore and sustain the chemical, physical as well as biological integrity of the nation's waters by preventing pollution from point and non point sources. Later, the 1987 amendments to the CWA established the Section 319 for the management of NPS pollution, which emphasizes the role of federal government to help focus state and local nonpoint source efforts. Section 303(d) of the CWA entails states to assess the condition of their waters and to implement plans to improve the quality of water bodies that are identified impaired by EPA. Each individual state has its own 303(d) impaired waters list that identifies segments where anthropogenic loads of pollutants are principal sources leading to - reduction of water quality and will continue to remain on the list until the identified pollution problem has been addressed (EPA, 1996). Addressing an identified water quality problem is a complex and potentially expensive process. Starting from establishing total maximum daily loading (TMDL) that can be discharged into a segment to meet water quality standards, there are a series of steps to allocate responsibility for load reduction, to identify pollution sources, and to secure those reductions over time (EPA, 1996).

NPSs of nutrients and sediments are always difficult to assess and control as they originate from dispersed areas and are variable in time due to climatic variations. It is extremely important to identify these sources of pollution for the effective management of water and the entire watershed. Since a watershed is composed of various land use/cover and soil types, not all parts of a watershed are critical and responsible for high pollution loads. Some areas with particular soil, land use/cover and topography are more vulnerable to generating and contributing higher nutrient and sediment loads are called Critical Source Areas (CSAs). Identification of CSAs that contribute most of the sediment and nutrients is important for cost-effective implementation of best management practices. Because, direct field studies and continuous water monitoring are usually costly and labor intensive and sometimes even spatially impractical at the watershed level, identification of such areas is often done through watershed modeling. Use of watershed models like the Soil and Water Assessment Tool (SWAT) and Generalized Watershed Loading Function (GWLF) can be useful in identifying and prioritizing sub-watersheds for management practices (Tripathi et al, 2003; Ouyang, 2007; White, 2009). However, it has not been explored yet how model choice and complexity can affect location of CSAs. In the first part of this study, the effect of model choice and complexity on location of CSAs in a medium watershed in east central Alabama is investigated.

It is common in watershed modeling studies to calibrate model parameters related to flow, sediment or nutrients using observed data at only one or two gauging stations, generally at the watershed outlet (Chu et al, 2004; Bracmort et al, 2006; Santhi et al, 2006; Ouyang et al, 2008; Ahl et al, 2008; Kumar and Marwade, 2009). This is accomplished through lumped model calibration, where model parameters are systematically changed over the entire watershed, without adequate calibration at sub-watershed scale. That means model parameters are methodically changed without even making use of the distributed nature of distributed watershed models. The most common reason for this is the lack of availability of observed data at sub-watershed level (Santhi et al, 2008). This study deals with the effect of such calibration technique on CSAs location.

If a lumped calibration results in systemic increase/decrease in loadings from all areas, then the locations of CSAs may not be affected by the calibration process at all. The second part of this thesis looks into this problem using the SWAT model in two watersheds with differing characteristics (physiography, land use distribution, topography).

Objectives

There are two main objectives of the study, which are as follows:

1. To study the effect of model choice and complexity on location of CSAs, and
2. To study the role of lumped calibration on locating N, P and sediment source areas with SWAT

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CHAPTER II

Identifying Watershed Critical Source Areas: Effect of Model Complexity

Abstract

Identification of critical source areas (CSAs) contributing most of the pollutants is important for cost-effective implementation of best management practices (BMPs). Identification of such areas is often done through watershed modeling. Various watershed models can be used for this purpose. However, it is not clear if the choice (and complexity) of model would lead to differences in locations of CSAs. Therefore, the objective of this study was to use two models of different complexity for identifying CSAs. The Soil and Water Assessment Tool (SWAT), which is a complex semi-distributed watershed model, and the Generalized Watershed Loading Function (GWLF), which is a simple lumped watershed model, were used in this study to identify CSAs of sediment and nutrients in the Saugahatchee Creek Watershed in east central Alabama. Models were calibrated and validated for streamflow, sediment, total nitrogen (TN) and total phosphorus (TP) at a monthly time scale. While both models performed well for streamflow, SWAT performed slightly better than GWLF for sediment, TN and TP. Sub-watersheds dominated by urban land use were among those producing the highest amounts of sediment, TN and TP loads, and thus identified as CSAs. Also sub-watersheds with some amount of agricultural crops were identified as CSAs of TP and TN. Hay/pasture dominated sub-watersheds were especially identified as CSAs of TN. Only 10% of the watershed was

responsible for generating approximately 39% of the sediment, 31% of the TP and 20% of the TN based on the SWAT model. Similarly, 10% of the watershed was responsible for contributing 42% of the sediment, 22% of the TP and 16% of the TN based on the GWLF model. A combined index (CI) was used to identify the sub-watersheds (CSAs) that need to be targeted for overall reduction of sediment, TN and TP. While many CSAs identified by SWAT and GWLF were the same, some CSAs were different. Therefore, this study concludes that although a simple model (such as GWLF) is useful in CSAs identification, it may not capture all the CSAs properly.

Introduction

Water body impairment due to nutrients and sediments originating from a watershed is a serious problem around the world. Approximately 47% of lakes and reservoirs and 45% of rivers and streams in the U.S. are recognized as impaired. These water bodies are listed as impaired that need immediate attention (USEPA, 2003). Nitrogen (N) and phosphorus (P) loadings from agricultural runoff are often cited as the major causes of impairment. Urban and agricultural activities are considered major sources of nutrients and sediment loading to aquatic ecosystems. Nonpoint sources of nutrients and sediments are difficult to identify and control because they originate from spatially and temporally varying areas (Carpenter et al., 1998). These nutrients can cause problems such as toxic algal blooms, oxygen deficiency, fish kills, and loss of biodiversity, among others. Nutrient enrichment can also make the water unsuitable for drinking, industrial, agricultural and recreational use (Carpenter et al., 1998).

Management of water resources and attenuation of pollutants are often done at a watershed scale. Watershed management offers a strong basis for developing and implementing effective management strategies to protect water resources (USEPA, 2003). Past efforts in reducing pollutant loads from watersheds have mainly focused on point sources and have failed to adequately address the impact of nonpoint sources that contribute to water quality impairments. If nonpoint sources of pollutants are not addressed, water bodies can continue to be impaired (USEPA, 2003). Not all parts of a watershed are equally critical and responsible for contributing high amounts of sediment and nutrient loads. Some areas with a particular type of soil, land use/cover and slope are more vulnerable than the others. These areas are known as Critical Source Areas (CSAs). It is extremely important to identify these sources of pollutants for cost-effective management practices. Identifying nutrient and sediment loss prone areas in a watershed and concentrating management efforts to these areas have been recommended by numerous studies (e.g., see Zhou and Gao, 2008). Identification of such areas can be done through either direct measurement or through simulation models (Sharpley et al., 2002). Direct water monitoring and field studies are usually costly and labor intensive, and require a number of years of monitoring to sufficiently account for climatic fluctuations. The use of watershed models, such as Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2002) and Generalized Watershed Loading Function (GWLF) (Evans et al., 2002), can avoid most limitations associated with field studies and can help in identifying and prioritizing sub-watersheds for cost-effective implementation of management practices (Tripathi et al., 2003; Ouyang, 2007; Georgas et al., 2009).

GWLF has been widely used for modeling water yield, N and P (Swaney et al., 1996; Lee et al., 2000), hydrochemistry (Schneiderman et al., 2002) and for changes in streamflow under different land use scenarios (Chang, 2003; Wu et al., 2007). GWLF has also been used for identification of CSAs at sub-watershed level (Markel et al., 2006; Georgas et al., 2009). Similarly, SWAT has been used around the world for watershed modeling of flow, sediments and nutrients (Spruill et al., 2000; Krish et al., 2002; Veith et al., 2005; Srivastava et al., 2006; Jha et al., 2007). Wagner et al. (2006) studied the impact of alternative water quality models, by comparing GWLF and SWAT, on pollutant loading for TMDL development. The use of alternative water quality models resulted in differences in required sediment reduction. The SWAT model load estimates were consistently larger than loads from GWLF. SWAT has also been used in several studies for identification and prioritization of CSAs (Tripathi et al., 2003; Kalin and Hantush, 2009; Ouyang et al., 2007; White et al., 2009). However, it is not clear if the choice (and complexity) of model would lead to differences in locations of CSAs. Therefore, the objective of this study was to use two models of different complexity for identifying CSAs. The Soil and Water Assessment Tool (SWAT), which is a complex semi-distributed watershed model, and the Generalized Watershed Loading Function (GWLF), which is a simple lumped watershed model, were used in this study to identify sediment and nutrients CSAs in the Saugahatchee Creek watershed in east central Alabama. Results of this study can help the selection of an appropriate model that can identify CSAs with high accuracy.

Methodology

Study Area

The 570 km^2 Saugahatchee Creek watershed (Fig. 1), selected for this study, is a sub-watershed of the Lower Tallapoosa sub-basin in east central Alabama. The watershed, as determined using National Land Cover Data (NLCD, 2001), is comprised of 67.8% forest, 10.0% grassland, 11.7% agricultural land (hay/pasture and row crops) and 8.4% urban area (Fig. 1). Although most of the watershed lies in the Piedmont physiographic province, a small portion lies in the Coastal Plain. The Piedmont covers a transitional area between the mostly mountainous

Appalachians in the northeast and the relatively flat Coastal Plains in southern Alabama. While the soils in the Piedmont are dominated by loam and sandy loam, soils in remaining coastal plains tend to be sandy loam based on the STASTGO soil database. The elevation ranges from 103 m to 255 m. The study area is characterized by hot summers and mild winters with average temperatures of 26 ^{o}C and 7 ^{o}C, respectively. The average annual rainfall in the watershed is 1336 mm. Alabama Department of Environmental Management (ADEM) has identified two segments within the Saugahatchee Creek watershed (Fig. 1) as being impaired for nutrients and organic enrichment/dissolved oxygen (ADEM, 2008). The nutrient of concern in both of the tributaries is phosphorus. ADEM also recommended development of TMDL for addressing water quality problems in this watershed.

Watershed Models

Soil and Water Assessment Tool (SWAT)

The SWAT model was primarily developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds over long periods of time (Neitsch et al., 2005). The model inputs consist of topography, soil properties, land use/cover type, weather/climate data, and land management practices. The study watershed is divided into several sub-watersheds (Neitsch et al., 2005). Each sub-watershed is further divided into several hydrological response units (HRU) based on topography, land use, and soil. HRUs are the smallest computational units in SWAT with unique land use, soil type and slope within a sub-watershed.

Surface runoff in each HRU is estimated using a modification of the Soil Conservation Service (SCS) curve number method (USDA, 1972). In the curve number method, daily precipitation is partitioned between surface runoff and infiltration as a function of antecedent soil moisture condition. Green & Ampt infiltration method (Green and Ampt, 1911; Mein and Larson, 1973) is another option available within SWAT to simulate surface runoff and infiltration, but this method requires sub-daily rainfall. Runoff from all HRUs in the sub-watershed yields the total sub-watershed discharge. The curve number method was used in this study. SWAT provides three possible methods to estimate potential evapotranspiration (PET): Modified Penman-Montieth, Hargreaves, and Priestley-Taylor. Modified Penman Montieth method was used in this study. Flow in SWAT is routed through channels using either Muskingum routing method or variable storage coefficient method (Neitsch et al., 2005). The latter was used in this study. Erosion and sediment yield from each HRU are estimated based on the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). MUSLE uses runoff volume and peak flow rate to simulate sediment erosion and yield instead of rainfall as erosive energy, which is used in USLE. This improves prediction accuracy and eliminates the need of delivery ratio. Sediment is routed through channels using a modification of Bagnold's sediment transport equation (Bagnold, 1977). This equation estimates sediment transport capacity as a function of flow velocity. The model either deposits or erodes sediment, depending on the sediment load entering the channel and the capacity of the flow.

SWAT models nitrogen and phosphorus cycles in detail. SWAT monitors five different pools of nitrogen and six different pools of phosphorus in soil. Three are organic (fresh residue, active humus and stable humus) while the others are organic forms. Two inorganic pools of N are nitrate and ammonia. Three inorganic pools of P are stable, inactive and active inorganic P. Mineralization, decomposition, and immobilization are important processes in both cycles, which are allowed to take place only when the temperature of the soil layer is above 0°C.

Organic N and P transport with sediment is estimated using a loading function developed by McElroy et al. (1976) and modified by Williams and Hann (1978). Daily organic N and P runoff losses are calculated by loading functions based on the concentrations of these elements in the top soil layer, the sediment yield, and an enrichment ratio. Nitrate concentration in mobile water is calculated and multiplied with total volume to estimate total nitrate lost from the soil layer. Mobile water is the sum of runoff, lateral flow and percolation. The soluble P removed in runoff is estimated using the top soil P concentration, runoff volume and a P soil partitioning coefficient. A comprehensive theoretical description of SWAT can be found in Neitsch et al. (2005).

Generalized Watershed Loading Function (GWLF)

The GWLF model is considered to be a combined distributed/lumped parameter, continuous watershed model, which has the ability to simulate runoff, sediment, and nutrient (N and P) loads from various source areas (i.e., agricultural, forested, and developed land) in a watershed. GWLF uses land use, soil, and daily weather data for calculation of water balance. For estimation of sediment and nutrient loads, monthly calculations are made based on the daily water balance aggregated to monthly values. It is considered a distributed model for surface loading because it allows multiple land uses within an area, but each area is considered to be uniform for other parameters used in the model. This model does not spatially distribute the source areas, but simply adds the loads from different source areas. The model works as a lumped parameter model using a water balance approach for modeling sub-surface loading (Haith and Shoemaker, 1987; Haith et al., 1999).

In GWLF, surface runoff is simulated using the SCS curve number method. Erosion and sediment yield is modeled using the Universal Soil Loss Equation (USLE). GWLF simulates soil erosion considering 1) soil detachment by rainfall and 2) runoff transport relationships developed by Meyer and Wischmeier (1969). A sediment delivery ratio, based on watershed size, and a transport capacity, based on average daily runoff, is then used to estimate sediment yield from each source area. Nutrient loads from rural source areas are calculated by dissolved N and P coefficients in surface runoff and a sediment coefficient in sediment load. All N and P inputs from urban areas are assumed to be in solid phase. The model uses an exponential accumulation and wash-off function for estimating urban loadings. Sub-surface losses are simulated with dissolved N and P coefficients considering a single lumped-parameter contributing area (Evans et al., 2002).

Model Inputs

The ArcSWAT 2.1 (Winchell et al., 2008) and AVGWLF 7.1 (Evans et al., 2008) were used to set up and develop models for the Saugahatchee Creek watershed. Data required in this study included Digital Elevation Model (DEM), soil properties (such as texture, soil erodibility, hydraulic conductivity, hydrologic soil group, depth , organic matter content, available water capacity), land use/cover, weather and climate, and point sources. A 10-m resolution DEM downloaded from the United States Geological Service's (USGS) seamless web server (USGS, 2008), was used to delineate the watershed and sub-watershed boundaries. State Soil Geographic (STATSGO) Database obtained from the United States Department of Agriculture National Resource Conservation Service (USDA-NRCS) was used to derive soil parameters mentioned above. Land use/cover data were obtained from the National Land Cover Dataset (NLCD) for the year 2001 (Fig. 1). Point source discharge from three point sources (North Auburn and Opelika waste water treatment plants, and West Point Stevens) were also obtained and fed into the model. Daily precipitation, minimum and maximum temperature data between January 1995 and December 2008 were collected from three NOAA weather stations (Fig. 1). Flow data for the period from 2000 to 2008 were obtained from a USGS gauging station located within the watershed (Fig. 1).

Calibration and Validation of Models

Both SWAT and GWLF models were run from 1995 to 2008; the first five years were used as a warm up period to minimize uncertain initial conditions (e.g., soil moisture, groundwater level, etc.). Models were first calibrated for flow using data from the USGS gauge station at Loachapoka (Fig. 1). Monthly flows were calibrated for the period 2000 to 2004 and validated for the period 2005 to 2008. Once the models were calibrated for flow, they were calibrated subsequently for sediment, TN and TP. Due to lack of sufficient water quality data, monthly sediment was calibrated for year 2000 and validated for year 2002. High quality data were available only for those years. Similarly, TN and TP were calibrated for the year 2000 and validated for the period 2001-2002. Various hydrologic and water quality parameters were changed within their range to get the best fit with the observed data. The parameters that were calibrated to obtain the best fit with the observed flow, sediment, TN and TP for SWAT and GWLF are listed in Table 1.

Model Evaluation Criteria

Four evaluation criteria were used to assess streamflow, sediment, TN and TP simulated by SWAT and GWLF. The first three criteria were quantitative measures while the last criterion was a visual comparison of plots of simulated and observed values. Brief description of the quantitative criteria is given below.

Percent Bias (PBIAS): *PBIAS* measures the average tendency of the simulated data to be greater or smaller than the observed data. The optimal value of *PBIAS* is 0. Positive values indicate model over estimation, and negative values signify model under estimation (Yapo et al., 1999).

$$PBIAS(\%) = \frac{(\sum S - \sum O)}{\sum O} * 100 \quad (1)$$

In equation (1), *O* and *S* are observed and simulated values, respectively. Model performances are considered satisfactory if *PBIAS* is ± 25% for streamflow, ± 55% for sediment, and ± 70% for N and P (Moriasi et al., 2007).

Nash-Sutcliffe efficiency (NSE): *NSE* determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970). *NSE* indicates how well the plot of observed versus simulated data fits the 1:1 line. *NSE* is computed as

$$NSE = 1 - \frac{\sum (O-S)^2}{\sum (O-\bar{O})^2} \quad (2)$$

where, *O* and *S* are observed and simulated values, respectively, and $\bar{O}$ is the mean of observed values. *NSE* value ranges between -∞ and 1 with *NSE* of 1 being the optimal value. Simulation results are considered very good if *NSE* > 0.75, while values above 0.5 is considered to be satisfactory (Moriasi et al., 2007).

Coefficient of Determination (R^2): R^2 describes the proportion of the total variance in the observed data that can be explained by a linear model. Its range is from 0 to 1, and is calculate as

$$R^2 = \frac{[\sum(O-\bar{O})(S-\bar{S})]^2}{[\sum(O-\bar{O})^2][\sum(S-\bar{S})]^2} \quad (3)$$

where, O and S are observed and simulated values, respectively. In the equation, $\bar{O}$ and $\bar{S}$ are the mean of observed and simulated values, respectively. While R^2 >0.5 is generally considered acceptable for modeling, a higher value is better (Moriasi et al., 2007).

Identification of Critical Source Areas (CSAs)

CSAs were identified at sub-watershed level. The sediment and nutrient yields from each sub-watershed were analyzed based on loadings per unit area to identify the CSAs. Maps were created based on these loadings to depict the CSAs separately for sediment, TN and TP based on simulation results from both SWAT and GWLF models. Sub-watersheds were ranked in descending order based on loads per unit area. The sub-watershed with the highest load per unit area was ranked first and so on. Cumulative percent loads were then plotted against cumulative percent area. Moving from the highest ranking to the lowest, sub-watersheds that collectively contribute 20% of the sediment, TP and TN were considered CSAs. Different CSAs for sediment, TN and TP were obtained. The 20% threshold was an arbitrary choice. The purpose here was to demonstrate the methodology. Actual threshold is a function of cost of implementing management practices. For instance, if there is little money for implementation of management practices a lower threshold is needed.

A combined index was also defined to identify the sub-watersheds that can be considered as CSAs and need to be targeted for overall reduction of sediment, TN and TP. This index is given by

$$I_j = \sum(\omega_i * Y_{i,j}) \quad (4)$$

where, I_j is the combined index for watershed j, $Y_{i,j}$ is an index for sediment (i = 1), TN (i = 2) and TP (i = 3) for sub-watershed j, and is defined as

$$Y_{i,j} = \frac{R_{i,min} - R_{i,j}}{R_{i,min} - R_{i,max}} \tag{5}$$

where, $R_{i,j}$ is the rank of watershed j for constituent i, and $R_{i,min}$ and $R_{i,max}$ are respectively the lowest and highest ranks for constituent i. Note that $R_{i,max}$ = 1, $R_{i,min}$ = total number of sub-watersheds and $0 \leq Y_{i,j} \leq 1$. For our study watershed $R_{i,min}$ and $R_{i,max}$ are 106 and 1, respectively. In equation (4), ω_i is a subjectively chosen weight given to each Y_i based on their importance, where $\Sigma\omega_i = 1$.

Results and Discussion

Calibration/Validation of SWAT and GWLF (monthly time scale)

Flow: Table 1 shows calibrated parameters for SWAT and GWLF models, respectively. Both SWAT and GWLF models were able to predict the monthly streamflows with high accuracy (Fig. 2a). According to the performance statistics (Table 2), SWAT and GWLF performed equally well with respect to *NSE* and R^2. However, SWAT performed slightly better than the GWLF on the basis of *PBIAS*. During both calibration and validation periods, *PBIAS* with SWAT (+3.1% and -1.4%, respectively) was better than those with GWLF (-6.7% and +3.5%, respectively). Both models were able to capture the months with high- and low-flows (Fig. 2a).

Sediment: Although both SWAT and GWLF models were able to predict the monthly sediment loading with sufficient accuracy (Fig. 2b & Table 2), SWAT performed better than GWLF during both calibration and validation periods on the basis of *NSE* and R^2. However, SWAT and GWLF performed equally well based on *PBIAS* during both calibration and validation periods.

SWAT overestimated sediment by 0.9% and 3.7% during the calibration and validation periods, respectively, while GWLF underestimated the monthly sediment loadings by 0.5% during the calibration period and overestimated by 4.0% during the validation period.

Total Nitrogen: Both models predicted the monthly TN loadings with sufficient accuracy (Fig. 2c & Table 2). SWAT performed slightly better than GWLF on the basis of *NSE* and R^2 during both calibration and validation periods. However, SWAT performed better based on *PBIAS*. SWAT underestimated TN loading by 2.4% during the calibration period and underestimated by 0.3% during the validation period. GWLF overestimated TN loading by 7.8% during the calibration period and underestimated by 9.0% during the validation period.

Total Phosphorus: Even though both SWAT and GWLF models predicted monthly TP loadings well (Fig. 2d & Table 2), SWAT performed better than GWLF on the basis of performance statistics (*NSE*, R^2 and *PBIAS*) during both calibration and validation periods. SWAT overestimated phosphorus loading by 7.0% during the calibration period and underestimated by only 0.1% during the validation period. GWLF overestimated TP by 10.2% and underestimated by 7.8% during the calibration and validation periods, respectively.

Critical Source Areas (CSAs)

We applied the calibrated and validated SWAT and GWLF models to identify the CSAs in the Saugahatchee Creek watershed at sub-watershed level and compared the CSAs identified by each model. Different CSAs were identified with respect to sediment, TN and TP loadings because the factors driving each are likely to be different, but not mutually exclusive. To eliminate the effect of differences in areas of the sub-watersheds, annual loadings per unit area were used to identify the CSAs.

Results showed that, only 10% of the watershed was responsible for generating approximately 39% and 42% of the sediment yield based on SWAT and GWLF results, respectively (Fig. 3). Similarly, 10% of the watershed was responsible for contributing 31% and 22% of the TP loads based on SWAT and GWLF models (Fig. 3). However, 10% of the watershed was responsible for generating approximately 20% of TN loads based on SWAT results and only 16% based on GWLF results (Fig. 3).

***CSAs of Sediment*:** Both models produced somewhat similar areas as CSAs of sediment (Fig. 4a & 4d). Based on 20% contribution, 5 sub-watersheds covering 4.2% area of the watershed area were identified as CSAs by GWLF. Similarly, 6 sub-watersheds covering 4.6% area were identified as CSAs by SWAT. Although the ranks are not exactly in the same order, sub-watersheds 25, 53, 56, 69 and 73 were identified as CSAs by both SWAT and GWLF models. Sub-watershed 23 was also identified as a CSA of sediment by SWAT. While average sediment yield ranged from as high as 9.77 tons/ha/yr to as low as 0.06 tons/ha/yr based on the SWAT results (Fig. 4a), it ranged between 0.07 tons/ha/yr and 6.15 tons/ha/yr based on GWLF results (Fig. 4d). This showed that sediment yields obtained by SWAT showed larger variation than GWLF generated sediment yields. However, sediment yield only from the CSAs ranged from 5.42 tons/ha/yr to 9.77 tons/ha/yr based on SWAT and 4.46 tons/ha/yr to 6.15 tons/ha/yr based on GWLF. These rates are much higher than other CSA studies. For instance, White et al. (2009) found the average sediment yield of 2.0 tons/ha/yr from CSAs in the Wister Lake Basin.

***CSAs of TP*:** In spite of the fact that most of the CSAs of TP identified by each model overlap, several sub-watersheds were identified as CSAs by one model and not by the other. While SWAT identified 7 sub-watersheds (5.8% area) as CSAs for TP, GWLF identified 11 sub-watersheds (9.6% area) as CSAs. Although the ranks are not exactly in the same order, sub-watersheds 25, 51, 53, 56, 59, 69, and 73 were identified as CSAs of TP by both the SWAT and the GWLF models. Sub-watersheds 64, 79, 88 and 97 were also identified as CSAs of TP by GWLF but not by SWAT. While TP loadings ranged from 0.02 kg/ha/yr to 0.87 kg/ha/yr according to results from SWAT (Fig. 4b), TP loadings varied between 0.06 kg/ha/yr and 0.71 kg/ha/yr according to results from GWLF (Fig. 4e). This again showed that SWAT generated outputs showed wider range than GWLF generated outputs. TP yields only from the CSAs ranged from 0.55 kg/ha/yr to 0.87 kg/ha/yr based on SWAT and between 0.40 kg/ha/yr and 0.71 kg/ha/yr based on GWLF. Not exactly comparable, but Ouyang et al. (2007) found the organic P yields from the CSAs in Bahe River watershed ranging from 0.16 kg/ha/yr to 0.34 kg/ha/yr.

***CSAs of TN*:** While 10 sub-watersheds (10.5% area) were identified as CSAs by SWAT model, 13 sub-watersheds (13% area) were considered as CSAs by GWLF. Both models identified sub-watersheds 4, 56, 69, 79, 88, 97 and 103 as CSAs. Sub-watersheds 25, 73 and 102 were also identified as CSAs based on SWAT, but not by GWLF. Similarly, sub-watersheds 1, 11, 14, 53, 59 and 85 were identified as CSAs by GWLF, but not by SWAT. While TN loadings ranged between 0.57 kg/ha/yr and 5.31 kg/ha/yr based on SWAT results (Fig 4c), it ranged between 0.85 kg/ha/yr and 4.73 kg/ha/yr according to GWLF (Fig. 4f). Again, SWAT had more variation in TN loadings. TN yield only from the CSAs varied between 3.57 k/ha/yr and 5.31 kg/ha/yr based on SWAT and between 3.00 and 4.73 kg/ha/yr based on GWLF. Ouyang et al. (2007) found the

Organic N yield from the CSAs in the Bahe River watershed varying from 0.68 kg/ha/yr to 1.32 kg/ha/yr. Georgas et al. (2009) found high residential urban areas as the most important sources of TN with an average yield of 11.9 kg/ha/yr from those areas.

Combined CSA Index

Combined CSA index I_j was determined for each sub-watershed j by assigning the same weights to sediment, TN, and TP (ω_i = 1/3). Sub-watersheds with $I_j \geq 0.9$ were subjectively identified as CSAs collectively for all parameters (sediment, TN and TP). Again, the purpose here was to present the idea. The threshold 0.9 was chosen so that we deal with a manageable number of CSAs. A map (Fig. 5) was produced to show these CSAs based on results from both SWAT and GWLF models to visualize the differences. Sub-watersheds 25, 53, 56, 59, 69 and 73 had $I_j \geq 0.9$ based on both models and thus were identified as CSAs by both models. However, sub-watersheds 23 and 51 had $I_j \geq 0.9$ only based on SWAT results and thus were also identified as CSAs based on SWAT. Likewise, sub-watershed 88 had $I_j \geq 0.9$ only based on GWLF results and thus was identified as a CSA. The CSAs identified by SWAT covered only 6.5% of the watershed area and contributed 26.5% of the sediment, 23.1% of TP and 13.9% of TN loadings. Similarly, CSAs determined by GWLF covered 5.6% of the watershed and were responsible for contributing 23.1% of sediment, 16.5% of TP and 12.7% of TN.

While sub-watersheds 23, 25, 51, 53, 56, 59, 69 and 73 were all dominated by urban land use/cover with considerable amount of pasture land, sub-watershed 88 was comprised of some cropland and lay predominantly on the coastal plain soils. It was clear from this study that, sub-watersheds dominated by urban area were among those producing highest amount of sediment and nutrient loads and thus were identified as CSAs. Also sub-watersheds with some amount of agricultural crops were identified as CSAs of TP and TN. Hay/pasture dominated sub-watersheds were especially identified as CSAs of TN. In all these sub-watersheds, except sub-watershed 88, urban areas cover more than 40% of the sub-watershed areas. In the case of sub-watershed 88, it constitutes higher cropland area compared to other sub-watersheds. Detail land use compositions of combined CSAs are provided in Table 3.

Differences in Model Performances and Identified CSAs

As mentioned earlier, both SWAT and GWLF performed equally well for streamflow. This could be because both models use the same method (USDA SCS Curve Number) for estimating runoff. However, in the case of sediment, TN and TP, SWAT performed better than GWLF. In the case of sediment, there was also a difference in one of the CSAs identified by the two models. While GWLF uses the conventional USLE method for estimating soil erosion, SWAT uses the MUSLE equation. USLE uses rainfall intensity as the erosive energy, whereas MUSLE uses runoff volume and peak flow rate to simulate sediment erosion and yield. This improves the prediction accuracy and also eliminates the need for delivery ratio. In the case of TN and TP, GWLF simply uses dissolved coefficient for estimating loads from rural areas and export coefficients for estimating loads from urban areas. On the other hand, SWAT models N and P cycles comprehensively. Processes like mineralization, decomposition, immobilization is allowed to take place in the soil in each HRU. Thus, SWAT provides a more mechanistic and process-based approach than GWLF. As a result SWAT predicted sediment, TN and TP loads better than GWLF. Further, because SWAT and GWLF conceptualizes sediment, TN and TP processes differently, there were some variations in the locations of identified CSAs. Also, since SWAT divides the sub-watersheds into smaller computational units, i.e. HRUs, there is a greater chance that it can distinguish sub-watersheds with higher loadings than the others. It was also illustrated by the wide range of outputs generated for sediment, TN and TP.

Implications of Not Choosing the Right Model

Results showed that not choosing the right model may have important implications. For instance, GWLF identified 4 extra sub-watersheds as CSAs for TP compared to SWAT. They had 7 sub-watersheds in common as CSAs. So, if GWLF is used as the base in deciding where to implement BMPs, about 65% more area should be targeted compared to SWAT. This might have extremely important economic implications. The differences in locations of CSAs were more evident with TN. Out of the 13 CSAs identified by GWLF only 7 were also recognized as CSA by the SWAT model. That means GWLF has 6 sub-watersheds not identified as CSA by SWAT. Note that we are not promoting one model over another, rather pointing out the differences in CSAs due to the use of two different models. On the other hand, SWAT has its advantages over GWLF. It can capture CSAs at much smaller scale than sub-watershed level (i.e. HRU level), which GWLF cannot. Further, SWAT relies less on empirical relationships than GWLF and has more physical basis. Therefore, we have more confidence in areas identified as CSA by the SWAT model.

Summary and Conclusions

Two watershed models, SWAT (a complex semi-distributed model) and GWLF (a simple lumped model), with different complexities were set up, calibrated, and validated in a southeastern Alabama watershed. The models were then utilized to identify critical source areas

(CSAs) of sediment, TN and TP for implementation of cost- effective management practices in the watershed.

Based on the overall model performance statistics, it can be concluded that SWAT performed slightly better than GWLF. Although, performance of GWLF was similar to SWAT for streamflow for both calibration and validation periods, SWAT performed better for sediment, TN and TP. The calibrated and validated models were used to identify the CSAs in the study watershed at the sub-watershed level based on loadings per unit area. In general, sub-watersheds dominated by urban area were among those producing the highest amount of sediment, TN and TP loads, and thus were identified as CSAs. However, sub-watersheds with some amount of agricultural crops were also identified as CSAs of TP and TN. Hay/pasture dominated sub-watersheds were identified as CSAs especially for TN.

This study revealed that CSAs can vary based on the parameters of interest (sediment, TN or TP). Based on a combined index, while 8 sub-watersheds were identified as CSAs by the SWAT model, 7 sub-watersheds were identified as CSAs by the GWLF, among which 6 sub-watersheds were identical. Therefore, although there were similarities in many of the identified CSAs based on the two models, not all CSAs identified by the models were mutual. GWLF failed to recognize two sub-watersheds - identified as CSAs by SWAT model. Similarly SWAT did not detect one sub-watershed that was identified as CSA by GWLF. Dissimilarities in CSAs are attributed to the differences in model conceptualizations implemented in the SWAT and GWLF models. GWLF rely more on empirical relationships compared to SWAT. On the other hand, SWAT is more process-based. Furthermore, since SWAT computes sediment and nutrient loads at HRU level, it can identify CSAs within sub-watersheds if required, which is not possible with GWLF. This study concluded that although a simple model (GWLF) is useful in watershed modeling and identification of CSAs, it may not capture all the CSAs properly.

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Table 1: SWAT and GWLF adjusted parameters.

SWAT adjusted parameters	GWLF adjusted parameters
Initial SCS Runoff curve number for moisture condition II (CN2)	Curve number
Soil evaporation compensation factor (ESCO)	Recession coefficient
Threshold depth of water in shallow aquifer required for the return flow to occur (GWQMIN)	Seepage coefficient
Exponent parameter for calculating sediment re-entrained in channel sediment routing (SPEXP)	Sediment A factor
Peak rate adjustment factor for sediment routing in the main channel (PRF)	Erosivity coefficient
Surface runoff lag time (SURLAG)	Nitrogen in sediments
Peak rate adjustment factor for sediment routing in the main channel (ADJ_PKR)	Phosphorus in sediments
Support practice factor (USLE_P)	C factor
Phosphorus percolation coefficient (PHOSKD)	P factor
Phosphorus soil partitioning coefficient (P-UPDIS)	Nitrogen runoff coefficient
Phosphorus uptake distribution factor (PSP)	Phosphorus runoff coefficient
Phosphorus sorption coefficient (PPERCO)	Nitrogen in groundwater
Rate constant for decay of organic phosphorus to dissolved phosphorus (BC4-BSN)	Phosphorus in groundwater
Michaelis-Menton half saturation constant for phosphorus (K_P)	
Initial soluble P concentration in surface soil layer (SOL_LABP)	
Nitrogen percolation coefficient (NPERCO)	
Michaelis-Menton half saturation constant for nitrogen (K-N**)**	
Initial NO_3 concentration in the soil (SOL_NO_3)	

Table 2: Performance measures of the SWAT and the GWLF during calibration and validation periods for flow, sediment, TN and TP.

Parameter	Model	Calibration			Validation		
		NSE	R^2	PBIAS (%)	NSE	R^2	PBIAS (%)
Streamflow	SWAT	0.90	0.90	+3.1	0.74	0.78	-1.4
	GWLF	0.91	0.92	-6.7	0.79	0.82	+3.5
Sediment	SWAT	0.72	0.72	+0.9	0.86	0.87	+3.7
	GWLF	0.68	0.68	-0.5	0.78	0.81	+4.0
TN	SWAT	0.75	0.81	-2.4	0.90	0.92	-0.3
	GWLF	0.70	0.78	+7.8	0.87	0.91	-9.0
TP	SWAT	0.85	0.89	+7.0	0.88	0.91	-0.1
	GWLF	0.65	0.79	+10.2	0.87	0.88	-7.8

Table 3: Land use composition of combined CSAs.

Sub-watershed	Urban (%)	Forest (%)	Hay/Pasture (%)	Agricultural Crop (%)
23	43.2	43.1	8.8	N/A
25	74.8	20.6	2.4	N/A
51	54.0	41.8	0.6	0.1
53	64.1	31.0	2.7	0.1
56	82.0	13.0	3.4	N/A
59	64.0	20.8	3.4	0.02
69	69.0	25.3	2.5	2.5
73	54.3	34.2	5.2	0.8
88	60.0	25.4	3.3	6.3

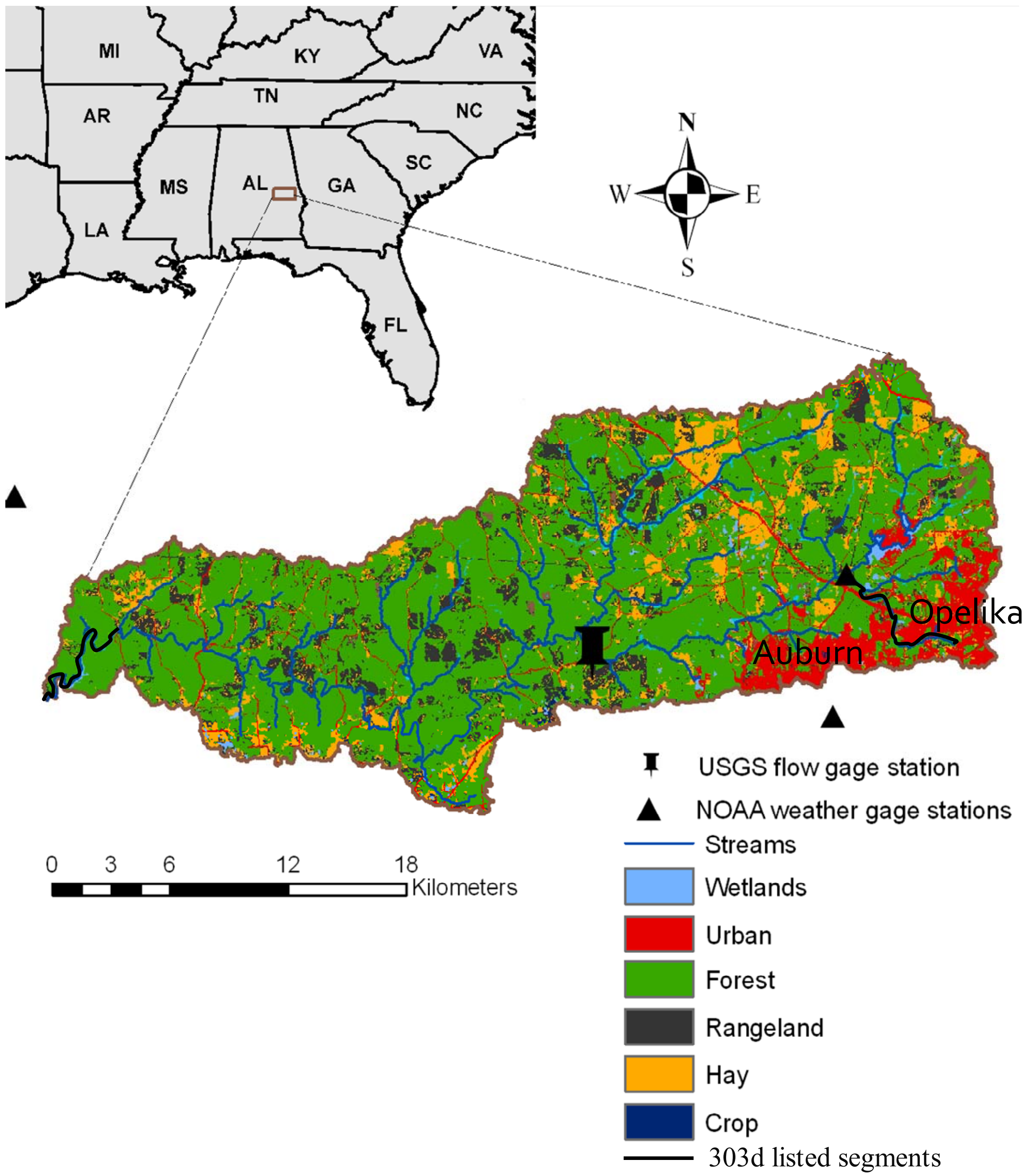

Fig. 1. Saugahatchee Creek Watershed in east central Alabama. Also shown are land use/cover and USGS flow and NOAA weather gaging stations.

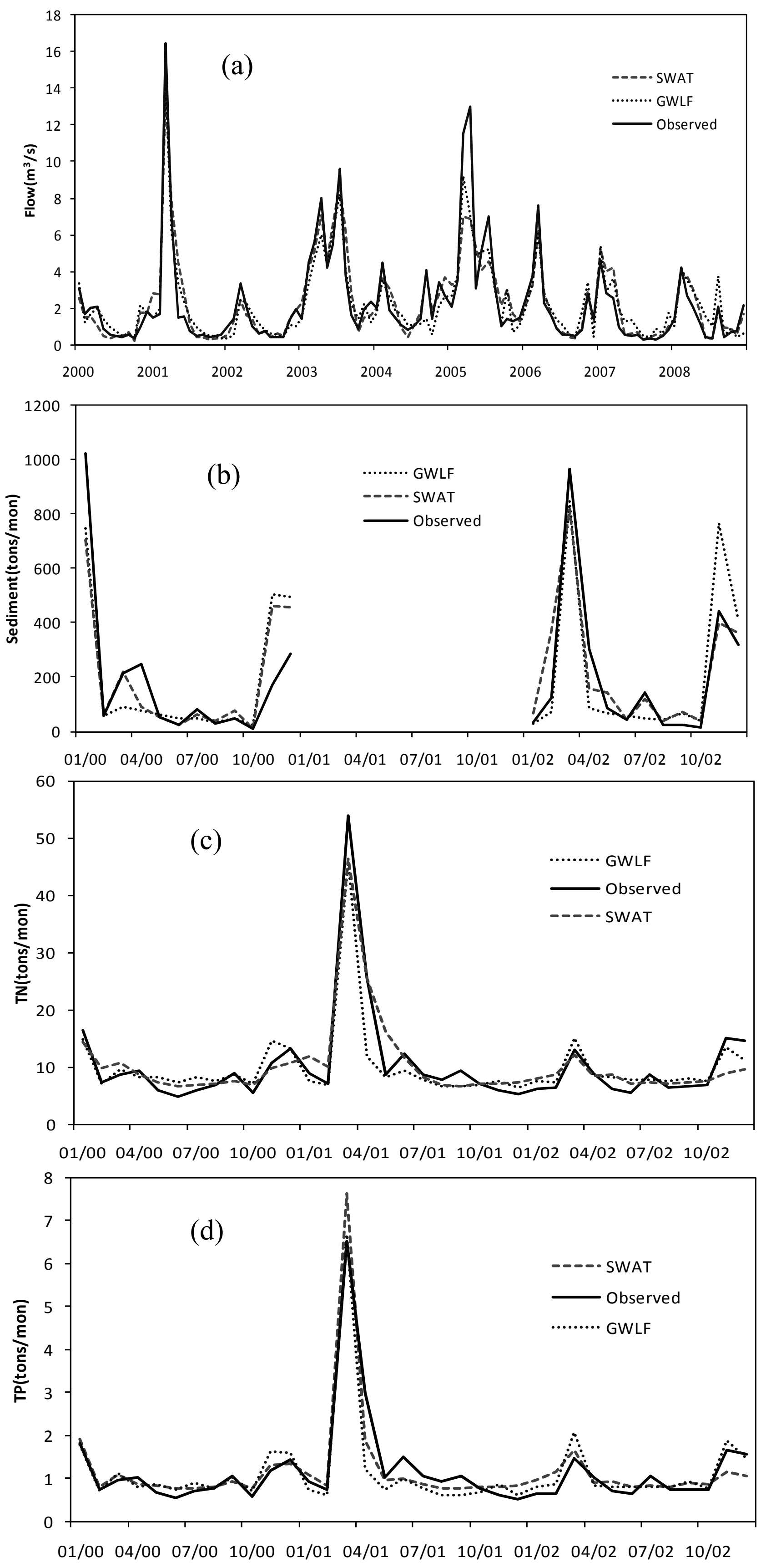

Fig. 2. Observed, SWAT-simulated, and GWLF-simulated monthly (a)flows, (b)sediment, (c)TN, and (d)TP, for the calibration and validation periods.

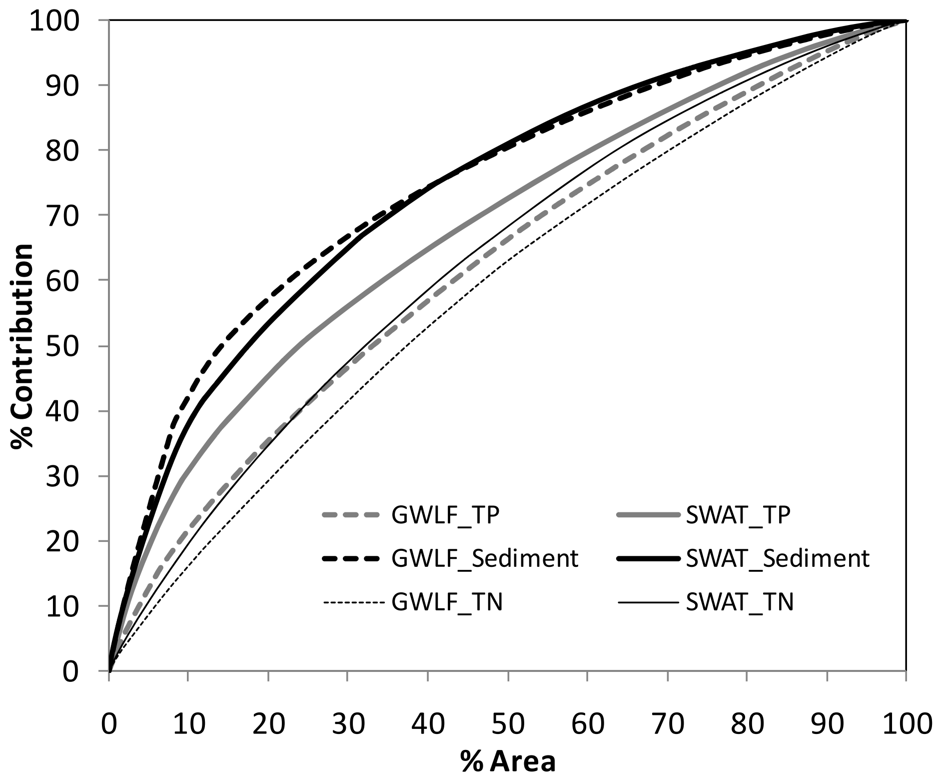

Fig. 3. Contribution of sediment, TN and TP load fraction as a function of watershed fraction.

SWAT **GWLF**

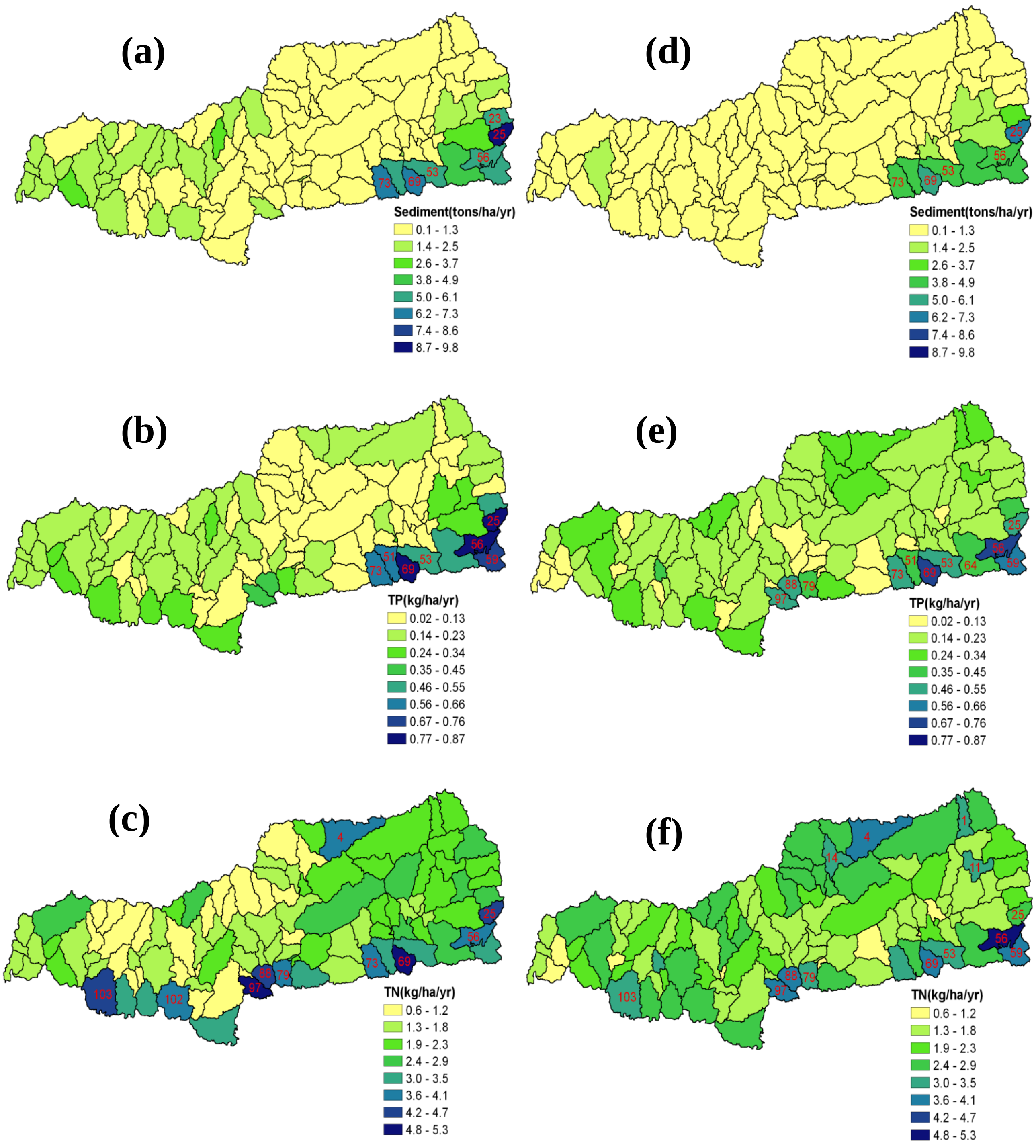

Fig.4. Sediment, TP and TN yields from each sub-watershed as estimated by (a, b, c respectively) SWAT and (d, e, f respectively) GWLF models.

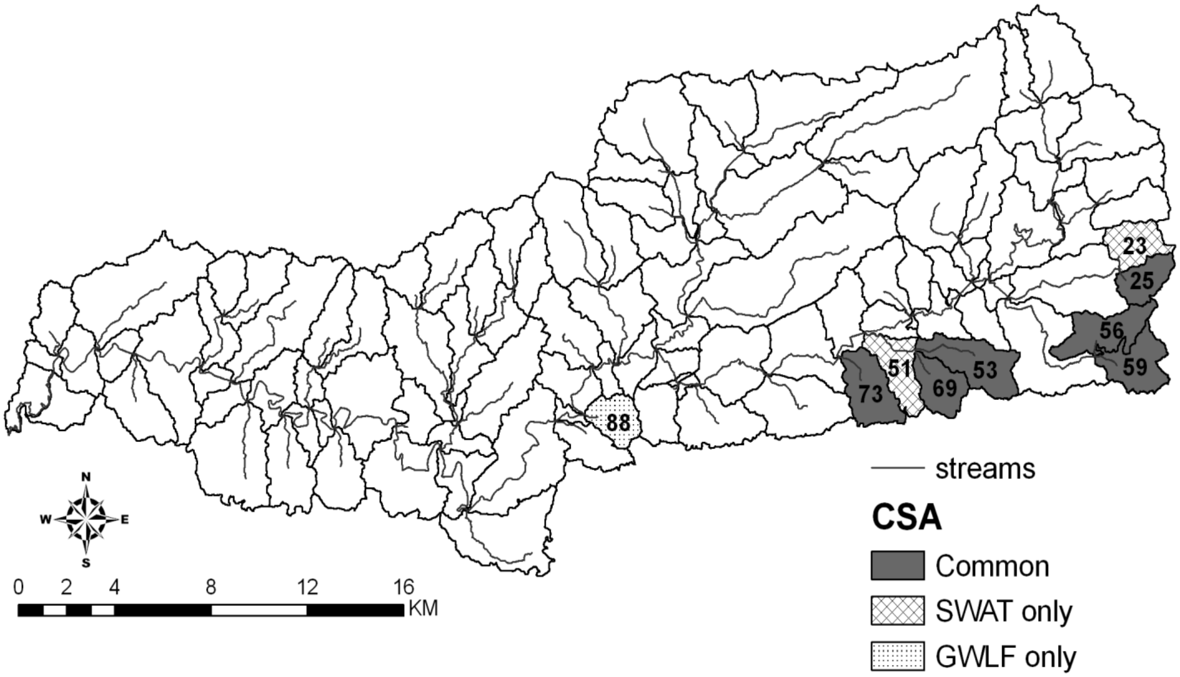

Fig. 5. Critical source areas based on combined index. These sub-watersheds should be first targeted for management practices for overall reduction of sediment, TP and TN loads.

CHAPTER III

Role of Lumped Calibration on Locating N, P and Sediment Source Areas with SWAT

Abstract

In most watershed modeling studies, due to limited data, model parameters for flow, sediment and nutrients are calibrated and validated against observed data only at the watershed outlet. Model parameters are adjusted systematically for the entire watershed to obtain the closest match between model simulated and observed data at the watershed outlet (*lumped calibration*). The relative loadings of pollutants and/or sediments contributed by each computational unit may or may not be affected by this calibration procedure. In other words, areas generating relatively higher pollutant loads with an uncalibrated model may likely keep generating higher loads after calibration. This study explored the effect of lumped calibration of the SWAT model on locations of sediment and nutrient critical source areas (CSAs). Two watersheds in Alabama, USA, with differing size, topography, hydrology, and land use/cover characteristics were used to study the effects of model calibration on locations of sediment, total phosphorous (TP), and total nitrogen (TN) CSAs. It was found that land use/cover, soil type, and slope can equally play significant roles in determining CSAs. Results revealed that, identified CSAs for sediment, TP and TN were mostly the same with and without the calibration of the model in both watersheds. This study thus concluded that lumped calibration of the SWAT model using data at the watershed outlet, which is commonly practiced, has little effect on the locations of CSAs. Thus,

if the objective is to identify CSAs, SWAT can be used without calibration in watersheds that lack sufficient observed data for model calibration.

Keywords: Source Area, SWAT, Watershed, Sediment, Nutrient, Model, Calibration

Introduction

Nonpoint source (NPS) pollution, unlike pollution from specific point sources, such as discharge from industries and wastewater treatment plants, originates from numerous diffuse sources. It is caused by excess precipitation moving over and under the ground where it picks up and carries away natural and anthropogenic pollutants from agricultural lands, urban areas, construction sites, forested lands, and pasture lands, and ultimately depositing them into surface water bodies as well as groundwater (USEPA 2010). Major agricultural activities that are responsible for NPS pollution are poorly managed animal feeding operations, overgrazing, frequent plowing, and excessive application of fertilizers and pesticides (USEPA 2002). Construction and use of roads are the prime NPS of pollution from forest areas (USEPA 2002). Urbanization can enhance the variety and quantity of pollutants carried into water bodies (USEPA 2002). Five different source areas, mainly lawns, parking lots, roofs, roads and streets, located in the residential, commercial and industrial portion of urban areas are primarily responsible for most of the phosphorus and heavy metals in urban watersheds (Bannerman and others 1993).

NPSs are considered the principal contributors of nitrogen (N) and phosphorus (P) to most surface waters. N and P inputs from these sources can cause eutrophication of lakes and reservoirs (USEPA 2004). Approximately 82% of N and 84% of P discharged to US surface water bodies come from NPSs (Carpenter and others 1998). Spatial distribution of sediment sources is not homogeneous across a watershed (Ballantine and others 2009). While some areas may erode and contribute more to sediment, other parts may have no contribution at all. The critical sources of sediment associated with P are those hydrologically active areas that overlap with easily erodible soil with high P concentrations (Pionke and others 2000; Ballantine and others 2009). These source areas are often located in relatively small definable areas near the streams (Russell and others 2001; Ballantine and others 2009). Thus, not all parts of a watershed are equally critical and responsible for producing high amounts of sediment and nutrient loads (Ouyang and others 2008). Some unique areas within a watershed with particular soil, land use/cover, and topography are responsible for contributing higher sediment, nitrogen and phosphorus loads, which are known as critical source areas (CSAs). Available, but often limited, resources should be directed at these identified CSAs to improve water quality (Smith and others 2001). Management practices implemented in these targeted areas have the potential of being more effective at treating larger quantities of pollution (White and others 2009).

Distributed watershed models are often used to identify these CSAs. In most watershed modeling studies, models are calibrated for flow, sediment or nutrients using observed data at one or two locations, generally at the watershed outlet (Chu and others 2004; Hoa and others 2005; Santhi and others 2006; Ouyang and others 2008; Ahl and others 2008; Kumar and Marwade 2009). This is the case even with distributed models, where model parameters for the entire watershed are adjusted, without adequate calibration and validation at sub-watershed level, to ensure that model simulations match observed data at the outlet (Santhi and others 2008). This means that parameters are systematically changed without actually making use of the distributed nature of the models, which we refer in this study as “lumped calibration.” The most common reason for this is the lack of observed data at various locations inside the watershed (Santhi and others 2008). What makes one area a CSA as compared to another is its relatively higher loading. If a lumped calibration results in a systematic increase or decrease in loadings from all areas, or if there is a monotonic relationship between model parameters and model outputs, then location of CSAs may not be affected by the calibration process.

Watershed models such as the Soil and Water Assessment Tool (SWAT) (Neitsch and others 2005) can be used to predict the locations of pollution CSAs in watersheds (White and others 2009). Although SWAT was primarily developed for use with no calibration in ungauged basins (Santhi and others 2001), its widespread application is with calibration because of improved performance. The SWAT model has been used around the world for various purposes ranging from modeling daily stream flow (Spurill 2000), predicting sediment and phosphorus (Krish and others 2002; Veith and others 2005), impact of urbanization on hydrology (Kalin and Hantush 2006; Jha and others 2007), impact of land use and climate change (Wang and others 2008) and management practices (Vache and others 2002; Santhi and others 2001). There are limited studies in the literature that used the SWAT model without calibration. Some studies used SWAT in an uncalibrated mode to eliminate the bias caused by parameter optimization for modeling streamflow (Rosenthal and others 1995; Heathman and others 2008). The SWAT model was also used in the uncalibrated mode to predict changes in water yield in a large river basin resulting from doubled CO_2 concentration (Stone and others 2001), to estimate surface water quality impacts from riparian buffers (Qiu and Prato 2001) and to study the impacts of soil and land use/cover datasets on simulated flow (Heathman 2009). Calibrated SWAT model has also been used to identify and prioritize critical sub-watersheds for soil conservation management in small watersheds (Tripathi and others 2003) and for identification of critical source areas of NPS pollution (Ouyang and others 2008; Kalin and Hantush 2009; Busteed and others 2009; White and others 2009).

Past studies on identification of pollutant CSAs relied on either calibrated or uncalibrated watershed models. Yet, to the best of our knowledge, no study has explored how locations of CSAs are affected due to a calibrated/uncalibrated model. When model parameters are systematically adjusted over the entire watershed, the relative loadings of pollutants and/or sediments contributed by each computational unit may not be affected. Thus, we hypothesize that the locations of CSAs may not change due to lumped calibration. In this paper, we use calibrated and uncalibrated SWAT models in two watersheds with different characteristics to identify and compare the locations of sediment, TP and TN CSAs.

Methods

Study Area

Two watersheds differing in size, physiographic characteristics, land use/cover composition, climate, and hydrology (Table 1) were selected for this study to test the above hypothesis. Brief descriptions of each watershed are provided below.

Saugahatchee Creek watershed

The Saugahatchee Creek watershed at Loachapoka (Fig. 1), which covers an area of 180 km^2, is part of the Lower Tallapoosa basin in eastern Alabama. Although major portion of the watershed lies in the Piedmont physiographic province, a very small portion lies in the Coastal Plain. The soils in the Saugahatchee Creek watershed are dominantly sandy loam based on the STATSGO soil database. The watershed is comprised of 59.0% forested land, 21.0% urban area, 9.4% agricultural land (hay/pasture and row crops), and 6.8% grassland (NLCD 2001). The elevation ranges between 158 m and 255 m with an average elevation of 213.5 m. The average slope of the watershed is 6.6% based on DEM analysis.

Magnolia River watershed

The Magnolia River watershed (Fig. 1) is located on the Gulf of Mexico in Baldwin County, south Alabama and drains to Weeks Bay, a sub estuary to Mobile Bay. The watershed covers an area about 45 km^2. It is dominantly agricultural land (43.0%) followed by pasture (25.0%), wetland (11.5%), urban (11.0%) and forest (8.2%) (NLCD 2001). The watershed is in a coastal area, and the majority is covered by sandy soil based on SSURGO soil database. Unlike the Saugahatchee Creek watershed, this watershed is relatively flat with an average slope of 1.0% and average elevation of 25.3 m based on DEM analysis.

SWAT Model

SWAT is a process-based, semi-distributed watershed model. It was primarily developed to predict the impact of management practices on water, sediment and agricultural chemicals in watersheds comprising different soils, land use and management conditions over long periods of time (Neitsch and others 2005). The major model inputs are topography, soil properties (such as texture, soil erodibility, hydraulic conductivity, hydrologic soil group, depth , organic matter content, available water capacity), land use/cover type, weather/climate, and land management practices. SWAT requires the watershed divided into several sub-watersheds, which are further divided into several hydrological response units (HRUs) according to topography, land use, and soil. An HRU is a combination of unique land use, soil type and slope. Surface runoff from daily precipitation is estimated with a modification of the SCS curve number method (USDA 1972). Runoff from all HRUs in the sub-watershed yields the total sub-watershed discharge. Potential evapotranspiration (PET) can be calculated with Modified Penman-Montieth, Hargreaves or Priestley-Taylor methods. Either the Muskingum routing or the Variable Storage routing method can be applied for routing flow through channels.

In SWAT, erosion and sediment yield from each HRU are predicted based on the modified universal soil loss equation (MUSLE) developed by Williams (1975). Channel sediment is routed based on a modified Bagnold's sediment transport equation (Bagnold 1977). SWAT has complex N and P cycles, where mineralization, decomposition, and immobilization are important processes. Plant use of N and P is estimated using the supply and demand approach of Williams and others (1984). Organic N and P transport with sediment is calculated with a loading function (Williams and Hann 1978). Daily organic N and P loss through runoff are calculated by loading functions based on the concentrations in the top soil, sediment yield, and an enrichment ratio. Concentration of nitrate in mobile water is calculated and multiplied with volume of water moving in each pathway to obtain nitrate lost from the soil layer. The soluble P removed in runoff is estimated using the top soil P concentration, runoff volume and a phosphorus soil partitioning coefficient. Neitsch and others (2005) provides a detailed description of the SWAT model.

Model Evaluation

The performance of the SWAT model was evaluated qualitatively by visual observation of graphs and quantitatively using Nash-Sutcliffe efficiency (E), Percent Bias (P_b) and coefficient of determination (R^2). The E (Eq. 1) indicates how well the plot of observed against simulated data fits the 1:1 line (Nash and Sutcliffe 1970). Its value lies between -∞ to 1 with 1 indicating a perfect model. P_b (Eq. 2) is the measure of average deviation of simulated set of data from the observed ones and theoretically varies from -∞ to ∞ with 0 representing a perfect model. R^2 (Eq. 3) describes the degree of linear correlation between observed and simulated values with a range from 0 to 1.

$$E = 1 - \frac{\Sigma(O-S)^2}{\Sigma(O-\bar{O})^2} \tag{1}$$

$$P_b(\%) = \frac{(\Sigma S - \Sigma O) * 100}{\Sigma O} \tag{2}$$

$$R^2 = \frac{[\Sigma(O-\bar{O})(S-\bar{S})]^2}{[\Sigma(O-\bar{O})^2][\Sigma(S-\bar{S})]^2} \tag{3}$$

where, O and S are observed and simulated values, respectively. In equations (1) and (3), $\bar{O}$ and $\bar{S}$ are the mean of observed and simulated values, respectively.

Model calibration and validation

The SWAT model was first setup at the Saugahatchee Creek watershed and run for 14 consecutive years, from 1995 to 2008. The first five years was to warm up the model in order to minimize uncertainties due to initial unknown conditions, especially to reduce the effect of antecedent soil moisture conditions. Streamflow, sediment, TP and TN were calibrated and validated on a monthly time scale at the watershed outlet. Streamflow was calibrated for the period from January 2000 to December 2004 (5 years) and validated for the period January 2005 to December 2008 (4 years). Once the model was calibrated/validated for flow, it was subsequently calibrated for sediment, TP and TN. Due to lack of sufficient water quality data, monthly sediment was calibrated for year 2000 and validated for year 2002. Similarly, TP and

TN were calibrated for the year 2000 and validated for the period from January 2001 to December 2002.

The SWAT model was also set up in the Magnolia River watershed. Similar to the Saugahatchee Creek watershed, it was calibrated and validated for flow, sediment, TP and TN on a monthly time scale at the outlet. Flow was calibrated for the period from October 1999 to September 2004 at the USGS gage (Fig. 1) and validated for the period from October 2004 to September 2009. Sediment, TN and TP were calibrated for the period from February 2000 to January 2001 and validated for the period from February 2001 to January 2002. All the parameters that were calibrated to obtain the best fit with the observed flow, sediments, TN and TP are presented in Table 2.

Identification of CSAs

CSAs were identified at the HRU level. Analyzing results at the HRU level helps identify CSAs with more accuracy, compared to the sub-watershed scale analysis. At the sub-watershed scale, the averaging effect can hinder small size CSAs. The sediment and nutrient loads from each HRU were analyzed to identify and compare the locations of CSAs. While Saugahatchee Creek was subdivided into 256 HRUs, the Magnolia River was subdivided into 281 HRUs. HRUs were ranked based on load per unit area. Percent contribution of each HRU with respect to the total loading from the entire watershed was calculated. The top 20 HRUs yielding significantly higher sediment, TP and TN loads compared to the remaining HRUs were considered CSAs. The choice of top 20 HRUs was a subjective choice. It could have been some other number too. The objective here is to demonstrate how calibration effects locations of CSAs. This procedure was repeated for both calibrated and uncalibrated models. Maps were created to depict the location of CSAs for sediment, TP and TN in both Saugahatchee Creek and Magnolia River watersheds.

Results and Discussion

Model performance before and after calibration

Since our objective was to compare the location of CSAs at the HRU level with and without model calibration, we first compared the performance of the SWAT model in predicting flow, sediment, TP and TN before and after the calibration.

Saugahatchee Creek Watershed

Before calibration, the model was consistently over predicting flow (Fig. 2), sediment (Fig. 3), TP (Fig. 4) and TN (Fig. 5). SWAT was overestimating streamflow for the entire period by 70% before calibration - due to low evapotranspiration predicted by the model - which was reduced to 1% after model calibration (Fig. 2). A high value of R^2 suggested that the model was picking up the trend with the observed data before the calibration. Model calibration improved all three performance measures for flow (Fig. 2). The same trend occurred in sediment, TP and TN. High R^2 values for sediment, TP and TN clearly showed that the model was able to pick up the trend (Figs. 3, 4 and 5). On the other hand, low E along with high R^2 values suggested systematic under/over estimation. Sediment was overestimated by 18% before model calibration, which was reduced to 2% with model calibration (Fig. 3). Similarly, TP was overestimated by 44% before model calibration. Calibration improved it to 2% (Fig. 4). Likewise, TN was overestimated by 31% before the calibration. Calibration reduced this error to 1% (Fig. 5).

Magnolia River Watershed

In the case of the Magnolia River watershed, the SWAT model showed mixed trends for predicting flow (Fig. 6), sediment (Fig. 7), TP (Fig. 8) and TN (Fig. 9). While SWAT was underestimating flow and TN, it was overestimating sediment and TP before calibration. Streamflow was underestimated by 18% before calibration. Calibration reduced it to 4% (Fig. 6). Similarly, TN was underestimated by 49% before the calibration, which was reduced to 5% after model calibration (Fig. 9). Sediment was being overestimated by 169% before model calibration. Calibration brought this overestimation down to 3% (Fig. 7). While TP was significantly overestimated before the calibration (almost 600%), calibration improved model performance dramatically (5% underestimation) (Fig. 8). Although R^2 values before model calibration were not as high as the R^2 values of the Saugahatchee Creek watershed, the model was able to pick up the general trend to some extent compared to the observed data before calibration. Model calibration substantially improved all the performance measures. The reliability of model in uncalibrated mode was acceptable for streamflow and TN, but poor for sediment and TP.

Effect of calibration on distribution of sediment, TP and TN loadings

Before exploring the spatial configurations of CSAs of sediment, TP and TN, it is worth exploring how calibration affected distribution of sediment, TP and TN yields at HRU level. This was done by plotting cumulative percent area of HRUs versus percent cumulative loading. HRUs were ranked from the highest loading per unit area to the lowest before calculating the cumulative loads. We arbitrarily picked 10% of the watershed area to be targeted for management practices. The purpose is to demonstrate how calibration affects distributions of sediment, TN and TP loadings for target CSAs for a given threshold area.

Saugahatchee Creek watershed

Results from the calibrated model showed that only 10% of the watershed is responsible for 52% of sediment, 39% of TP and 36% of TN loadings (Fig. 10). When the same analysis was carried out with the uncalibrated model, we found that the same fraction of the watershed is responsible for 52% of sediment, 31% of TP and 49% of TN loadings (Fig. 10). Based on 10% contributing area there was almost no effect of calibration on sediment. The most significant effect of calibration was on TN. Adjusting the parameters to get the best fit with observed data caused significant reduction in TN loadings from HRUs contributing higher TN with little effects on low TN contributing HRUs. It was also observed that, after model calibration, there was a significant reduction in percent contribution of TN from four large HRUs that were covered with hay. Thus, contribution of TN loadings from 10% of the area is reduced from 49% to 36% by calibration.

In a reverse role, we also compared the estimated area of the watershed that is needed to be targeted for reduction of sediment, TP and TN by 50% with and without the calibration of the model. This is a totally hypothetical case, since, in reality, we cannot eliminate 100% of the loadings from a particular area. Based on both calibrated and uncalibrated model, only 9% of the watershed area that is responsible for 50% of the sediment yield can be targeted for implementing management practices (Fig. 10). While 14% of the watershed area was responsible for 50% of the TP loadings based on the calibrated model, the uncalibrated model revealed 19% of the watershed area to be targeted (Fig. 10). The biggest difference between calibrated and uncalibrated results was for TN again. While 19% of the watershed area should be targeted for 50% reduction in TN loadings based on the calibrated model, only 11% of the watershed area needed to be targeted for the same purpose based on the uncalibrated model (Fig. 10).

Magnolia Watershed

Calibrated model revealed that only 10% of the watershed is responsible for 36% of sediment, 32% of TP and 23% of TN loadings. However, based on the uncalibrated model, only 10% of the watershed is responsible for 31% of sediments, 25% of TP and 31% of TN loadings (Fig. 11). The relatively low contribution from 10% of the area compared with the Saugahatchee Creek watershed is mostly due to high acreage of agricultural land in the Magnolia River watershed. In this watershed, calibration affected sediment, TP and TN distribution almost equally. Like in the Saugahatchee Creek watershed, we compared the estimated area of the watershed that has to be targeted for 50% reduction on sediment, TP and TN. While approximately 20% area of the watershed needs to be targeted for 50% reduction of the sediment loadings based on the uncalibrated model, 16% of the area appears sufficient to be targeted based on the calibrated model (Fig. 11). Similarly, 28% and 20% of the watershed should be targeted for 50% TP reduction based on the uncalibrated and calibrated models, respectively (Fig. 11). Based on the calibrated model, 27% of the watershed area should be targeted for the reduction of TN by 50% (Fig. 11). Only 24% of watershed area is required to be targeted based on the uncalibrated model for 50% TN reduction (Fig. 11). Again, calibration effects on sediment, TP and TN appears similar.

Comparison of sediment, TP and TN loads from NPSs in two watersheds

Sediment, TN and TP loads from the Saugahatchee Creek watershed were compared with the loads from the Magnolia River watershed (Table 3). Based on results from the calibrated model, on annual average, Saugahatchee Creek watershed discharged 27.2 tons of sediment, 0.18 tons of

TN, and 0.022 tons of TP per km^2. On the other hand, Magnolia River watershed discharged 5.4 tons of sediment, 2.8 tons of TN, and 0.031 tons of TP per km^2. Urban areas with steep slopes and comparatively high erodible soils in Saugahatchee Creek watershed are responsible for higher sediment loadings per unit area. Although TP loads from the two watersheds were comparable, major sources were different. Urban areas were the major TP sources in the Saugahatchee Creek watershed, while agricultural areas were mainly responsible for TP loadings in the Magnolia River watershed. Average annual TN loading was significantly higher from the Magnolia River watershed. This can be related with the high coverage of agricultural lands in the Magnolia river watershed.

Effects of calibration on location of CSAs

The top twenty HRUs that yielded the highest amount of sediment, TP and TN per unit area were first identified with results from the calibrated and uncalibrated models. Those HRUs, which constituted CSAs, were compared to assess the effects of calibration on CSA locations. The same analysis was carried out at both Saugahatchee Creek and Magnolia River watersheds.

Saugahatchee Creek watershed

Sediment: Among the top 20 HRUs considered as sediment CSAs by the calibrated and uncalibrated models, 15 of them were common. These common HRUs are located in sub-watersheds 8, 11, 13, 19, 26, 25, 30, 33 and 35 (Fig. 12). The remaining five CSAs with the calibrated model were located in sub-watersheds 9, 25, 33, 34 and 38 (Fig. 12). Similarly, the five HRUs identified as CSAs based on the uncalibrated model were located in sub-watersheds 12, 19, 23, 25 and 33 (Fig. 12). In the case of sub-watershed 33, the identified HRUs were different with the calibrated and uncalibrated models but lie in the same sub-watershed. The top 8 HRUs (located in sub-watersheds 31, 19, 26, 30, 33, 11, 35 and 25) identified as CSAs by the calibrated model were also identified as CSAs by the uncalibrated model. The different ones were among the lower ranked HRUs. Identified CSAs were medium density urban, low density urban and agricultural lands with slopes greater than 10%. Information on the land use, soil properties, and slope of the sediment CSAs in the Saugahatchee Creek watershed are provided in Appendix 1.1 to 1.4. Although, construction areas and roads are known sources of sediment from urban areas, high sediment from urban areas, as identified by SWAT, is also partly due to the way SWAT calculates sediment loads from urban areas. SWAT uses a regression model developed by Driver and Tasker (1998) that was developed from a national urban water quality database, which relates urban storm runoff with urban physical, land use and climatic characteristics.

TP: Similar to sediment, the top 20 HRUs were considered as CSAs of TP with both uncalibrated and calibrated models. Out of 20, 19 HRUs were common. These common HRUs were located in sub-watersheds 9, 21, 25, 26, 29, 30, 31, 33, 34, 35 and 38 (Fig. 13). While an HRU, identified as CSA by the uncalibrated model only, is located in sub-watershed 2, the one identified only by the calibrated model lies in sub-watershed 31 (Fig. 13). The lower ranked HRU was different in this case also. Top 18 HRUs identified as CSAs by the calibrated model were also captured by the uncalibrated model as CSAs. Most of the identified CSAs of TP are agricultural lands with slopes greater than 10%. High amount and untimely application of P-fertilizers for crops are always major sources of inorganic P from agricultural fields. P attached with eroded sediment is the source of organic P from agriculture areas. Properties of TP CSAs are provided in Appendix 1.2 and 1.4.

TN: Based on both calibrated and uncalibrated models, the top 20 HRUs were again considered as CSAs. The set of HRUs identified as CSAs by the calibrated and uncalibrated model were identical. These common HRUs are located in sub-watersheds 2, 9, 21, 25, 26, 29, 30, 31, 33, 34, 35 and 38 (Fig. 14). This is interesting because, earlier when we looked at the TN contribution from 10% watershed area with the calibrated and uncalibrated models, the highest difference was with TN. There was a 13% reduction after model calibration. Yet, when we analyzed the top 20 HRUs, they ended up being exactly the same. It was found that although same HRUs were contributing higher percentage of TN, there was a significant reduction in TN contribution from four large HRUs covered with hay after model calibration, which reduced the total TN contribution from the 10% watershed area by 13%. Similar to sediment and TP, identified CSAs of TN were agricultural lands. Excess use of N-fertilizers for improving crop yield is the major sources of TN form agricultural areas. Information regarding land use, soil properties and slope of TN CSAs are provided in Appendix 1.3 and 1.4.

Magnolia River watershed

Sediment: In the Magnolia River watershed, out of the top 20 HRUs considered as sediment CSAs by both calibrated and uncalibrated SWAT models, 18 were the same and were located in sub-watersheds 1, 3, 7, 10, 11, 12, 17 and 19 (Fig. 15). The remaining 2 HRUs, only identified as CSAs by the uncalibrated model, were both located in sub-watershed 16. Similarly, the 2 HRUs that were identified as CSA only by the calibrated model lie in sub-watersheds 4 and 17. Again, lower ranked HRUs were the ones that were different. The uncalibrated model was able to capture all the top 15 HRUs identified as CSAs by the calibrated model. In this case, the identified CSAs were agricultural lands and transportation. The regression equations used by SWAT in urban areas heavily rely on impervious percentage, with high impervious percent producing higher sediment loads. Urban transportation is considered to have the highest (95%) imperviousness in SWAT model, which explains why urban transportation is also identified as sediment CSA. Detailed information on land use, soil properties, and slope of common sediment CSAs are provided in Appendix 2.1 and 1.4.

TP: 17 out of the 20 HRUs identified as TP, CSAs by both calibrated and uncalibrated models were the same. They were located in sub-watersheds 10, 13, 14, 16, 17, and 19 (Fig. 16). The remaining 3 identified by the calibrated model were all located in sub-watershed 16 (Fig. 16). Similarly, among the remaining 3 identified CSAs by the uncalibrated model, one was located in sub-watershed 3 and the other two in sub-watershed 23 (Fig. 16). In this case too, the different CSAs were the lower ranked HRUs and the top 15 was captured by the uncalibrated model as well. Agricultural land, pasture land and urban transportation in combination with different soil type and slope were identified as CSAs. Similar to the case of sediment, identification of urban transportation as TP CSAs can be related to the regression model. Complete information regarding land use, soil properties and slope of common TN CSAs are provided in Appendix 2.2 and 2.4.

TN: The results for TN CSAs are similar to sediment and TP CSAs. Among the 20 HRUs, 17 were the same and are located in sub-watersheds 2, 5, 14, 19, 20, 21 and 23 (Fig. 17). The remaining 3 CSAs were located in sub-watersheds 13 and 14 with the uncalibrated, and sub-watersheds 3 and 19 with the calibrated model, respectively. Similar to the sediment and TP CSAs, the different ones were lower ranked HRUs and the top 18 HRUs identified as CSAs by the calibrated model were again identified as CSAs by the uncalibrated model. In this case, identified CSAs had the similar soil type (wet loamy alluvial land) that has extremely high organic matter content. Thus, soil type dominated more than land use in this particular case of TN CSAs in the Magnolia River watershed. Forested wetland, pasture land and deciduous forest on wet loamy alluvial land that have extremely high organic matter were identified as CSAs of TN. What is likely happening is that abundant organic matter is mineralized into ammonia by bacteria, which is later nitrified into nitrate. Those nitrates then leach into shallow groundwater and eventually reach the streams with baseflow. Also, SWAT assumed that there is no denitrification with its default denitrification coefficient. Forested wetlands (located in sub-watersheds 19, 20, 21 and 23) are normally expected to act as a sink rather than a source. Thus, they should not really be considered as CSAs, although they are identified as CSAs in this particular case due to the high organic matter content in the soil. Detailed properties of common TP CSAs are provided in Appendix 2.3 and 2.4.

Summary and Conclusions

The Soil and Water Assessment Tool (SWAT) was used in both calibrated and uncalibrated modes at the Saugahatchee Creek and Magnolia River watersheds to identify the CSAs of sediment, TN and TP, so that management practices can be concentrated on those areas for water quality improvement. Identified CSAs from both calibrated and uncalibrated modes were then compared to determine the effect of calibration on locations of CSAs. The models were calibrated and validated at monthly time scale. SWAT consistently overestimated flow (70%), sediment (18%), TP (44%) and TN (31%) in the Saugahatchee Creek watershed before calibration. Model calibration substantially improved model performances. In the Magnolia River watershed, the uncalibrated model underestimated flow (-18%) and TN (-49%) but overestimated sediment (169%) and TP (594%). Model calibration again considerably reduced those over/under estimations. This indicates the importance of calibrating model parameters in SWAT. Model outputs were then analyzed at HRU level to identify the CSAs and their locations at sub-watersheds. Results based on the calibrated model revealed that only 10% of the Saugahatchee Creek watershed area was responsible for almost 52% of sediment, 39% of TP and 36% of TN loadings. Some differences were observed in the distribution of TP and TN loadings when compared with the uncalibrated model. In the case of Magnolia River watershed, 10% area was responsible for 36% of sediment, 32% of TP and 23% of TN yield based on the calibrated model. In this case too we observed some differences in the distributions of sediment, TP and TN compared to the uncalibrated model. Relatively low contribution from 10% of the area compared to the Saugahatchee Creek watershed is mostly due to the high acreage of agricultural land in the Magnolia River watershed.

Based on rankings, top 20 HRUs were identified as CSAs and their locations within sub-watersheds were determined based on the results from both calibrated and uncalibrated SWAT models. Results revealed that identified CSAs and their locations for sediment and TP were mostly the same with and without the calibration of the model in the Saugahatchee Creek watershed. The CSAs of TN were exactly the same with and without model calibration in the Saugahatchee Creek watershed. To find out whether these results were particular to the Saugahatchee Creek watershed, a similar analysis was also carried out at the Magnolia River watershed, which has different characteristics than the Saugahatchee Creek watershed. In the Magnolia River watershed, SWAT again identified almost same areas as CSAs of sediment, TP and TN by the calibrated and uncalibrated models. This convincingly validated the findings that lumped calibration of SWAT has little effect on locations of CSAs. Although, two watersheds of different characteristics were chosen, the results were similar.

Similar areas were identified as CSAs for TP and TN in the Saugahatchee Creek watershed. CSAs for sediment were slightly different than the CSAs for TP and TN. In the Magnolia River watershed, although few areas identified as CSAs for sediment, TP and TN were identical, they were mostly different. It was also found that, not only land use/cover, but also soil type and slope can equally play significant roles in determination of CSAs at the HRU level. In the Saugahatchee Creek watershed, agricultural land and urban areas with steep slopes were found to be CSAs of sediment. Similarly, high sloped agricultural lands were identified as CSAs for TP and TN in the Saugahatchee Creek watershed. However, no such effect of slope was observed in the Magnolia River watershed due to its relatively flat topography. Organic matter content of the soil can also have significant effect on CSA identification of TN as illustrated in the Magnolia River watershed. Various land use/cover intersected with wet loamy alluvial land and considerably high amount of organic matter content were identified as CSAs of TN in the Magnolia River watershed.

While high resolution SSURGO soil database was used in the Magnolia River watershed, low resolution STATSGO soil database was used in the Saugahatchee Creek watershed due to its much larger area. However, in both watersheds the effect of model calibration on CSAs was similar. Thus, we conclude that the choice of the soil database (SSURGO vs. STATSGO) has no effect on our finding that lumped calibration of SWAT does not result in different CSAs compared to uncalibrated SWAT model.

This study revealed that although absolute loadings may change substantially, relative loadings may not change after a lumped model calibration, which relies on data at the watershed outlet. Because model parameters are adjusted systematically for all HRUs over the entire watershed, similar effect occurred in each HRU. However, results may or may not change if the model is calibrated at various locations inside the watershed. This requires additional data at sub-watershed level, which is rarely available. This study thus concluded that although analysis of results with model calibration will identify the CSAs more accurately for sediment, TN and TP, SWAT may still be used to identify the CSAs in watersheds lacking sufficient data for model calibration and validation, but requiring immediate action for water quality improvement.

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Table 1: Differences/similarities in climate, hydrology, land use/cover, soil, and topography between the Saugahatchee Creek and Magnolia River watersheds.

	Saugahatchee Creek watershed	Magnolia watershed
Area	180.0 km^2	44.8 km^2
Physiographic Region	Piedmont	Coastal
Dominant Land use	Forested (59%)	Agricultural (43%)
Dominant Soil	Sandy loam	Sandy loam
Percent Urban	21.0	11.0
Avg. Slope (%)	6.6	1.0
Avg. Elevation(m)	213.5	25.3
Avg. Annual Min.Temp.(^{o}F)	11.4	20.8
Avg. Annual Max.Temp.(^{o}F)	98.2	98.0
Avg. Annual Pcp (2000-2008)	1314 mm	1756 mm
Avg. Annual Flow (2000-2008)	410 mm (31.2 % of Pcp)	763 (43.5% of Pcp)
Baseflow Index	0.52	0.57

Table 2: Adjusted parameters for model calibration in Saugahatchee Creek and Magnolia River watersheds.

Adjusted Parameters	Descriptions
Flow Parameters:	
CN2	Initial Curve number for moisture condition II
ESCO	Soil evaporation compensation factor
GWQMIN	Threshold depth of water in shallow aquifer required for the return flow to occur
GW_DELAY	Ground water delay
REVAPMN	Threshold depth of water in the shallow aquifer for revap to occur
ALPHA_BF	Baseflow alpha factor
SOL_AWC	Available water capacity of soil layer
SURLAG	Surface runoff lag time
Sediment Parameters:	
SPEXP	Exponent parameter for calculating sediment re-entrained in channel sediment routing
PRF	Peak rate adjustment factor for sediment routing in main channel
ADJ_PKR	Peak rate adjustment factor for sediment routing in the subbasins
USLE_P	Support practice factor
USLE_C(AGRR)	USLE crop factor for agricultural land
Phosphorus Parameters:	
PPERCO	Phosphorus percolation coefficient
PHOSKD	Phosphorus soil partitioning coefficient
P-UPDIS	Phosphorus uptake distribution factor
PSP	Phosphorus sorption coefficient
BC4-BSN	Rate constant for decay of Org. P to dissolved phosphorus
K_P	Michaelis-Menton half saturation constant for phosphorus
SOL_LABP	Initial soluble P concentration in surface soil layer (mg/kg)
BC4	Rate constant for mineralization of Org. P to mineral P in the reach
RS4	Org. P settling rate in reach at 20^{o}C
Nitrogen Parameters:	
NPERCO	Nitrogen percolation coefficient
K-N	Michaelis-Menton half saturation constant for nitrogen
SOL_NO_3	Initial NO_3 concentration in the soil (mg/kg)
BC1	Rate constant for biological oxidation of NH_4 to NO_2 in the reach
BC2	Rate constant for biological oxidation of NO_2 to NO_3 in the reach
BC3	Rate constant for hydrolysis of Org. N to NH_4 in the reach
RCN	Concentration of nitrogen in rainfall
RS5	Rate coefficient for Org. N settling

Table 3: Sediment, TN and TP loads from NPSs in the Saugahatchee Creek and the Magnolia River watersheds.

	Saugahatchee Creek watershed		Magnolia River watershed	
	Calibration	***Uncalibration***	***Calibration***	***Uncalibration***
Sediment (tons/km^2)	27.2	34.0	5.4	27.0
TN (tons/km^2)	0.18	0.42	2.80	2.10
TP (tons/km^2)	0.022	0.052	0.031	0.196

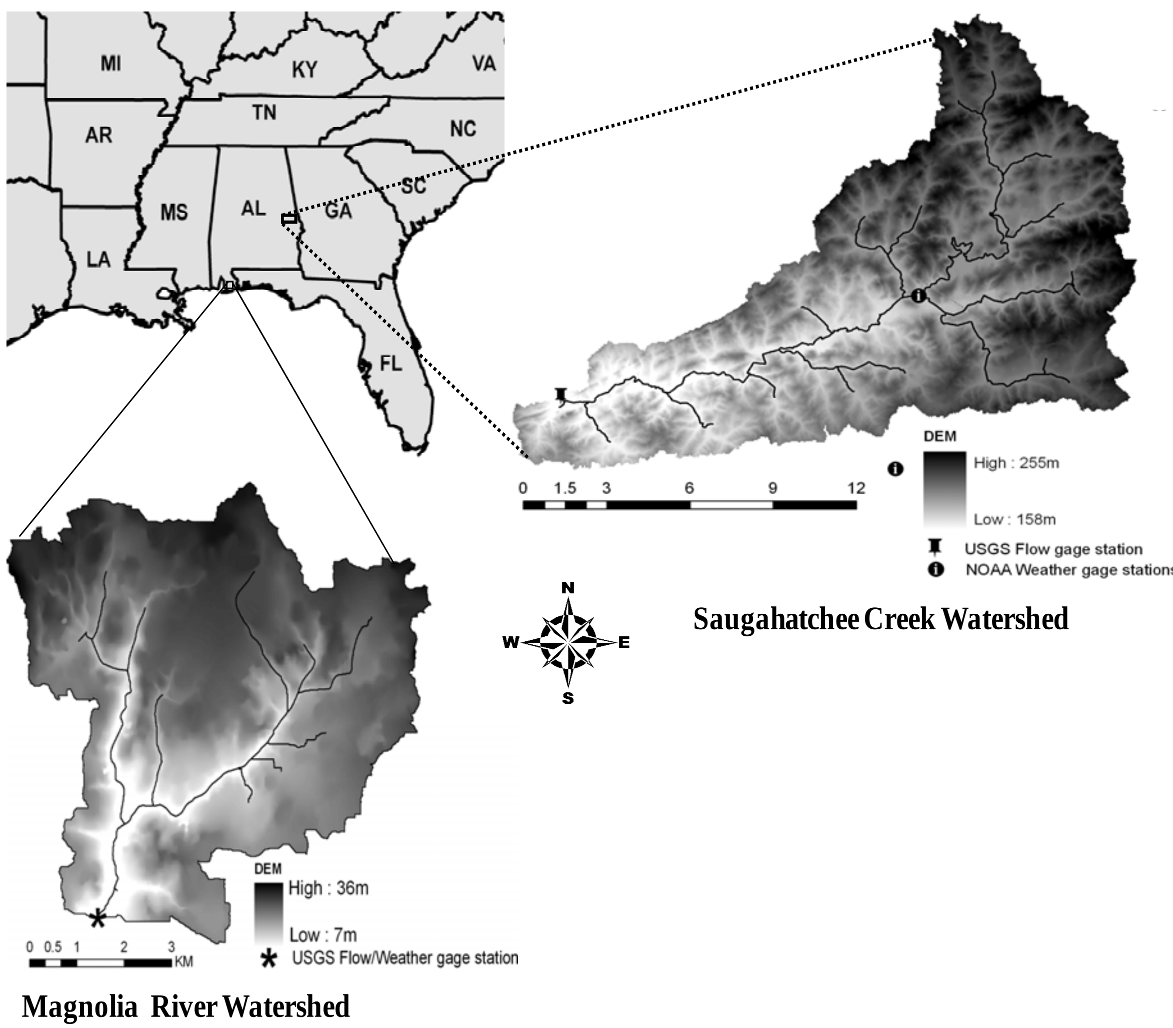


Fig. 1: Saugahatchee Creek and Magnolia River watersheds. Also shown are topography, and USGS flow and NOAA weather gaging stations.

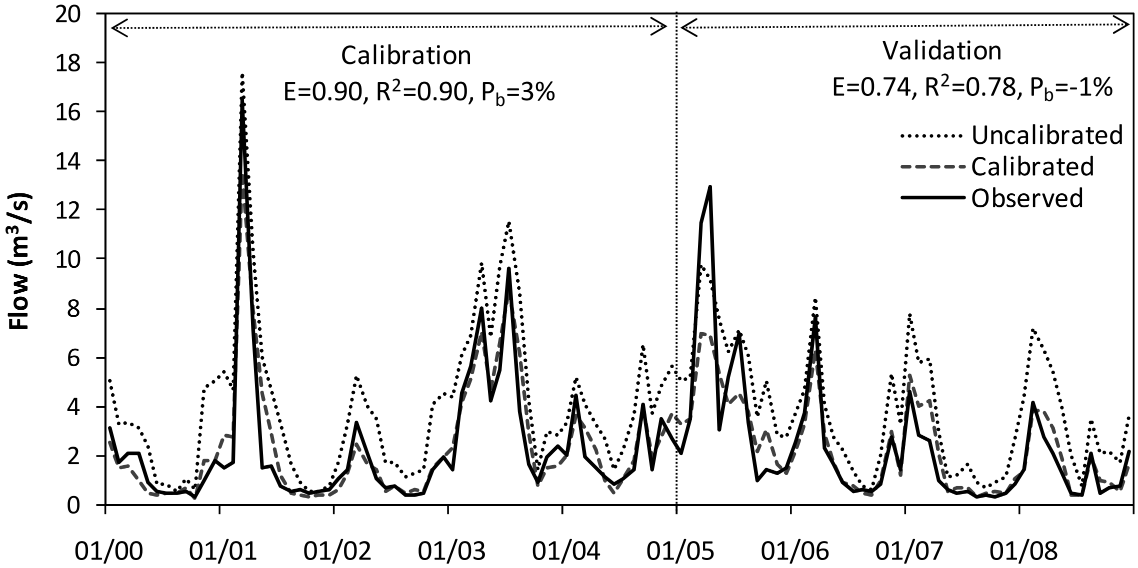


Fig 2: SWAT monthly streamflow predictions with the calibrated and uncalibrated parameters compared to the observed flows in the Saugahatchee Creek watershed. Performance statistics over the whole period were *$E=0.39$, $R^2=0.80$, $P_b=70\%$* for the uncalibrated and *$E=0.83$, $R^2=0.84$, $P_b=1\%$* for the calibrated model.

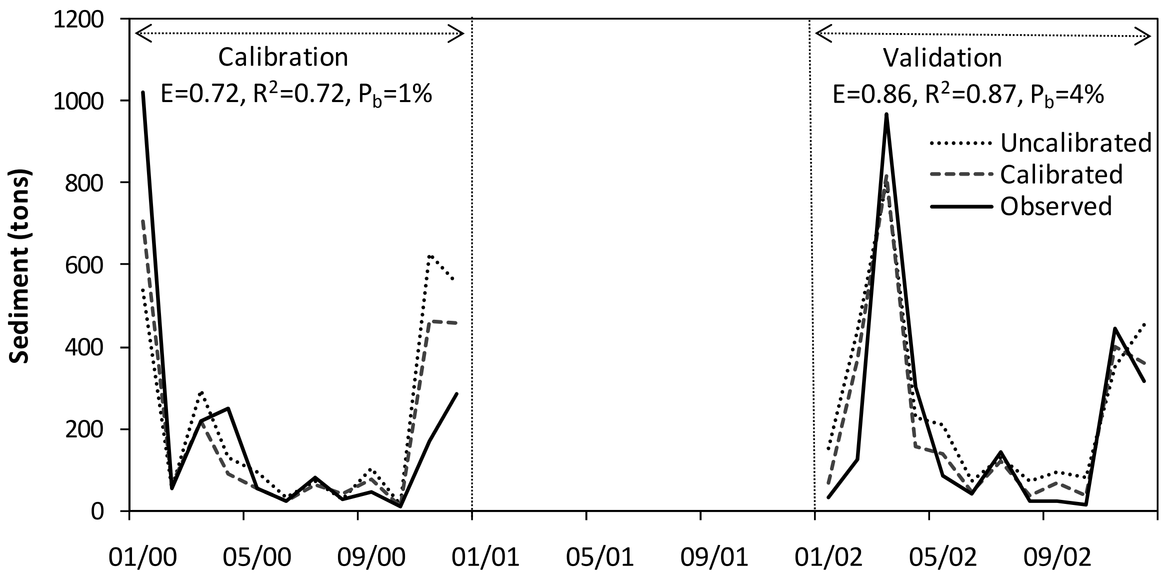


Fig 3: SWAT monthly sediment predictions with the calibrated and uncalibrated parameters compared to the observed sediment in the Saugahatchee Creek watershed. Performance statistics over the whole period were *$E=0.57$, $R^2=0.59$, $P_b=18\%$* for the uncalibrated and *$E=0.79$, $R^2=0.80$, $P_b=2\%$* for the calibrated model.

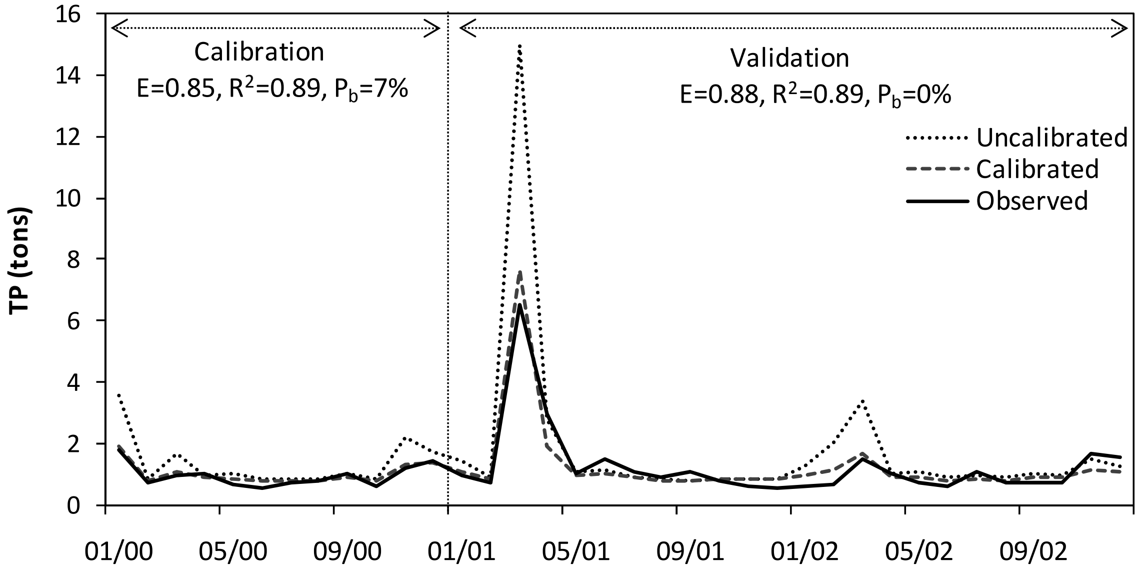


Fig 4: SWAT monthly TP predictions with the calibrated and uncalibrated parameters compared to the observed TP in the Saugahatchee Creek watershed. Performance statistics over the whole period were *E=-1.25, R^2=0.89, P_b=44%*for the uncalibrated and *E=0.88, R^2=0.91, P_b=2%* for the calibrated model.

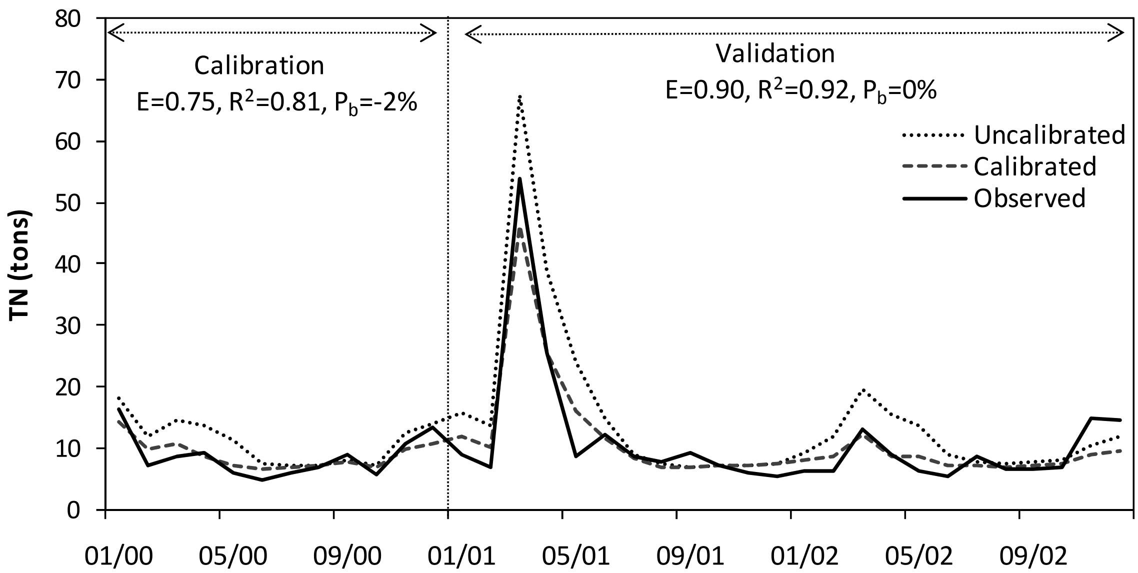


Fig 5: SWAT monthly TN predictions with the calibrated and uncalibrated parameters compared to the observed TN in the Saugahatchee Creek watershed. Performance statistics over the whole period were *E=0.59, R^2=0.87, P_b=31%* for the uncalibrated and *E=0.90, R^2=0.91, P_b=1%* for the calibrated model.

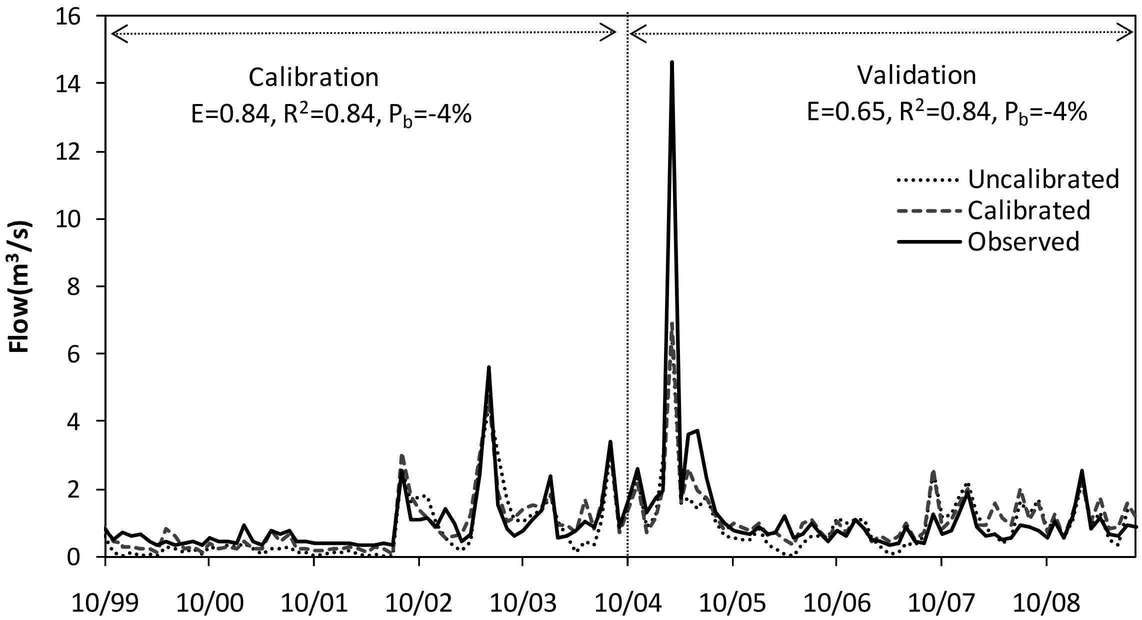


Fig 6: SWAT monthly streamflow predictions with the calibrated and uncalibrated parameters compared to the observed flows in the Magnolia River watershed. Performance statistics over the whole period were *$E=0.62$, $R^2=0.66$, $P_b=-18\%$* for the uncalibrated and *$E=0.69$, $R^2=0.75$, $P_b=-4\%$* for the calibrated model.

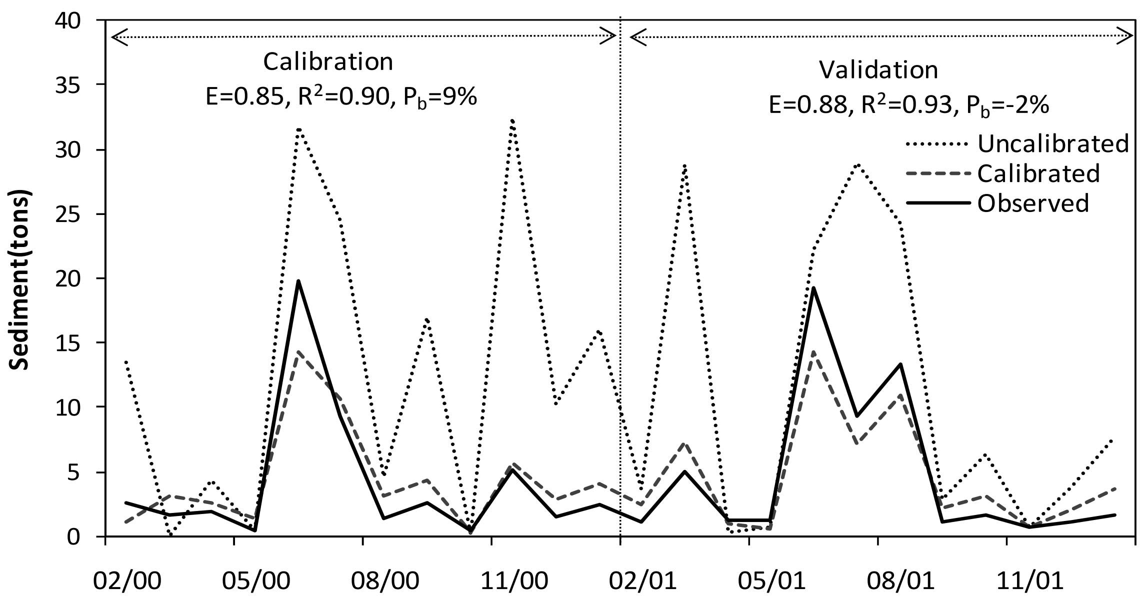


Fig 7: SWAT monthly sediment predictions with the calibrated and uncalibrated parameters compared to the observed sediment in the Magnolia River watershed. Performance statistics over the whole period were *$E=-2.89$, $R^2=0.55$, $P_b=169\%$* for the uncalibrated and *$E=0.87$, $R^2=0.92$, $P_b=3\%$* for the calibrated model.

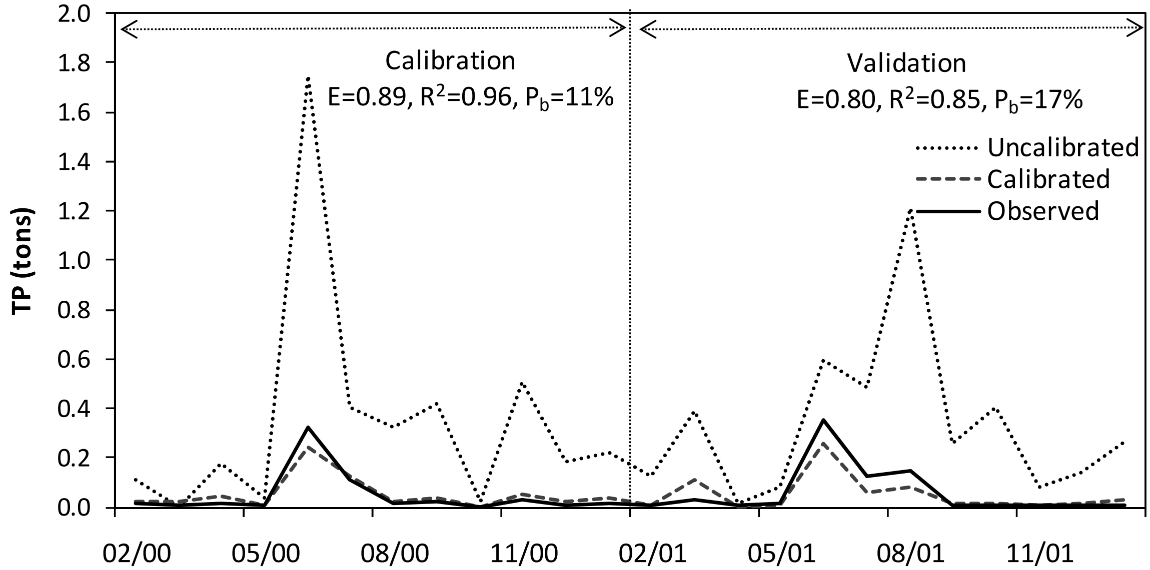


Fig 8: SWAT monthly TP predictions with the calibrated and uncalibrated parameters compared to the observed TP in the Magnolia River watershed. Performance statistics over the whole period were *E=-26.22, R^2=0.47, P_b=594%* for the uncalibrated and *E=0.84, R^2=0.89, P_b=-5%* for the calibrated model.

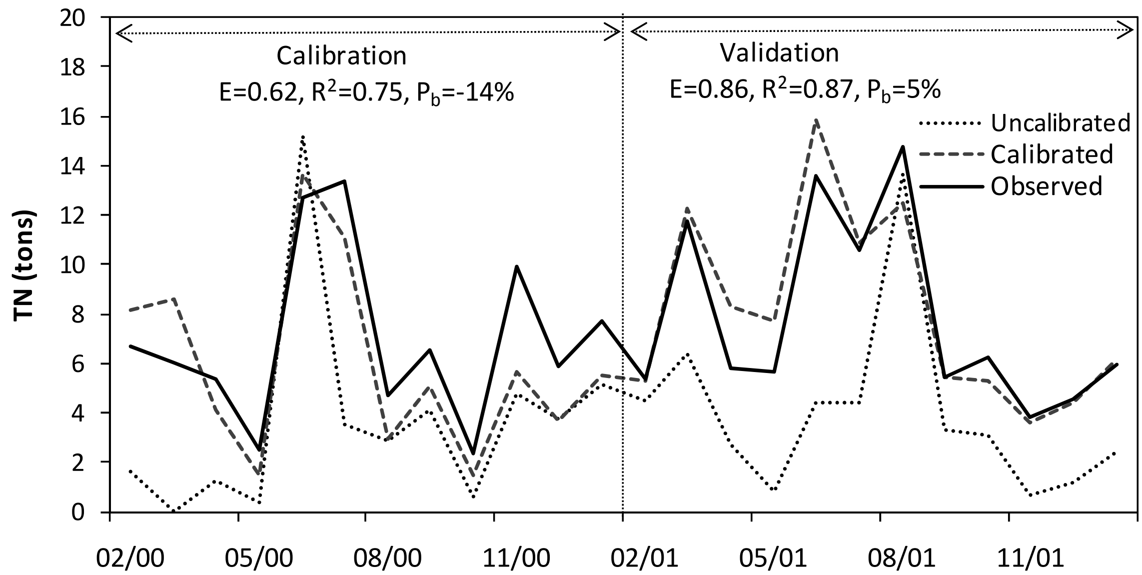


Fig 9: SWAT monthly TN predictions with the calibrated and uncalibrated parameters compared to the observed TP in the Magnolia River watershed. Performance statistics over the whole period were *E=-0.59, R^2=0.55, P_b=-49%* for the uncalibrated and *E=0.75, R^2=0.80, P_b=-5%* for the calibrated model.

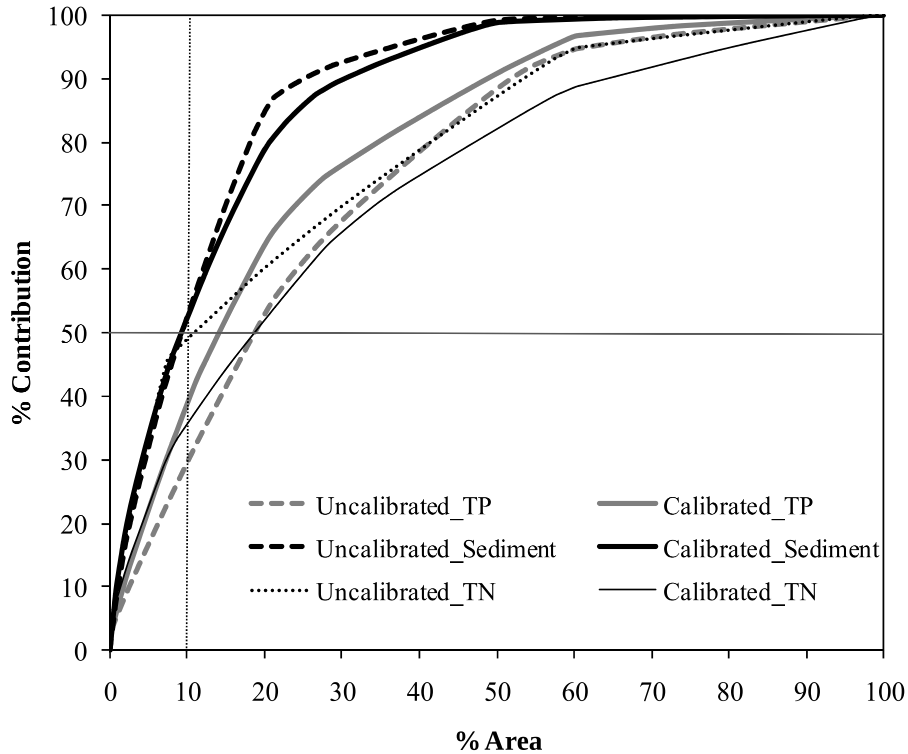


Fig. 10: Distribution of sediment, TP and TN load by area (in %) in the Saugahatchee Creek watershed.

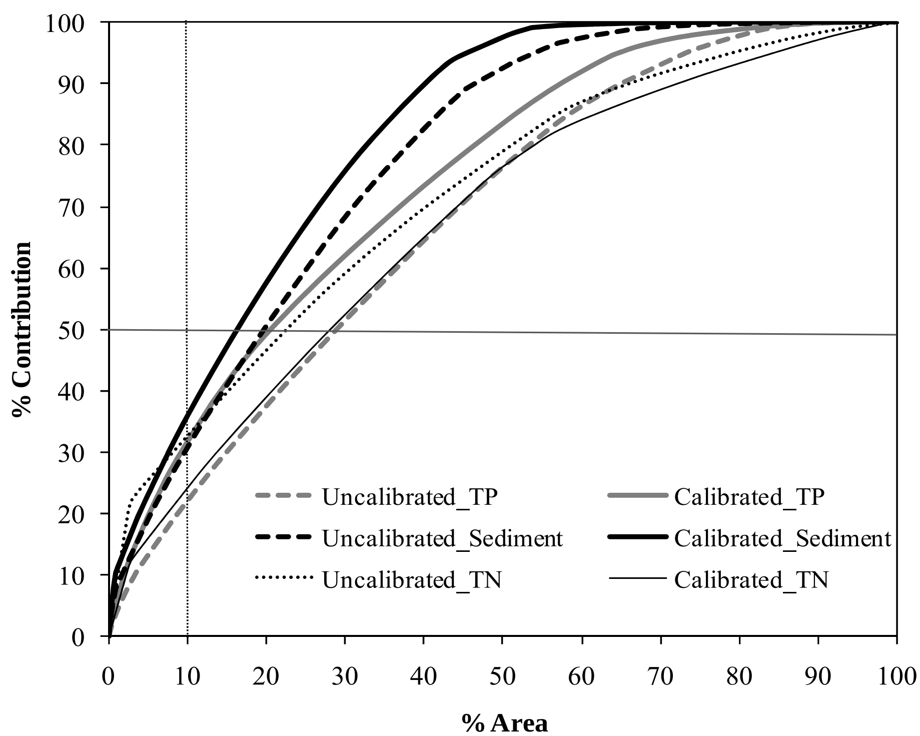
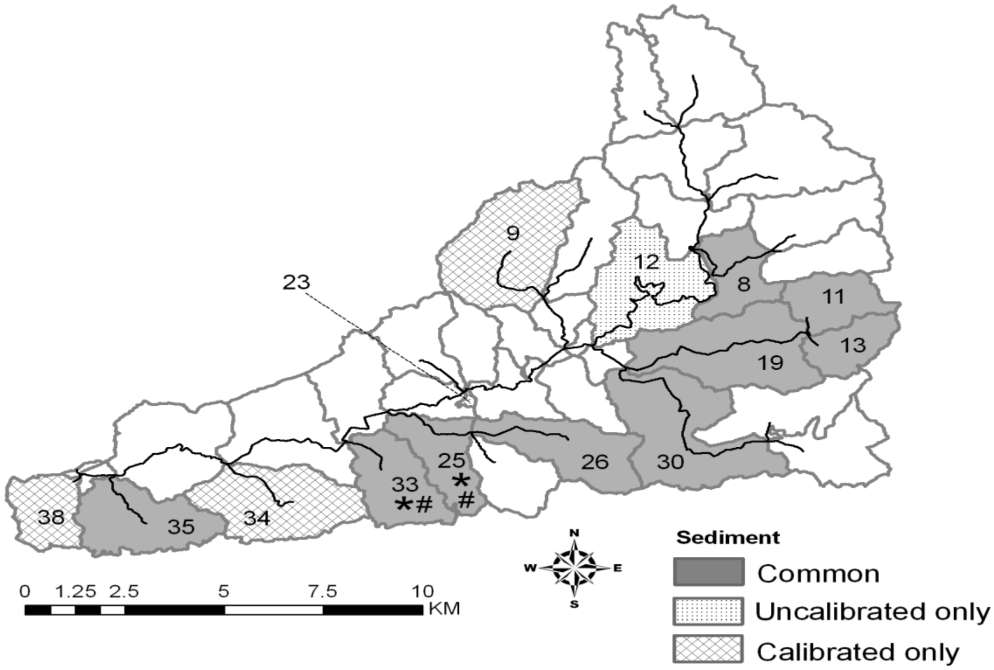
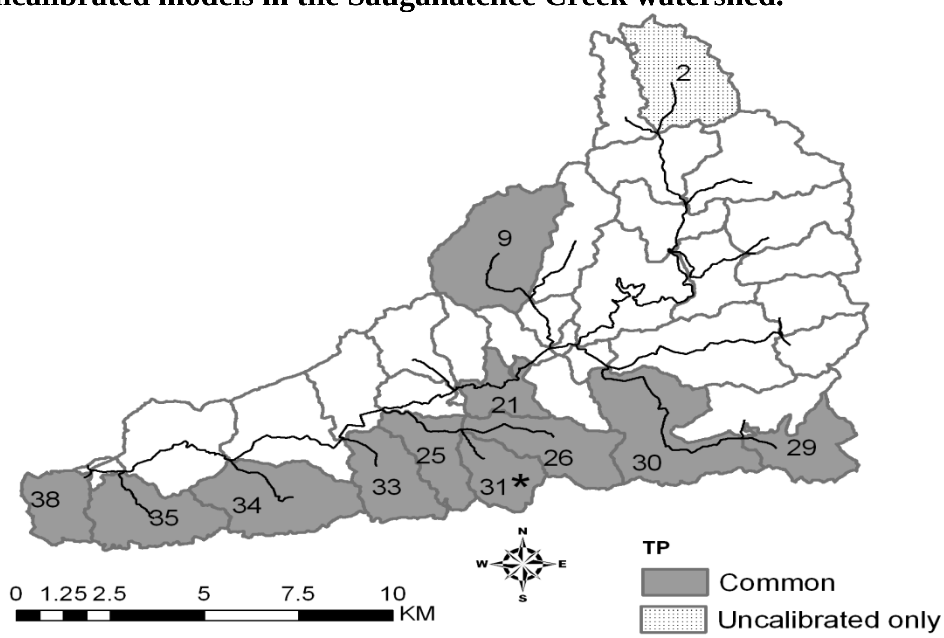


Fig. 11: Distribution of sediment, TP and TN load by area (in %) in the Magnolia River watershed.



* 1 uncalibrated HRU also lies in this sub-watershed
# 1 calibrated HRU also lies in this sub-watershed

Fig. 12: Sub-watersheds containing sediment CSAs based on the calibrated and uncalibrated models in the Saugahatchee Creek watershed.



* 1 calibrated HRU also lies in this sub-watershed

Fig. 13: Sub-watersheds containing TP CSAs based on the calibrated and uncalibrated models in the Saugahatchee Creek watershed.

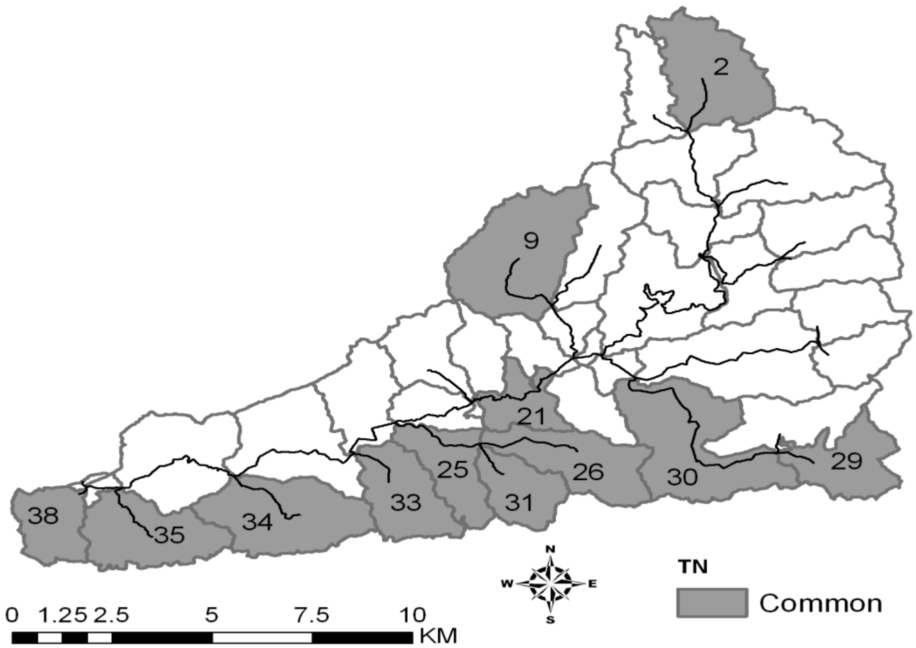
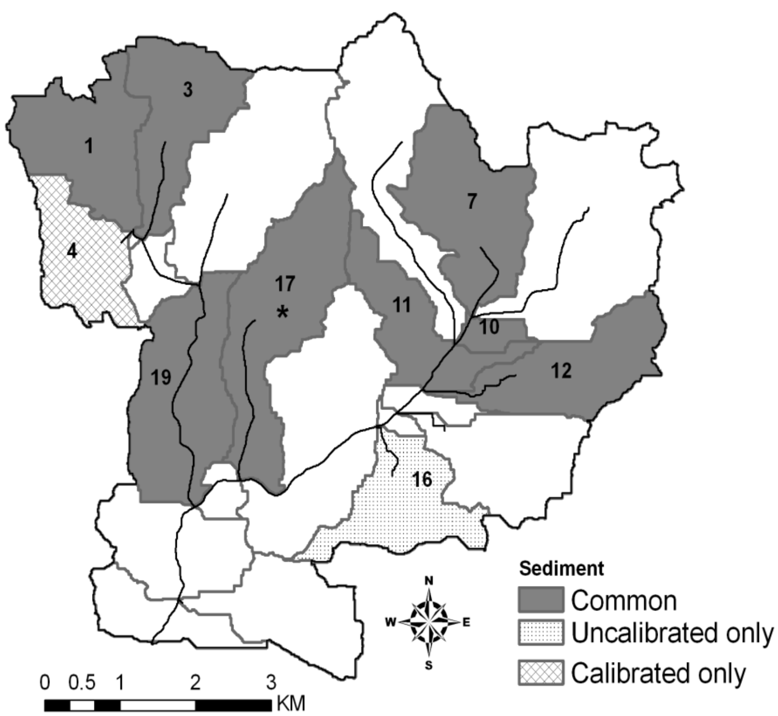
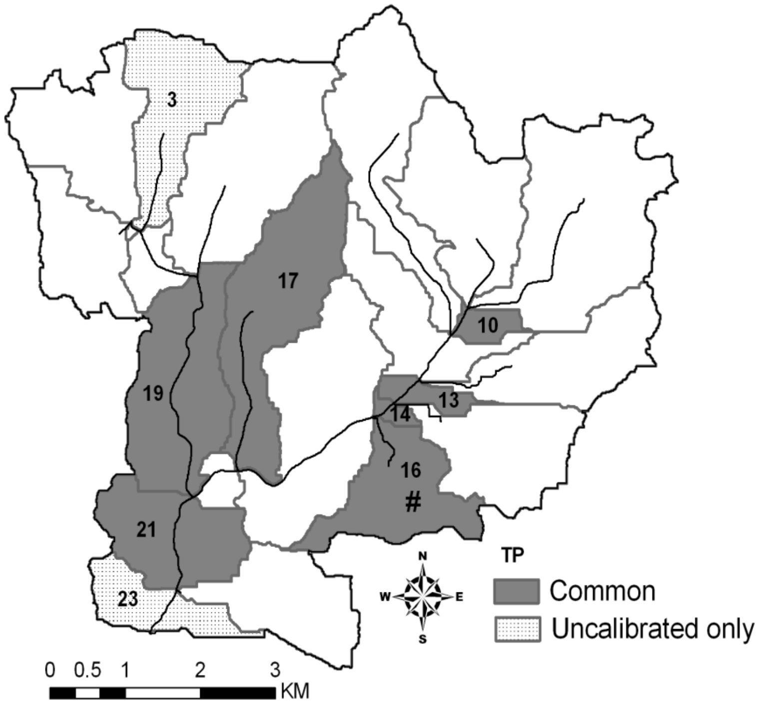


Fig. 14: Sub-watersheds containing TN CSAs based on the calibrated and uncalibrated models in the Saugahatchee Creek watershed.



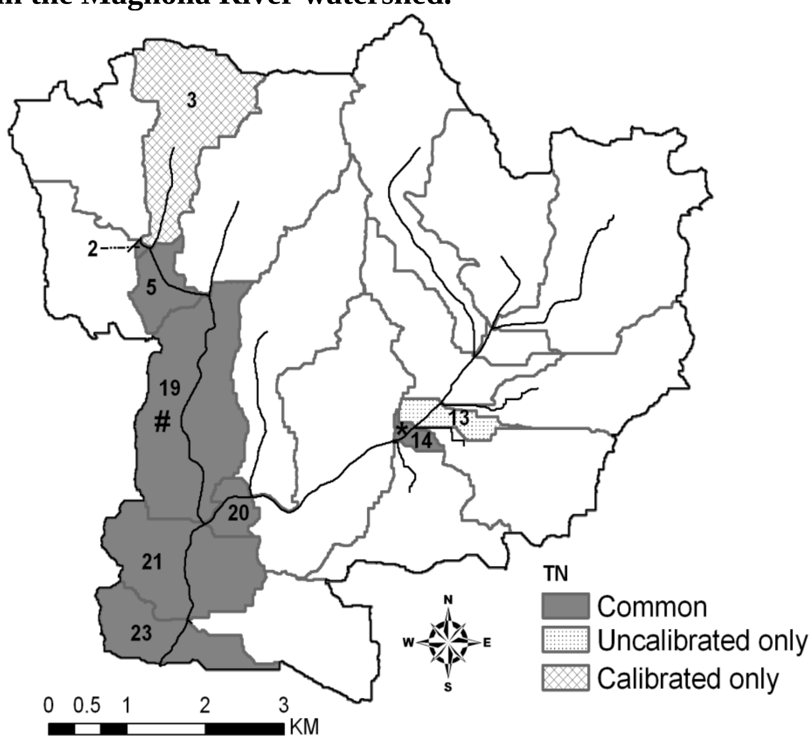
* 1 uncalibrated HRU also lies in this sub-watershed

Fig. 15: Sub-watersheds containing sediment CSAs based on the calibrated and uncalibrated models in the Magnolia River watershed.



3 calibrated HRUs also lie in this sub-watershed

Fig. 16: Sub-watersheds containing CSAs based on the calibrated and uncalibrated models in the Magnolia River watershed.



* 1 uncalibrated HRU also lies in this sub-watershed

1 calibrated HRU also lies in this sub-watershed

Fig. 17: Sub-watersheds containing TN CSAs based on the calibrated and uncalibrated models in the Magnolia River watershed.

Appendix 1.1: Properties of common Sediment CSAs in the Saugahatchee Creek watershed.

HRU	Subbasin	Land use	Soil	slope
1	13	URMD	AL140	>10%
2	19	URMD	AL140	>10%
3	26	URMD	AL140	>10%
4	30	URMD	AL140	>10%
5	33	URMD	AL140	>10%
6	11	URMD	AL140	>10%
7	35	AGR	AL128	>10%
8	25	URMD	AL140	>10%
9	13	URLD	AL140	>10%
10	30	URLD	AL140	>10%
11	8	URLD	AL140	>10%
12	11	URLD	AL140	>10%
13	33	URLD	AL140	>10%
14	26	URLD	AL140	>10%
15	19	URLD	AL140	>10%

Appendix 1.2: Properties of common TP CSAs in the Saugahatchee Creek watershed.

Top 20 HRU's	Subbasin	Land use	Soil	slope
1	35	AGR	AL128	>10%
2	33	AGR	AL128	>10%
3	34	AGR	AL128	>10%
4	26	AGR	AL140	>10%
5	9	AGR	AL140	>10%
6	38	AGR	AL140	<10%
7	35	AGR	AL128	<10%
8	33	AGR	AL140	<10%
9	31	AGR	AL140	<10%
10	34	AGR	AL140	<10%
11	26	AGR	AL140	<10%
12	31	AGR	AL140	<10%
13	9	AGR	AL140	<10%
14	35	AGR	AL140	<10%
15	38	AGR	AL140	<10%
16	30	AGR	AL140	<10%
17	29	AGR	AL140	<10%
18	21	AGR	AL140	<10%
19	25	AGR	AL140	<10%

Appendix 1.3: Properties of common TN CSAs in the Saugahatchee Creek watershed.

HRU	Subbasin	Land use	Soil	slope
1	34	AGR	AL128	>10%
2	33	AGR	AL128	>10%
3	35	AGR	AL128	>10%
4	38	AGR	AL140	<10%
5	35	AGR	AL128	<10%
6	33	AGR	AL140	<10%
7	31	AGR	AL140	<10%
8	34	AGR	AL140	<10%
9	9	AGR	AL140	>10%
10	35	AGR	AL140	<10%
11	38	AGR	AL140	<10%
12	26	AGR	AL140	<10%
13	38	AGR	AL140	<10%
14	36	AGR	AL140	<10%
15	9	AGR	AL140	<10%
16	25	AGR	AL140	<10%
17	21	AGR	AL140	<10%
18	30	AGR	AL140	<10%
19	29	AGR	AL140	<10%
20	2	AGR	AL140	<10%

Appendix 1.4: Soil properties of CSAs in the Saugahatchee Creek watershed.

Soil Name	Texture	O.M. (%)	USLE_K	Soil-AWC	HSG
AL128	Sandy loam	1.16	0.20	0.13	C
AL140	Sandy loam	0.73	0.24	0.13	C
Average		0.68	0.23	0.12	

Appendix 2.1: Properties of common Sediment CSAs in the Magnolia River watershed.

HRU	Subbasin	Land use	Soil	Slope (%)
1	19	AGR	AL180	5-8
2	19	AGR	AL180	2-5
3	3	AGR	AL175	2-5
4	3	AGR	AL175	0-2
5	17	AGR	AL179	2-5
6	3	AGR	AL197	2-5
7	10	AGR	AL179	2-5
8	19	AGR	AL180	0-2
9	19	AGR	AL158	2-5
10	11	AGR	AL158	2-5
11	7	AGR	AL102	0-2
12	1	AGR	AL175	0-2
13	19	AGR	AL175	0-2
14	10	AGR	AL158	2-5
15	17	AGR	AL179	0-2
16	12	AGR	AL139	0-2
17	12	AGR	AL166	0-2
18	7	AGR	AL166	0-2

Appendix 2.2: Properties of common TP CSAs in the Magnolia River watershed.

HRU	Subbasin	Land use	Soil	Slope (%)
1	14	UTRN	AL189	5-8
2	14	UTRN	AL158	0-2
3	14	UTRN	AL206	2-5
4	14	UTRN	AL158	2-5
5	14	UTRN	AL189	2-5
6	13	UTRN	AL158	2-5
7	14	UTRN	AL189	0-2
8	14	UTRN	AL206	0-2
9	14	UTRN	AL156	0-2
10	19	AGR	AL180	5-8
11	13	UTRN	AL189	0-2
12	13	UTRN	AL189	2-5
13	16	UTRN	AL158	2-5
14	13	UTRN	AL158	0-2
15	19	AGR	AL180	2-5
16	17	AGR	AL179	2-5
17	10	AGR	AL179	2-5

Appendix 2.3: Properties of common TN CSAs in the Magnolia River watershed.

HRU	Subbasin	Land use	Soil	Slope (%)
1	19	WETF	AL224	0-2
2	23	WETF	AL224	0-2
3	20	WETF	AL224	0-2
4	21	WETF	AL224	0-2
5	20	WETF	AL224	2-5
6	21	WETF	AL224	2-5
7	19	WETF	AL224	2-5
8	23	WETF	AL224	2-5
9	14	UTRN	AL189	5-8
10	5	PAST	AL224	2-5
11	5	PAST	AL224	0-2
12	14	UTRN	AL158	0-2
13	14	UTRN	AL206	2-5
14	2	FRSD	AL224	0-2
15	2	FRSD	AL224	2-5
16	14	UTRN	AL189	2-5
17	14	UTRN	AL158	2-5

Appendix 2.4: Soil properties of CSAs in the Magnolia River watershed.

Soil Name	Texture	O.M. (%)	USLE_K	Soil-AWC	HSG
AL328102	Silt loam	1.16	0.20	0.13	C
AL328139	Sandy loam	0.73	0.24	0.13	C
AL328156	Loamy sand	0.73	0.10	0.08	A
AL328158	Loamy sand	1.02	0.10	0.07	B
AL328166	Sandy loam	0.73	0.20	0.13	C
AL328175	Sandy loam	0.44	0.24	0.13	B
AL328179	Sandy clay loam	1.16	0.20	0.13	B
AL328180	Sandy clay loam	1.16	0.20	0.13	B
AL328189	Loamy sand	1.16	0.10	007	B
AL328197	Loam	0.44	0.24	0.13	C
AL328206	Loamy sand	0.66	0.10	0.06	B
AL328224	Wet loamy alluvial land	29.0	0	0.32	D
Average		0.85	0.20	0.14	

Soil-AWC = Soil Available Water Capacity
USLE_K = Soil Erodibility
HSG = Hydrologic Soil Group
O.M. = Organic Matter content in the soil
URTN = Urban Transpiration

URMD = Medium density urban
URLD = Low density urban
AGR = Agriculture
PAST = Pasture
WETF = Wetland Forest
FRSD = Deciduous Forest

CHAPTER IV

Summary and Conclusions

Several new findings pertaining to the application of watershed models in identifying Critical Source Areas (CSAs) emerged from this study. We used the Soil and Water Assessment Tool (SWAT) – a complex semi distributed watershed model and the Generalized Watershed Loading Function (GWLF) – a simple lumped watershed model in the Saugahatchee Creek watershed in eastern Alabama to study the effect of model choice and complexity on locating critical source areas (CSAs). Both models were set up, calibrated and validated to identify CSAs of sediment, total nitrogen (TN) and total phosphorus (TP) for implementation of management practices in those small areas. Based on overall model performance statistics, SWAT performed slightly better than GWLF. Although there were similarities in many of the identified CSAs based on the two models, not all the CSAs identified by the SWAT and GWLF models were mutual. This study demonstrated that although a simple model (GWLF) appears to be useful in predicting flow and water quality, and identification of CSAs, it may not capture all the CSAs properly. Thus implementing best management practices (BMPs) in areas identified as CSA by the GWLF model may not be as effective as SWAT.

It was observed that sediment, TN and TP CSAs in a watershed could be different. Therefore, developing a combined index that identifies CSAs for sediment, TN and TP could be especially useful if the watershed is facing both sediment and nutrient problems. However, if only one parameter is the water quality concern, then CSAs for that individual parameter should be targeted. Urban areas produce high amounts of sediment, TN and TP at sub-watershed scale and are often identified as CSAs. Agricultural areas are also highly responsible for sediment, TN and TP loadings. However their contributions were not reflected much at sub-watershed scale in this study due to the very low acreage of agricultural lands in the study watershed.

Watershed models are usually calibrated using data at the watershed outlet in most studies. This is mainly due to lack of data at sub-watershed scale. Model parameters are systematically changed throughout the watershed (lumped calibration). This is often the case with distributed models too. We used the SWAT model in both calibrated and uncalibrated mode at the Saugahatchee Creek and Magnolia river watersheds to study the effect of lumped model calibration on location of CSAs. Since observed data for model calibration is not always available, the purpose of the study was also to test the reliability of the SWAT model in an ungauged watershed for identifying the location of CSAs. The model consistently overestimated flow sediment, TP and TN in the Saugahatchee Creek watershed. In the Magnolia River watershed, it underestimated flow and TN, but overestimated sediment and TP. Model calibration substantially improved model performance for predicting flow, sediment, TP and TN in both watersheds. Although uncalibrated model performance was acceptable for predicting sediment, TN and TP in the Saugahatchee Creek watershed, its performance for predicting sediment and TP was poor, and it was acceptable for TN in the Magnolia River watershed. Hence, no concrete conclusion can be reached about the reliability of the SWAT model in predicting sediment, TP and TN when it is not calibrated. On the other hand, calibrated SWAT model was found very reliable for predicting flow, sediment, TP and TN.

Model outputs were then analyzed at HRU level to identify the CSAs and their locations at sub-watersheds. Model calibration results revealed that only 10% of the Saugahatchee Creek watershed area was responsible for almost 52% of the sediment, 39% of the TP and 36% of the TN loadings during the study period, which differed slightly from the uncalibrated model results. In the case of the Magnolia watershed, 10% area contributed 36% of sediment, 32% of TP and 23% of TN yield based on calibrated model, which also differ slightly from the uncalibrated model results. Relatively low contribution from 10% of the area compared to the Saugahatchee Creek watershed is mostly due to high acreage of agricultural land in the Magnolia River watershed. According to this study, most of the CSAs of sediment, TP and TN are similar with and without model calibration. This study thus illustrated that a lumped model calibration won't make a significant difference in relative loadings, although absolute loadings can be altered substantially by model calibration. Thus, if the purpose of the study is only to identify the location of CSAs, calibration may not seem to be essential. Further, lumped calibration at the watershed outlet will not help much for identification of CSAs. It was also found that, not only land use/cover, but also soil type and slope can equally play significant roles in determining CSAs at HRU level. Agricultural land and urban areas with steep slopes were found to be CSAs of sediment in the Saugahatchee Creek watershed. Similarly, agricultural lands with high slopes were identified as CSAs for TP and TN in the Saugahatchee Creek watershed. However, no such effect of slope was observed in the Magnolia River watershed. Relatively flat land with little elevation differences in the Magnolia River watershed minimized the effect of slope. Thus, it was also concluded that effect of slope will be higher when identifying CSAs in watersheds having steep topographies compared to flat coastal watersheds.

The background organic matter content of the soil, if considerably high, can also have significant effect of CSA identification of TN as illustrated in the Magnolia River watershed. Various land use/cover intersected with wet loamy alluvial land and considerably high amount of organic matter content were identified as CSAs of TN in the Magnolia River watershed. This study thus concluded that although analysis of results with model calibration will identify the most accurate CSAs for sediment, TN and TP with accurate loadings from each area, SWAT (without calibration) may still be used to identify the CSAs in watersheds lacking sufficient data for model calibration but requiring immediate action for water quality improvement.

Future Directions

Although we tried to answer some question related to the effect of model choice and model calibration on location of CSAs, several potential new ideas originated from this study. The following studies are recommended for future studies:

1. Several watershed models can be used simultaneously to understand how model choice and complexity can affect prediction of flow, sediment and nutrients and consequently locations of Critical Source Areas (CSAs).
2. SWAT model can be used throughout the Southeast US to study its reliability in predicting flow, sediment, TN and TP in uncalibrated mode.
3. More studies at various other watersheds are recommended to see the effect of lumped model calibration on location of CSAs.
4. Studies are also recommended to study the effect of distributed calibration (sub-watershed scale calibration) vs lumped calibration (only at the outlet) for finding the location of CSAs.

5. Simultaneous field and modeling studies can be helpful in validating the location of CSAs identified by models.