

**Modeling impact of Land Use/ Cover changes on Water Quality and Quantity of  
Fish River Watershed**

by

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## Abstract

Hydrologic and water quality models are widely used for assessing the impacts of land use/cover (LULC) changes on water quality and quantity. However, their credibility for predicting LULC change impacts has not been tested with observed water quality. The main objective of this study was to test the Soil and Water Assessment Tool (SWAT), in predicting variations in water quality/quantity due to alterations in LULC over time in the Fish River watershed. Fish River is the main freshwater source of the Weeks Bay, which is one of the only three designated Outstanding National Resource Waters in the state of Alabama. A water quality model was setup for the Fish River watershed using the SWAT model. The model was first calibrated and validated for hydrology at a USGS flow monitoring station on the Fish River for the period 1990 to 1998 using the 1992 National Land Cover Dataset as the LULC input. The SWAT model was then calibrated and validated for water quality ( $\text{NO}_3^-$ , Org-P and TSS) using data collected during 1994-1998 at six tributaries of the Fish River. Model performance was best for flow, and weakest for  $\text{NO}_3^-$ . The calibrated SWAT model was later fed by 2008 LULC data and model simulations of flow and water quality were compared to their observed counterparts from the period 2008–2009 (post-validation). Post-validation results closely followed the calibration and validation trends. This study showed that SWAT is a reliable tool in predicting the impact of LULC changes on flow and water quality.

Often, it is not adequate to know that changes in LULC will cause a certain amount of increase or decrease of a particular or group of water quality constituents. In case of undesired increases, locating the critical source areas (CSA) of pollutants has practical implications from management perspective. Distributed watershed models are frequently used for identification of CSAs of pollutions in watersheds. One of the main inputs to these models is the spatially-explicit soils data. The second objective of this study was to evaluate if the use of two commonly used soil datasets, the State Soil Geographic (STATSGO) and the Soil Survey Geographic (SSURGO) data, can lead to differences in location of CSAs of sediment. The use of STATSGO soil data resulted in higher soil erodibility factor and surface runoff. As a result, higher sediment yield was obtained from the use of the STATSGO data as compared to the sediment yield obtained from the use of the SSURGO data. Therefore, for accurate identification of CSAs of sediment (and potentially other pollutants) and for effective implementation of economically-feasible best management practices (BMPs), it is important to use the most detailed spatial dataset available.

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## **CHAPTER 1**

### **1. Introduction**

#### **1.1 Introduction**

Coastal areas, around the world, are experiencing significant changes in land use/cover (LULC) due to population increase. One of the consequences of population growth is urban sprawl, which often have adverse impacts on the environment. Urbanization gives rise to impervious areas in the form of more roof tops, roads, and other impervious surface types. Impervious areas affect the hydrologic cycle and water quality due to increase in the volume of runoff. A study conducted by Booth and Jackson (1997) showed that even a rise as low as 10% in the percentage of impervious areas can result in an irreversible loss of aquatic-system function. Other studies conducted in different areas with similar results include Bledsoe and Watson (2001) and Schueler (1995). Urbanization has also shown to increase heavy metal (Callender and Rice 2000), and bacteria loadings (Gregory and Frick 2000). Runoff transports various pollutants, resulting in non-point sources (NPS) of pollution. NPS of pollution are the distributed sources from which pollutants are carried by runoff or snowmelt and are deposited in water bodies such as lakes, rivers, wetlands and oceans. Increased percentages of imperviousness and NPS sources may lead to a rise in sediment and nutrients loading in the streams (Arnold and Gibbons 1996 and Nelson and Booth 2002). Due to the

complexities involved in identifying distributed sources of pollution, NPS pollution is much more difficult to manage compared to point source pollution. The U.S. Environmental Protection Agency (EPA) defines point source of pollution as “any single identifiable source of pollution from which pollutants are discharged, such as a pipe, ditch, ship, or factory smokestack.”

Watershed models have been used successfully in assessing water quantity and quality changes due to varying LULC. For instance, Bhaduri et al. (2000) used the Long-Term Hydrologic Impact Assessment (L-THIA) model to study the effect of LULC changes on water quantity and quality in a watershed near Indianapolis, Indiana. They found that changes in LULC due to an 18% rise in an urban area resulted in an 80% increase of average annual runoff and a rise in average annual loadings of lead, copper, and zinc, by more than 50%. However, there was a 15% decrease in loadings of nutrients due to the reduction in agricultural acreage. Similarly, Shirinian-Orlando and Uchirin (2007) using the Hydrologic Simulation Program, Fortran (HSPF) found that increasing urbanization will cause a significant decrease in the recharge to the unconfined aquifer system lying below their study watershed in New Jersey. Similar studies have been conducted by Pikounis et al. (2002), Kalin and Hantush (2006b), Kalin and Hantush (2009), Tong et al. (2009), among others.

The Soil and Water Assessment Tool (SWAT) (Neitsch et al. 2005) is one of the more effective and widely used tools to assess NPS pollution problems, LULC change impacts, management practices, etc. For example, Kalin and Hantush (2006) used SWAT to study the effect of increasing urbanization on stream flow patterns in an Eastern

Pennsylvania watershed. Santhi et al. (2006) evaluated the long-term impact of implementation of water quality management plans on NPS pollution, at the farm level and watershed level using SWAT in the West Fork watershed, Texas. Tripathi et al. (2005) studied the affect of 60 different combinations of various management practices on sediment and nutrient concentration in water in the subwatersheds of Nagwan watershed, East India, using SWAT model.

This study focuses on the rapidly urbanizing Weeks Bay watershed in Coastal Alabama. Weeks Bay is one of only three designated Outstanding National Resource Waters in the state of Alabama, which is the highest standard for water bodies with no point-discharges allowed. The 398 km<sup>2</sup> watershed is in Baldwin County, which has the 2<sup>nd</sup> fastest population growth rate in the state of Alabama. The LULC of the watershed has seen significant changes during the past decades. It is, therefore, anticipated that these human induced LULC changes will impact the quality and quantity of the waters draining into the bay. Therefore, we explored the relationship between LULC changes and water quality in the Fish River Watershed (Fish River supplies about 75% of the fresh water of the bay) with the help of the SWAT model. Water quality data or has been collected in the past at different times in the tributaries of the Fish River from 1994 to 2001 by Basnyat (1998), and Geological Survey of Alabama, GSA (Neil and Chandler, 2003). Arial photos and on-site visits revealed that there has been a significant increase in urban areas in the watershed. Hence, we found a unique opportunity in this watershed for assessing LULC change impacts on water quality using the SWAT model.

The conventional practice, in most studies dealing with predicting the consequences of LULC changes, is to construct (calibrate and validate) a model based on

current (or past) conditions and observations, and then make predictions for future water quality/quantity conditions expected to occur due to projected LULC modifications (e.g., Pikounis et al. 2002; Kalin and Hantush 2006b; Kalin and Hantush 2009; Tong et al. 2009). However, the credibility and reliability of the predictive power of the developed model is never tested. In this study we tried to cover this gap by post-validating the SWAT model in predicting the impact of changes in LULC in the Fish River watershed.

Weeks Bay Reserve has designated reducing sedimentation as the first priority for minimizing NPS pollution in the Bay (Weeks Bay National Estuarine Research Reserve Management Plan, 2007). The most efficient and effective approach for doing this is to locate areas within the watershed that contribute significantly increased sediment than other areas. Since Fish River watershed is the major drainage system to the Weeks Bay, it is important to locate the critical source areas (CSAs) for sedimentation within Fish River watershed. Process based, distributed watershed models are often used to identify critical CSAs inside the watershed (Tripathi et al. 2003; Gitau et al. 2004; Srinivasan et al. 2005; White et al. 2009). In the second part of the thesis the SWAT model was employed to identify the CSAs of sediment within the Fish River watershed.

Model simulation results are affected by the quality (accuracy, spatial resolution, age, etc.) of the input datasets used in the model. The U.S. Department of Agriculture Natural Resources Conservation Service (USDA-NRCS) has two different Soil databases with different spatial resolutions that can be used to extract soil parameters for the SWAT model. They are the state level State Soil Geographic (STATSGO) dataset and the county level Soil Survey Geographic (SSURGO) dataset. The second part of this thesis also

explored the effect of soil database used to extract soil parameters on the location of CSAs, are investigated.

## **1.2. Objectives**

Major objectives of this study are:

1. To assess SWAT model's predictive power in estimating water quality and quantity due to changes in LULC over time.
2. To evaluate whether the use of different soil databases (SSURGO and STATSGO) can lead to differences in the location of critical source areas (CSAs) of sediment.

## **1.3 Overview**

Chapter 2: This chapter focuses on testing the SWAT model in predicting changes in water quality and quantity of the Fish River watershed in response to changes in LULC over time. SWAT is first calibrated and validated for flow during the period 1990-1998, and then for water quality (TSS,  $\text{NO}_3^-$  and Org-P) during the period 1994 to 1998. Thereafter, model simulations are compared to the water quality data collected during 2008 – 2009 to test it (post-validate) along with LULC data from 2008.

Chapter 3: Critical Source Areas (CSAs) of pollution in a watershed are often identified using watershed models. One of the main inputs to these models is the soil data. Two of the most widely used soil datasets are the STATSGO and the SSURGO soil databases. This chapter focuses on evaluating whether the use of the STATSGO and the SSURGO dataset can lead to differences in locations of CSAs of sediment. The study is again conducted in the the Fish River watershed. Two different SWAT model setups for the Fish River watershed are used; one using the STATSGO data and the other using the

SSURGO data. The Tukey-Kramer test is used to identify CSAs of sediment at the sub-watershed and HRU (smallest computational units in SWAT with uniform soil, LULC and slope) levels.

Chapter 4: This chapter summarizes and discusses the findings from the previous two chapters. It also highlights the implications of the study along with suggestions for future research.

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## CHAPTER 2

2. Post-Validation of SWAT model for predicting impact of land use/ cover changes on water quality and quantity.

### 2.1 Abstract

Hydrologic and water quality models are widely used for assessing impacts of land use/cover (LULC) changes on water quality and quantity. The conventional practice in such studies is to construct (calibrate and validate) a model based on current (or past) conditions and observations, and then predict future water quality/quantity conditions expected to occur due to projected LULC. However, the credibility and reliability of the predictive power of the developed model is hardly ever tested. In other words, the practice of “*post-validation*” is almost never performed. This paper assesses the SWAT model in predicting the impacts of changes in LULC over time in a coastal Alabama watershed. SWAT is first calibrated and validated for flow, total suspended solids (TSS), nitrate ( $\text{NO}_3^-$ ) and organic P (Org-P) using data collected from 1990 to 1998 along with a 1992 LULC map. The calibrated and validated model is then used to explore whether it can successfully predict flow and water quality conditions during 2008-2010 (post-validation) with a LULC significantly different than the 1992 LULC. Comparison of model simulations with flow and water quality data from the period 2008-2010 showed that SWAT can be a reliable tool in predicting the effect of LULC changes. Further,

findings from this research underline the importance of using the most accurate and up to date LULC data in modeling.

## **2.2 Introduction**

Quality and quantity of water flowing through a watershed depend upon various factors such as soil, land use/cover (LULC), climate, point and non-point sources (NPS), etc., among others. LULC affects the generation of runoff due to varying infiltration, interception loss, and evapotranspiration rates. It also affects the movement of water on land by applying resistance to flow. For example, rainfall drains off more quickly from an impervious area than a forested area where more rain soaks into the soil due to macro pores and higher soil moisture-holding capacity. Urbanization is the most commonly studied LULC change. Studies have shown that urbanization decreases the amount of water that infiltrates into the soil (Dunne and Leopold 1978; Klein 1979; Harbor 1994), causes quicker and larger pulses in the flow hydrograph (Dunne and Leopold 1978; Neller 1988; Beighley and others 2003), and increases the frequency of extremes, both at the high and low-flow end (Lazaro 1990; Shaw 1994; Moscrip and Montgomery 1997; Rose and Peters 2001). LULC is also shown to affect water quality (Arnold and Gibbons 1996; Worrall and Burt 1992; Nelson and Booth 2002; Schilling and Spooner 2006). Various studies have shown that an increase in impervious surface area by even 10% could result in stream degradation (Schueler 1995; Booth and Jackson 1997; Bledsoe and Watson 2001). High proportions of impervious surfaces can lead to increased loadings of nutrients and sediments (Harden 1992; Arnold and Gibbons 1996; Nelson and Booth 2002) and heavy metals (Callender and Rice 2000) to streams.

Coastal areas are often the center of attraction for people. Human settlements in coastal areas greatly impact the local water quality of these areas, and non-point sources of pollution are the major contributor to pollution in such places. The Weeks Bay watershed in coastal Alabama (Figure 1) is under the threat of water quality impairment due to the rapid increase in non-point sources of pollution. Weeks Bay is one of the only three designated Outstanding National Resource Waters in the state of Alabama. Outstanding National Resource Waters are those with no direct point sources of discharges permitted. In the Weeks Bay Watershed there has been a significant conversion of natural land cover to agriculture and urban development during the last decade. It is anticipated that this transformation would result in changes in hydrologic and water quality patterns across the watershed. The assessment of the impact of these LULC changes on the quantity and quality of the major water supplier of the area, the Fish River, is therefore, of paramount importance.

Hydrologic and water quality models are the most efficient and effective means for assessing impacts of LULC changes on water quality and quantity. The conventional practice in such studies is to construct (calibrate and validate) a model based on current (or past) conditions and observations, and then make predictions for future water quality/quantity conditions expected to occur due to projected LULC modifications (Pikounis et al. 2002; Kalin and Hantush 2006b; Kalin and Hantush 2009; Tong et al. 2009). However, the credibility and reliability of the predictive power of the developed model is hardly ever tested. In other words, the practice of “*post-validation*” is almost never performed. A natural question to be asked when the once projected LULC, and forecasted water quality/quantity characteristics based on models developed with past

data become measurable/observable is how would those past model predictions compare to observed/collected counterparts, or how rational is it to keep relying on this model shall the LULC undergo further alterations.

This paper deals with post-validating the process-based model Soil and Water Assessment Tool, SWAT (Neitsch et al. 2005) in predicting the impact of changes in LULC. SWAT model is widely used in addressing NPS pollution problems around the globe (Jha et al. 2007; Abbaspour et al. 2006; Kang et al. 2005). It's also being used for evaluating changes in water quality due to varying land use practices (King and Balogh 2001; Santhi et al. 2006; Schilling et. al. 2008; Tripathi et al. 2005). SWAT is first calibrated and validated in the Fish River watershed for flow, total suspended solids (TSS), nitrate ( $\text{NO}_3^-$ ) and organic P (Org-P) using data collected from 1990 to 1998 along with a 1992 LULC map. The calibrated and validated model is then used to explore whether it can predict flow and water quality conditions during 2008-2010 (post-validation) with a LULC significantly different than the 1992 LULC. Model predictions are compared to observed flow and water quality data collected between 2008 and 2010.

## **2.3 Methodology**

### **2.3.1 Study Area**

The Fish River watershed, located in Baldwin County, Alabama, drains into Weeks Bay and has a total drainage area of about 398 km<sup>2</sup> (Figure 1). Weeks Bay is a small sub-estuary of the Mobile Bay, receiving approximately 75% of its fresh water from the Fish River with the rest mainly coming from the Magnolia River (Figure 1). The watershed lies in two physiographic districts, the Southern Pine Hills and the Coastal

Lowlands. Baldwin County has the second fastest population growth rate in the state of Alabama. The watershed has seen significant changes in LULC during the past decade, mainly in the form of urbanization. It was therefore anticipated that these human induced land-use changes impacted the quality and quantity of the waters draining into the Weeks Bay. Major LULC types in the Fish River watershed are pasture, agriculture, evergreen forest and urban (Figure 2).

As shown in Figure 2, a large fraction of the watershed was covered by pasture in the early 1990's, which has gradually been converted into agricultural and medium-density residential areas by 2008 due to urbanization and the expansion of sod farming. Figure 2 depicts major LULC changes from 1992 to 2008 for the Fish River watershed. A major portion of the watershed is covered with sandy loam soil. The rest of the watershed is covered mainly with either sandy or loamy soil.

### **2.3.2 SWAT Model**

The Soil and Water Assessment Tool (SWAT) is commonly used to explore effects of management practices and for assessing the impact of LULC changes on flow and water quality. SWAT is a continuous time simulation model evolved from Simulator for Water Resources in Rural Basins (SWRRB) (Williams et al. 1985; Arnold et al. 1990). It models physical processes like movement of water, sediment, nutrients, etc. SWAT has undergone several developments since the early 1990's. For this study we used SWAT2005 (Neitsch et al. 2005). Model parameterization and processing of input and output files are carried out by ArcSWAT version 2.1.6 (Winchell et al. 2008).

SCS curve number method (SCS, 1972) and the Green & Ampt infiltration method (1911) can be used for calculating surface runoff within SWAT. The Green & Ampt infiltration method requires sub daily data, but due to unavailability of sub daily rainfall data for our study area we used SCS curve number method to calculate surface runoff. SWAT provides the option of using Penman-Monteith, Priestley-Taylor, or Hargreaves method for estimating potential evapotranspiration during the run. We used Penman- Monteith method for our study. Other than the soil water that is taken up by plants or that is evaporated, the rest of the soil water either percolates into the aquifer or moves laterally in the soil profile and finally contributes to the streamflow. SWAT uses modified form of Universal Soil Loss Equation (USLE), Modified Universal Soil Loss Equation (MUSLE) for calculating sediment loading (Neitsch et al. 2005). MUSLE uses runoff factor for calculating sediment loading. The movement and transformation of nitrogen and phosphorus in a watershed are also tracked by SWAT. Transformation of nitrogen and phosphorus is controlled during their respective cycles. Nitrogen and phosphorus cycles are connected to water, atmosphere, and land. Detailed description of flow and water quality processes used in SWAT are described in Neitsch et al. (2005) and are not repeated here.

### **2.3.3 Input data**

Input datasets required by SWAT include Digital Elevation model (DEM) data, stream flow, land use/cover (LULC) data, soil data, and weather data (Arnold & Allen, 1996). National Elevation dataset with a 1/3 arc second resolution (10 m pixels) was used for delineating the Fish River watershed and the drainage area of the sampling sites.

The county level Soil Survey Geographic (SSURGO) dataset was used in deriving soil parameters. Fish River watershed contained 106 different SSURGO soil types. Dominant SSURGO soil types for Fish River watersheds include Marlboro (very fine sandy loam, 0 to 2 percent slopes) and Lakeland (loamy fine sand, 0 to 5 percent slopes). Rainfall data for this study was available from three climate stations including one USGS rain gauge at the USGS flow monitoring site, and two NOAA stations (Figure 1). Temperature data was available only from the Robertsdale station. Streamflow prediction, especially at early stages in model simulations, is highly dependent on the soil antecedent moisture condition. Thus, a warm up period of about a decade long was used to minimize uncertainties associated with initial unknown conditions.

#### *LULC data*

Two different LULC dataset, 1992 National Land Cover Data (NLCD) and 2008 LULC for Baldwin County were used as an input for creating two different models. The 1992 NLCD was the most representative LULC dataset for the water quality data used to calibrate and validate the SWAT model. The water quality data were collected by two separate groups in the tributaries of the Fish River from 1994 to 1998 (Basnyat 1998, and Geological Survey of Alabama, GSA 2003). LULC data for 2008 was used as input for the second model to perform post validation during 2008-2010. The watershed in 1992 was dominantly pasture, forest, row crops, and urban. Due to its location Weeks Bay watershed attracts a large number of people every year, which has led to increases in medium density residential, large density residential and commercial areas. The urban area has increased from 2.1% in 1992 to 22.8% in 2008. Table 2 shows the changes in



LULC that had taken place at various sampling sites within Fish River watershed from 1992 to 2008.

LULC map for 2008 was developed specifically for this study. A Landsat TM image acquired on March 25, 2008 covering Weeks Bay was purchased from USGS Earth Resource Observation and Science (EROS) and geo-referenced to Digital Orthophoto Quarter-Quadrangle (DOQQ) corresponding to the GRS 1980 spheroid, NAD 83 datum and Universal Transverse Mercator (UTM) projection with Root Mean Square Error (RMSE) of less than 0.5 pixels. Unsupervised classification was then performed, producing 100 spectral clusters. Each spectral cluster was visually checked against the Landsat imagery as well as the ancillary data such as aerial photographs, existing LULC data, national wetland inventory, etc., and was labeled with the land cover type it represents. All unlabeled pixels remaining from the last step were then subjected to additional unsupervised classification, and each cluster was assigned with specific land cover type. Post refinements were performed, especially for developed areas, including commercial/transportation/industrial, high residential, medium residential and low residential by comparing the original TM images with aerial photographs of 2005 and LULC data of 2005 developed by Baldwin County as well as ground truth data. The obviously misclassified areas were manually corrected. Nearest neighbor functions were performed on the final classification image using a 3x3 window, producing a smooth LULC image. An overall accuracy of 85.43% was achieved.

### **2.3.4 Model Calibration, Validation and Post-Validation**

Model calibration refers to the adjustment of some of the input variables within their acceptable ranges by minimizing the differences between model generated outputs and observations. Validation is the testing of the calibrated model with a new set of observations. Model calibration and validation are generally carried out at a single point, usually the watershed outlet. This is achieved through a split-sampling method, where part of the observed data is used for calibration and the remaining used for validation. In this study flow component of the SWAT model was calibrated and validated in this manner (e.g. temporal or longitudinal calibration/validation) at the USGS gauge (Figure 1) for the time periods (Jan'1990- Dec'1994) and (Jan' 1995- Dec'1998), respectively.

Spatial calibration/validation was performed for water quality (TSS, nitrate and organic P) due to the nature of the data. Water quality data was only available from several tributaries of the Fish River (Figure 1) for the period 1994-1998 (Basnyat 1998; Neil and Chandler 2003). Unfortunately no past water quality data was available at the USGS site. Therefore split sampling was done at the spatial domain. Data from sites G5, G7 and G9 were used for model calibration, and data from sites G4, G6 and G10 were used for validation. These sites were selected in a way that each represents a different LULC type. While watershed G5 has more than 56% of its area as pasture land, watershed G7 has higher percentage of agricultural land, and G9 has the highest forest coverage comprising more than 62% of its watershed area (Table 2).

For comparing observed and simulated water quality data, observed instantaneous water quality data was converted into continuous monthly loadings with the widely used USGS software LOADESTimator (LOADEST) (Runkel and others 2004). LOADEST is

used to convert instantaneous water quality data into continuous data using regression models. LOADEST has been used in various studies related to water quality (Dornblaser and Striegl 2007; Eshleman et al. 2008; Maret et al. 2008). LOADEST requires flow data for estimating the water quality loadings. Since flow data was not available at the sampling sites, model simulated flows were used to obtain monthly water quality loadings. Model performance was evaluated using mass balance error (MBE), coefficient of determination ( $R^2$ ) and Nash-Sutcliffe efficiency ( $E_N$ ) (Kalin and Hantush 2006). MBE represents the percentage by which the sum of the simulated values differs from the sum of the observed values;  $R^2$  captures the degree of linear correlation between observed data and simulation; and  $E_N$  measures the deviation of simulated versus observed plot from a 1:1 line.

Next, the calibrated and validated SWAT model is used to predict flow and water quality using the 2008 LULC data for the period Oct' 2008 – March' 2010. Model simulations are then compared to observed flow and water quality data to test whether SWAT is a reliable tool in predict effect of LULC changes, which we called post-validated. Flow and water quality data are collected at the same sites (Kalin, unpublished data) where SWAT model was calibrated and validated.

## **2.4 Results and Discussion**

### **2.4.1 Calibration and Validation**

**Flow:** SWAT was manually calibrated for flow at two stages. For this, streamflow was separated into baseflow and surface runoff components by using the web based hydrograph separation system (WHAT) (Lim et al. 2005). Only most sensitive

parameters were calibrated following results reported in literature (Santhi et al. 2001; Jha et al. 2003; Srivastava et al. 2006; Green et al. 2006). Table 1 shows the calibrated parameters along with their default values. Model simulated and observed streamflow at the USGS gauge are shown in Figure 3 at monthly time scale for calibration (1990-1994) and validation (1995-1998) periods. In the figure model simulations closely follow observed values in both periods. The performance measures are also high with  $R^2$  and  $E_N$  values above 0.80 in both calibration and validation periods. Based on mass balance error, the model only slightly overestimated flow in the calibration period (MBE=3.3%). SWAT predicted flow successfully at daily time as well with  $R^2$  and  $E_N$  values of 0.69 and 0.68, respectively. Flow was overestimated by 10% during the validation period. Overall, the model was able to simulate streamflow during both calibration and validation periods with high accuracy.

***Total Suspended Solids (TSS):*** Instantaneous total suspended solid (TSS) concentrations were available for all the sampling sites for the period 1994-1998, which were converted into continuous monthly TSS loadings with LOADEST. Estimated monthly TSS loadings (called observed data henceforth) from three sites (G5, G7 and G9) were used for calibrating sediment related parameters of SWAT. Model is validated using TSS data from sites G4, G6 and G10. TSS is usually composed of clay and silt. Therefore, clay and silt loadings from the model output were added together to get the TSS loadings from the model. Table 1 shows the parameters that were adjusted to bring simulated sediment loading close to the observed values.

Figure 4 shows model simulated and LOADEST estimated monthly TSS loadings for both calibration and validation sites. Figures show that the model was successful in capturing TSS loadings for most of the watersheds during the calibration period (1994-1998) except for months July 1997 and September 1998. This may be attributed to large storms during which observed TSS may contain particles larger and heavier than silt and clay and even organic detritus. National Climatic Data Center (NCDC) recorded two floods in Baldwin County during July 1997 and September 1998. On the 19<sup>th</sup> day of the month of July in 1997, Hurricane Danny started falling at 2100 hrs (CST) on Baldwin County and the Fish River came out of its banks for several days. The highest estimated rainfall was 30 to 35 inches with even higher estimations near Weeks Bay. Another hurricane, Hurricane Georges hit Baldwin County on 28<sup>th</sup> September 1998 dropping about 15 to 25 inches of rainfall resulting in a 25 year return interval flood for Fish River. In order to get a better understanding of model performance during the calibration period, we removed the loadings for these two months.

Performance statistics confirm that simulated TSS loadings are adequately matching observed TSS data at sites G5 and G9 (Figure 4). Removal of July 1997 and September 1998 made a significant change in MBE. At site G5 the change in MBE was 89% (from 73% underestimation to 16% overestimation). At site G7 164% overestimation was reduced to 43%. Change in MBE at G9 was about 17%. In general, except for some extreme events, the model was able to simulate TSS loadings efficiently at the calibration sites. Similar results are obtained with the validation watersheds. TSS loadings during July 1997 and September 1998 are again underestimated substantially. High  $R^2$  and  $E_N$  values combined with low MBE for watersheds G4 and G6 after

removing the loadings of July 1997 and Sep 1998 indicate that SWAT successfully predicted the TSS loadings for these watersheds (Figure 4). The model did a very poor job at site G10. The main channel where water quality data was collected is narrow. During recent site visits we frequently observed streamflow overflowing its bank. This makes sediment data collected at this site less reliable.

**Nitrate ( $\text{NO}_3^-$ ):** Calibration of SWAT for nutrients was performed after calibrating for TSS loadings as erosion and sediment processes effect nutrient transport.  $\text{NO}_3^-$  concentrations were available for the same sampling sites for the period 1994-1998. Calibration and validation was carried out for  $\text{NO}_3^-$  loadings in a similar way to TSS calibration/validation. Sites G5, G7 and G9 were again used for calibration and G4, G6 and G10 were used for validation. Calibration was not performed for other forms nitrogen because of lack of data. Watershed G9 was calibrated separately, by adjusting the  $\text{NO}_3^-$  concentration of the soil (sol\_no3) to bring the final  $\text{NO}_3^-$  loadings for this particular watershed within comparable range of the observed  $\text{NO}_3^-$  loadings. The main soil type in watershed G9 is loamy soil which is different from the rest of the Fish River watershed, where the soil is either sandy or sandy loam. Calibrated parameters are presented in the Table 1.

Figure 5 shows graphical comparison of observed and simulated  $\text{NO}_3^-$  loadings.  $R^2$  and  $E_N$  values for  $\text{NO}_3^-$  loadings are lower in comparison to those for flow and TSS simulations. This is not totally unexpected as errors incurred during calibration of flow and TSS are carried over. Watershed G7 shows a relatively good match of simulated  $\text{NO}_3^-$  loadings with the observed values. Better model performance for this particular

watershed may be attributed to the fact that this is the closest watershed to the USGS gauging station, which was used for flow calibration. Summary of the literature review presented in Moriasi et al. (2007) show that the range of reported  $E_N$  values for monthly calibration of  $\text{NO}_3^-$  lie between -0.08 to 0.59, with a median of 0.26. According to this we can say that for watersheds G5, G7 and G9,  $E_N$  values are within comparable ranges when compared to literature values. Figure 5 shows a slight shift in the simulated  $\text{NO}_3^-$  loadings from the observed loadings for watersheds G5 and G7. Low average  $\text{NO}_3^-$  loadings for watershed G9 can be explained by the fact that about 62% of the watershed is covered with forests that can act like a sink or buffer, therefore preventing  $\text{NO}_3^-$  loadings into the tributary of Fish River. SWAT model was able to predict  $\text{NO}_3^-$  loadings adequately at the validation sites G6 and G10 (Figure 5). At G4 simulated loadings were higher compared to observed data. Since we do not have detailed knowledge on fertilizer application rates and practices or any BMPs that may have existed during this period, we have no clear explanation to these anomalies.

***Organic P (Org-P):*** The only available P data was Org-P concentrations. Watersheds G5, G7 and G9 were used for calibration, while the watersheds G4, G6 and G10 were used for validation. Table 1 presents all the parameters that were adjusted for calibrating Org-P loadings. Similar to  $\text{NO}_3^-$ , special calibration was needed for watershed G9 where the model was significantly underestimating Org-P content. In order to bring the simulated value in comparable range with the observed data for watershed G9, soil Org-P content was raised to 60 mg/kg. Again, this is most likely due to the differences in soils.

Calibration sites G7 and G9 show a good match between observed and simulated loadings of Org-P (Figure 6). Although there seems to be a slight over prediction during the times of high flows, overall the model satisfactorily predicted Org-P loadings at the monthly scale. Model performance measures at the calibration sites show that SWAT slightly over predicted Org-P loadings except at G9, where model underestimated Org-P loading by approximately 38%. It is evident from Figure 6 that the model is overestimating Org-P during high flows. Average loadings for Org-P were between 0.11 to 0.22 kg/ km<sup>2</sup>/ day suggesting low phosphorus content at all the sampling watersheds. Model performances at validation sites were also good, especially at site G4.

#### **2.4.2 Post-Validation (2008- 2010)**

In previous sections SWAT model is calibrated and validated for flow at the USGS gauging station for the period 1990 to 1998, and for TSS, NO<sub>3</sub><sup>-</sup>, and Org-P at various sampling sites (but not at the USGS site). In this section the calibrated SWAT model is further tested for its capabilities on predicting effects of changes in LULC on water quality. For this LULC data representing the year 2008 was used as an input to ArcSWAT in place of the previously used 1992 NLCD data. While the sub-watersheds and the stream network for the Fish River watershed remained the same for both LULC datasets of 1992 and 2008, there was a change in HRUs (the smallest representative element in SWAT with a uniform soil, LULC and slope) due to changes in LULC from 1992 to 2008. Model parameters were transferred according to soil and LULC combinations. For instance, the curve number which is a parameter related to LULC and soil, was decreased by 10% for every LULC type in the model with 2008 LULC data. A



similar reduction in the curve number had been performed while calibrating the model with the 1992 LULC dataset. Other model parameters, shown in Table 1, were also changed from their default to calibrated values. The model was then simulated for the period 1980-2010. The model was also simulated using 1992 LULC data for the same period, to visualize the differences in model simulations while using two different LULC datasets from 1992 and 2008. Model simulations for TSS,  $\text{NO}_3^-$  and TP were compared with their observed counterparts, at different sampling sites.

**Flow:** Although flow was measured at the sampling sites, due to lack of confidence in flow rating curves (insufficient flow measurements to develop a reliable Q-h relationship), they are not used in this study. Therefore, post-validation of SWAT for flow was limited to the USGS site. Simulated flow values obtained from the model using 1992 and 2008 LULC datasets at the USGS gauge were compared with the observed flow data. High  $R^2$  and  $E_N$  values of 0.88 and 0.86, respectively, along with low MBE of -5.8%, using 2008 LULC data suggested a good match between the observed and simulated flow values for the Oct' 2008 – Mar'2010 period at monthly time scale (Figure 7). The use of 1992 LULC data results in  $R^2$ ,  $E_N$  and MBE values of 0.80, 0.77 and 0.4%, respectively, for the same period. Although these performance measures are satisfactory from modeling perspective, the 2008 LULC clearly provided better flow estimates.

**TSS:** TSS data were collected at the same sampling sites within the Fish River watershed from Oct'2008 to Jan'2010. Instantaneous TSS concentrations were converted into monthly TSS loadings using LOADEST. Due to the unavailability of enough observed

flow measurements at the sampling sites, it was not possible to generate a reliable stage discharge curve for those sites. Consequently, model simulated flow was used for converting instantaneous TSS concentrations into monthly TSS loadings. Based on the availability and quality of the data four different sampling sites were chosen for evaluating the SWAT model in simulating water quality parameters during Oct'2008 - Jan'2010.

Figure 8 shows the comparison between observed and simulated TSS loadings using 1992 and 2008 LULC datasets at those four sampling sites for the period. It is clear that the model is simulating TSS loadings with good accuracy at all sites using the 2008 LULC data with the exception of March 2009. There was a severe storm event on March 29<sup>th</sup>, 2009 which caused the USGS gauge on Fish River to record a stage 4 feet above the flood level. NCDC described the event as “heavy rains causing widespread flooding of roadways”. Large scaled storms such as this could also erode channels and bring TSS from the floodplains. Typically, erosion and sediment deposition occur simultaneously in small events, which can be easily flushed out by a large storm. The inability of SWAT accurately predicting sediment in such big events was also evidenced during the calibration stage. Figure 8 show that the model did not predict TSS loadings accurately using 1992 LULC data as its input when compared to simulations with 2008 LULC. With the 1992 LULC data, the model underestimated the monthly average TSS loadings by more than 70% for watersheds G4, G6 and G9. Overall, the model performed clearly better with the 2008 LULC dataset.

**$NO_3^-$**  : Model performs well for  $NO_3^-$  loadings at all sites from May 2010 onward. Before May 2010, there appears to be a time lag between model simulations and observed data. When the whole period is considered predicted average  $NO_3^-$  loadings did not deviate more than 40% from the observed  $NO_3^-$  loadings. The model was doing a relatively good job with the 1992 LULC data too in simulating  $NO_3^-$  loadings at site G9.  $R^2$ ,  $E_N$ , MBE shown in Figure 9 indicate that SWAT was not able to simulate  $NO_3^-$  as accurately as flow and TSS. This was expected, as model performances in simulating  $NO_3^-$  loadings during the calibration and validation periods were also lower than the model performances in simulating flow, TSS and Org-P. Positive MBE values indicate overestimation of  $NO_3^-$  loadings at all sites using both 2008 and 1992 LULC datasets, except for G9 which shows marginal underestimation. Overall, the model performance in simulating  $NO_3^-$  loadings decreased compared to the calibration and validation periods. However, when considering the effect of change in LULC data as input and other unknowns (e.g. actually fertilizer application rates) model simulations can be deemed acceptable.

***Total Phosphorus (TP)***: Similar to the TSS and  $NO_3^-$  loadings, monthly total observed loadings for TP were also compared to the simulated loadings from the model using 2008 and 1992 LULC datasets. Here TP is used instead of Org-P, which was used during calibration and validation. The laboratory facilities were only equipped for analyzes of TP.  $R^2$  and  $E_N$  values show that the model is doing a better job in predicting TP loadings than simulating  $NO_3^-$  loadings using 2008 LULC data (Figure 10). When 1992 LULC is used as input, model performance in simulating TP loadings drops significantly, much

more than the drop observed in simulating  $\text{NO}_3^-$  loadings. The MBE using 1992 LULC data is higher than 80% for three out of four sites that were used for testing the accuracy of the model simulations. Figure 10 show that although simulated TP loadings using 2008 LULC data closely follow the pattern of loadings in different months, the model underestimated TP loadings at all sites.

## **2.5 Summary and Conclusions**

Watershed models are commonly used in assessing the impacts of land use/cover (LULC) changes on hydrology and water quality. They are typically calibrated using existing or past conditions and are then used in forecast mode to analyze various LULC change scenarios. In the absence of data, they are not calibrated at all. The credibility of those predictions of water quality and quantity due to LULC changes has not been explored in the literature, which is referred to as “post-validation” in this study. Hence, this study focused on “post-validating” the SWAT model at Fish River watershed in coastal Alabama. The model was used to assess the effects of LULC changes on flow and water quality of the Fish River and its tributaries. SWAT was first calibrated and validated for flow for the period 1990-1998, and then for water quality (TSS,  $\text{NO}_3^-$  and Org-P) during the period 1994 to 1998 using 1992 LULC dataset. Thereafter, the calibrated model was fed with 2008 LULC and simulations were compared to observed flow and water quality data during Oct’2008 - Jan’2010. SWAT was calibrated for flow only at the USGS gauge because observed flow data was not available at any of the sampling sites during the period of past water quality data collection (1994-1998). The model was calibrated and validated for water quality parameters at the sampling sites

only. It was assumed that once the model is calibrated for flow at the USGS gauge, which drains more than half of the Fish River watershed, it should provide satisfactory flow estimates at subwatershed level.

Visual comparisons through time series graphs and model performance statistics ( $R^2$ ,  $E_N$ , MBE) showed that SWAT was able to simulate flow with good accuracy at the USGS gauge. SWAT generally performed well for water quality during calibration/validation (1994-1998) and prediction periods (Oct'2008 – Jan'2010) at most of the sampling sites. Model performance was best for flow, and weakest for  $\text{NO}_3^-$ . It was observed that model simulations systematically underestimated TSS loadings at various sites during extreme events. TSS loading estimates in SWAT constitute silt and clay particles. During large storms TSS data may contain particles larger and heavier than silt and clay particles, resulting in high observed TSS loadings. Although, there seems to be a slight over prediction during high flows, overall the model satisfactorily predicted Org-P loadings at the monthly time scale.

As an exercise 1992 LULC was also tried to predict flow at the USGS gauge and water quality at the sampling sites during Oct'2008 – Jan'2010. Although flow simulations were good enough from the modeling standpoint, it was not as good as the results obtained through running the model with the 2008 LULC. Expectedly SWAT performed poorer with the 1992 LULC data in simulating water quality parameters. This further establishes that SWAT can be a reliable tool in predicting the effect of LULC changes. Moreover, these findings underline the importance of using the most accurate and up to date LULC data in modeling.

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Table 1. Calibrated SWAT parameters along with their default values.

Process	Parameters	Calibrated values	Default Values
Flow	<i>cn2</i>	-10%†	0
	<i>esco</i>	0.9	0.95
	<i>gw_delay(days)</i>	150	31
	<i>Gwqmn(mm)</i>	4	0
	<i>gwrevap</i>	0.2	0.02
	<i>surlag</i>	1.5	4
TSS	<i>spcon</i>	0.0002	0.0001
	<i>spexp</i>	1.2	1.0
Nitrate	<i>cmn</i>	0.003	0.0003
	<i>nperco</i>	0.02	0.2
	<i>rsdco</i>	0.1	0.05
	<i>sdnco</i>	1	1.10
	<i>sol_no3(mgN/Kg soil)</i>	1	0
Org-p	<i>phoskd</i>	80	175
	<i>psp</i>	0.5	0.40
	<i>sol_orgp(mgP/Kg soil)</i>	60	0

† percentage change

Table 2. Land use/cover (LULC) change from 1992 to 2008 at the studied sites.

		G4	G5	G6	G7	G9	G10
Drainage area (km <sup>2</sup> )		30.8	10.5	12.7	24.8	43.9	5.5
Forest (%)	1992	20.1	5.8	19.9	25.5	61.5	14.4
	2008	18.3	6.2	19.6	21.9	38.9	11.0
Agrr (%)	1992	24.9	32.3	22.7	33.0	9.5	25.9
	2008	28.9	73.3	33.4	38.9	10.6	44.9
Past (%)	1992	49.8	56.1	49.3	44.6	16.0	53.0
	2008	7.2	8.6	20.2	7.4	5.6	22.2
Urban (%)	1992	0.05	0.05	0.02	0.1	0.3	1.7
	2008	36.2	6.0	15.1	22.4	18.0	21.1

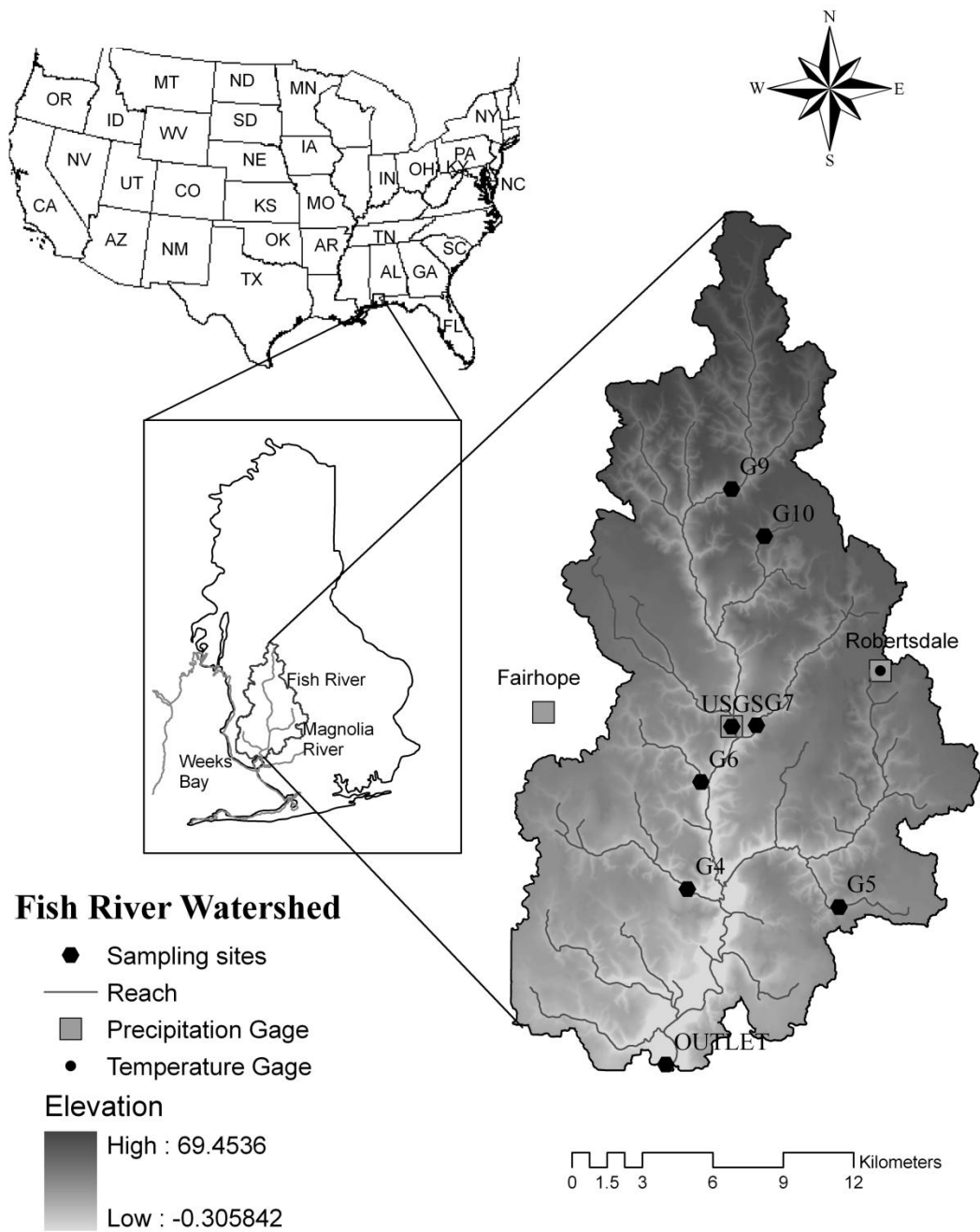


Figure 1. Location of the Fish River watershed along with the sampling sites. Locations of the precipitation and the temperature gauges are also shown.

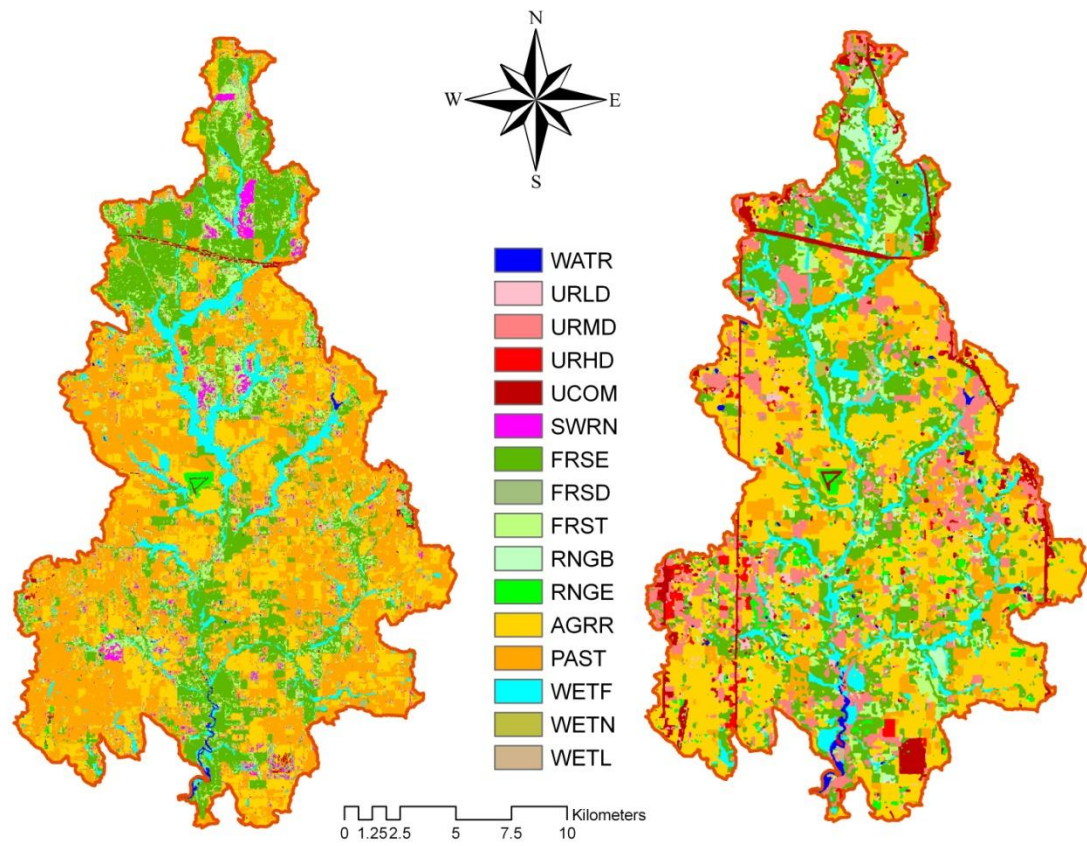


Figure 2. Land use/cover (LULC) distribution for the Fish River watershed in 1992 and 2008.

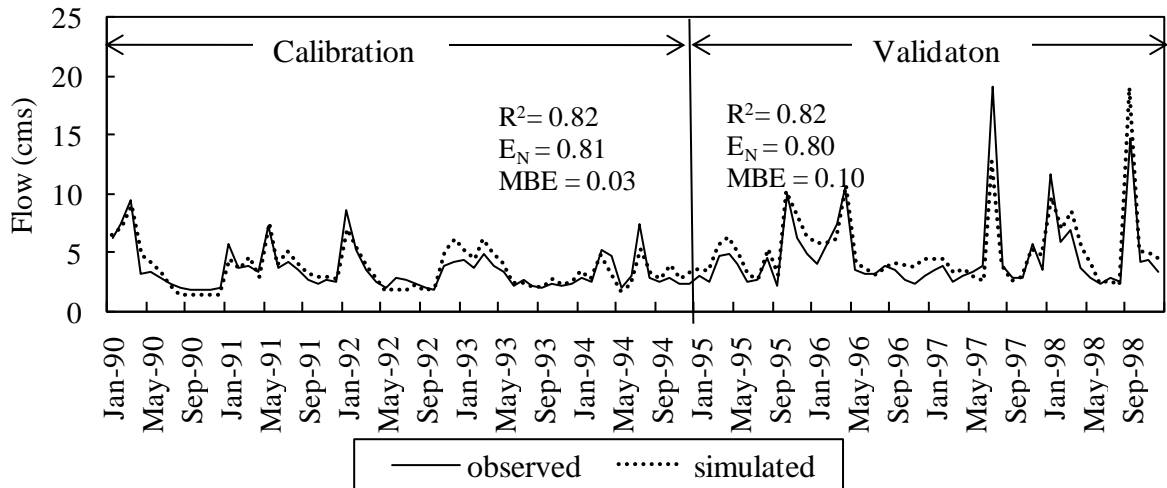


Figure 3. Comparison of simulated and observed monthly flows at the USGS gauge for the calibration period from Jan' 1990 to Dec' 1994 and for the validation period from Jan' 1995 to Dec' 1998.

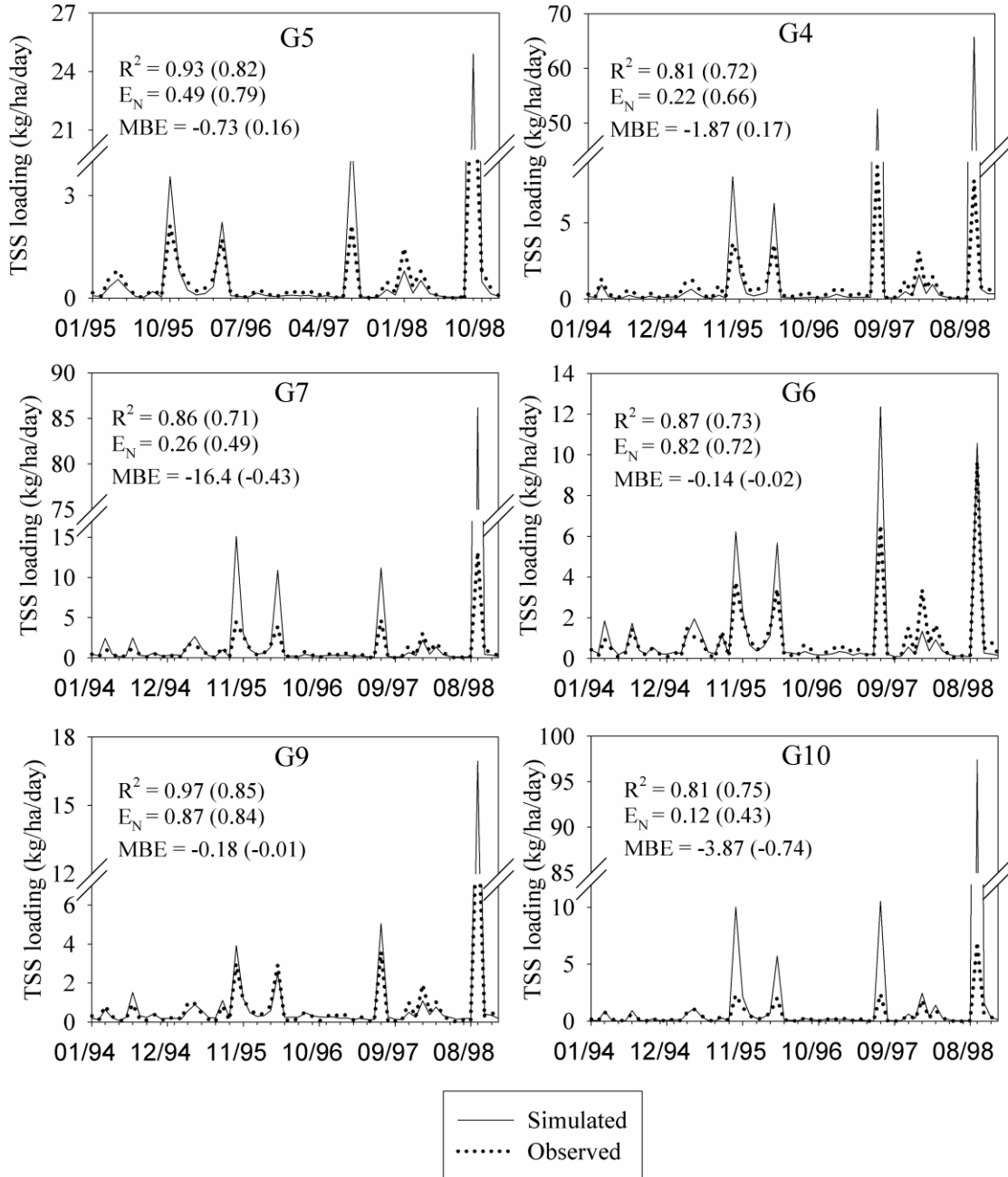


Figure 4. Comparison of simulated and observed monthly sediment loadings for calibration (G5, G7, and G9) and validation (G4, G6 and G10) sites. Values within brackets are those obtained after removing July 1997 and Sep 1998 (see text for discussion).

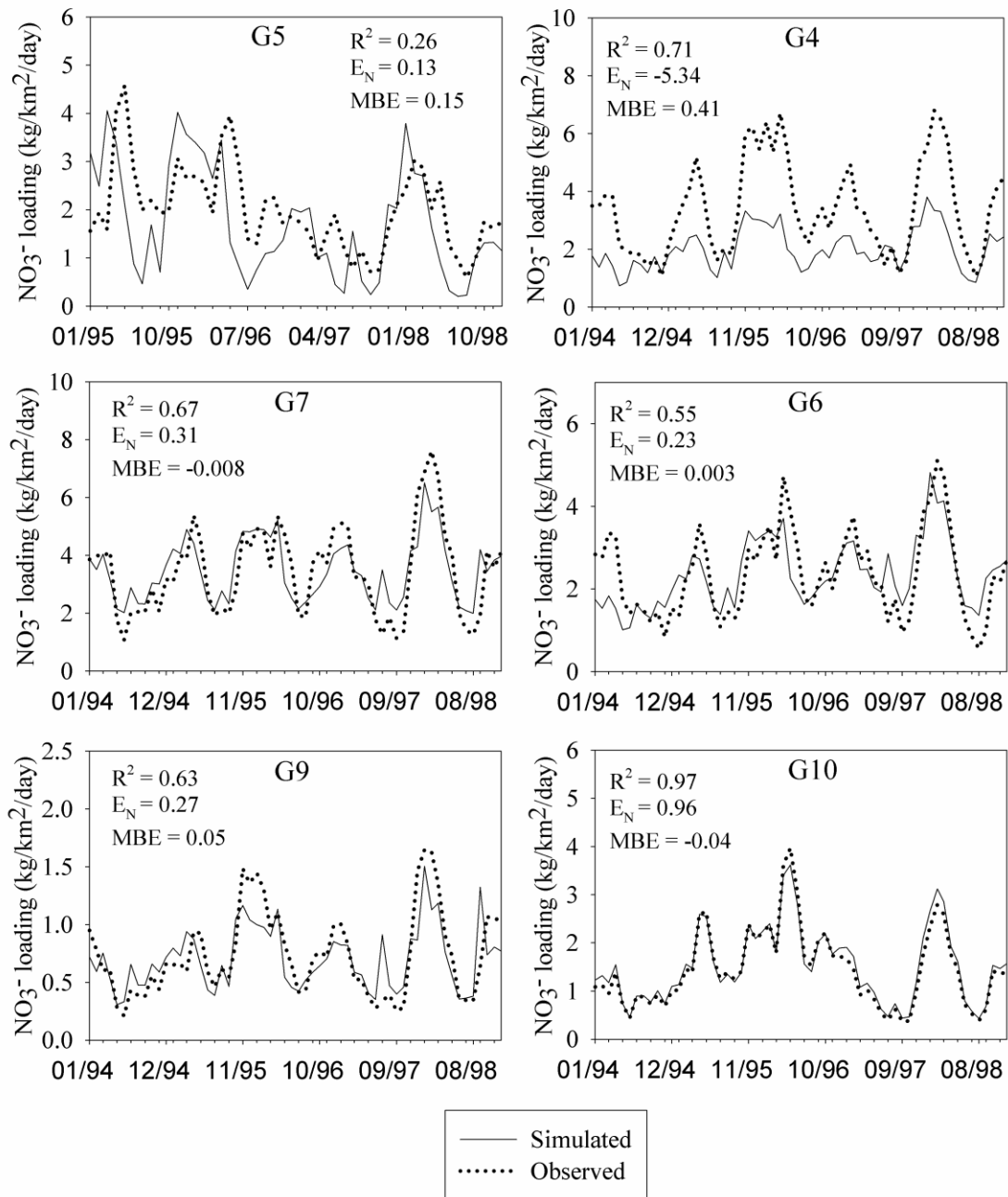


Figure 5. Comparison of simulated and observed monthly  $\text{NO}_3^-$  loadings for sites G5, G7, and G9 during calibration and for sites G4, G6 and G10 for validation.



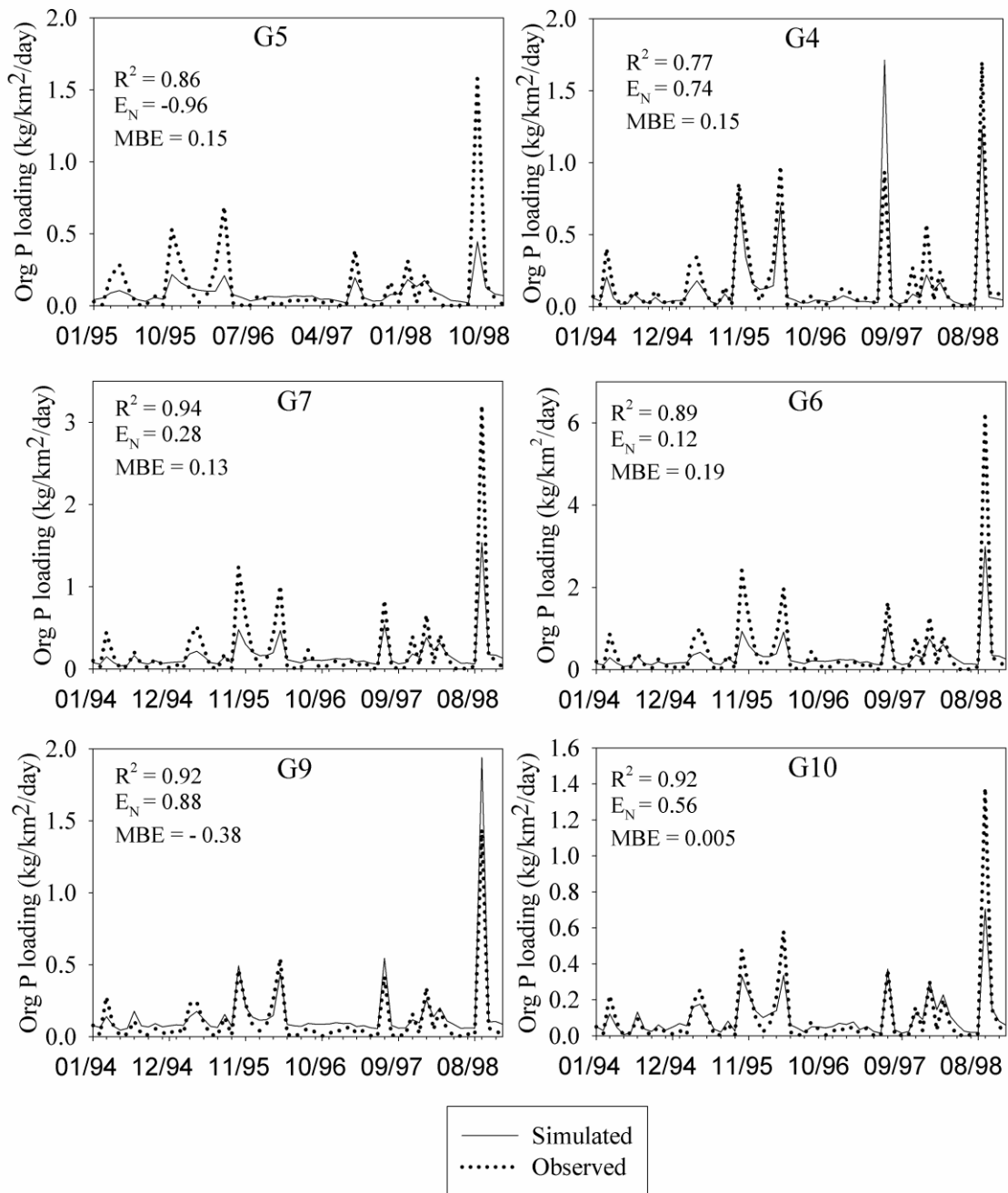


Figure 6. Comparison of simulated and observed monthly Org-P loadings for sites G5, G7 and G9 during calibration and for sites G4, G6 and G10 for validation.

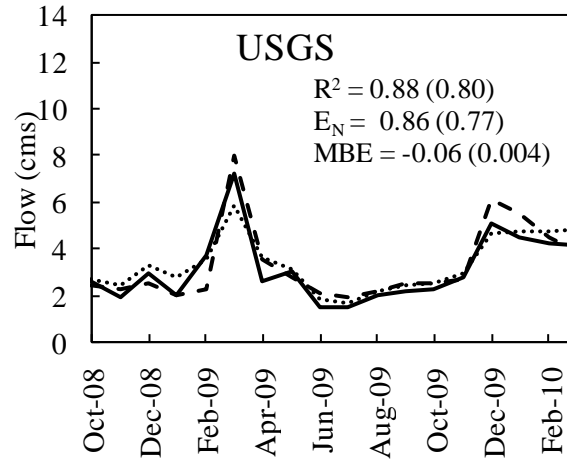


Figure 7. Comparison of simulated and observed monthly flow at the USGS gauge for the period Oct'2008 – Mar'2009. (—) Observed, (.....) Simulated with 2008 LULC (---) simulated with 1992 LULC. Values within brackets are those obtained from simulations using 1992 LULC data.

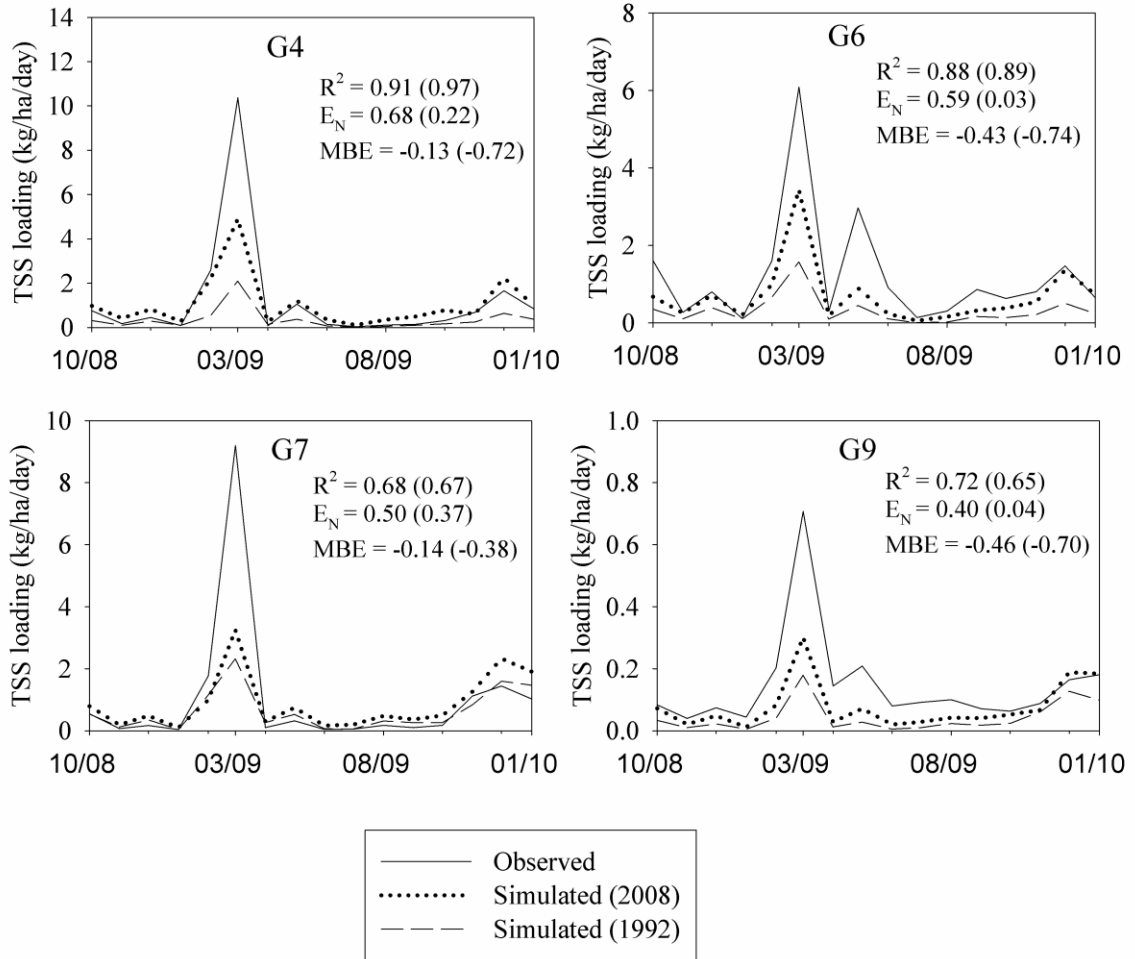


Figure 8. Comparison of simulated and observed monthly sediment loadings for different sampling sites for the period Oct'2008- Jan'2010. Values within brackets are those obtained using 1992 LULC data.

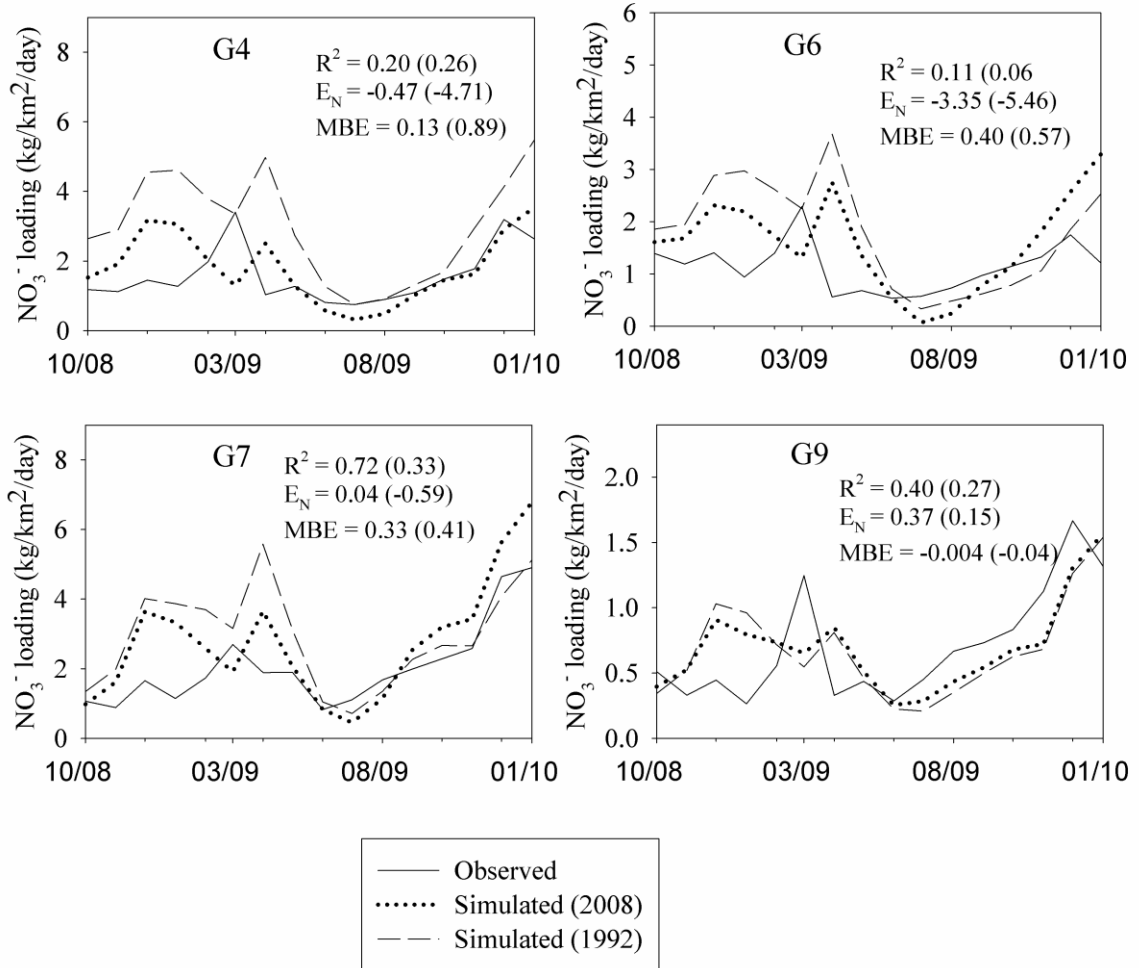


Figure 9. Comparison of simulated and observed monthly  $\text{NO}_3^-$  loadings for different sampling sites for the period Oct'2008 – Jan'2010. Values within brackets are those obtained using 1992 LULC data.

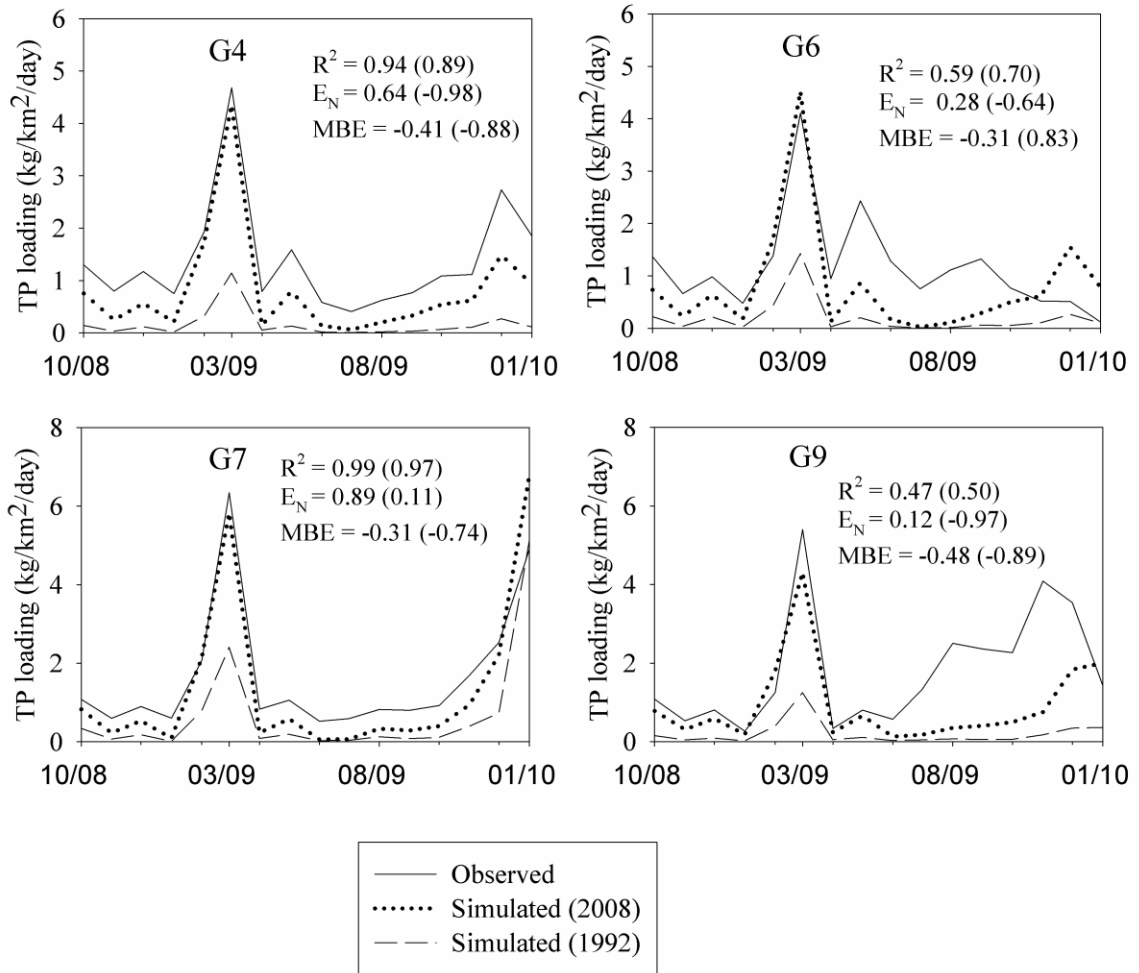


Figure 10. Comparison of simulated and observed monthly TP loadings for different sampling sites for the period Oct'2008 – Jan'2010. Values within brackets are those obtained using 1992 LULC data.

## **CHAPTER 3**

### **3. Effect of Soil Data Resolution on Identification of Critical Source Areas.**

#### **3.1 Abstract**

Identification of critical source areas (CSA) of pollution in a watershed is important for effective implementation of best management practices (BMPs). Process-based, watershed models are often used for this purpose. One of the main inputs to these models is the spatially-explicit soils data. The objective of this study was to evaluate if the use of two commonly used soil datasets, the State Soil Geographic (STATSGO) and the Soil Survey Geographic (SSURGO) data, can lead to differences in location of CSAs of sediment. A watershed model, Soil and Water Assessment Tool (SWAT) in combination with the Tukey-Kramer test was used for locating CSAs in the Fish River watershed, which is located in coastal Alabama, U.S.A. The model was calibrated and validated using flow data from a USGS gauging station located within the watershed. The locations of the CSAs of sediment were analyzed at subwatershed and Hydrologic Response Unit (HRU) levels. Results show that the locations of the CSAs were different for the two soil datasets. The locations of the CSAs varied at both subwatershed and HRU levels. The use of STATSGO soil data resulted in higher soil erodibility factor and surface runoff. As a result, higher sediment yield was obtained from the use of the STATSGO data as compared to the sediment yield obtained from the use of the SSURGO data. Therefore, for accurate identification of CSAs of sediment (and potentially other

pollutants) and for effective implementation of economically-feasible BMPs, it is important to use the most detailed spatial dataset available.

### **3.2 Introduction**

It is now widely accepted that, since the enactment of the Clean Water Act in 1972, point sources of pollutions causing surface waterbody impairments have been largely controlled. Therefore, greater attention is being paid by U.S. Environmental Protection Agency (USEPA) and state regulatory agencies to control non-point source (NPS) pollution. NPS pollutants originate from diffuse sources, and are carried off by runoff and/or snowmelt to surface waterbodies such as lakes, rivers, wetlands, oceans. Number of studies (Zollweg et al. 1995; Gburek and Sharpely 1998; Srinivasan et al. 2001) have shown that a few identifiable areas in a watershed, called critical source areas (CSAs) (White et. al. 2009), contribute disproportionately high amount of pollutants to a waterbody. Since funding to implement best management practices (BMPs) are often limited, effort is usually directed to control NPS pollutants from these areas.

Although identification of CSAs is important for effective implementation of BMPs and control of NPS pollution, it is often quite complex to identify these areas. Modeling techniques are often used for identifying and targeting CSAs. For example, Kalin et al. (2004) used a modified unit sedimentograph approach to identify potential sediment generating areas in two experimental watersheds in Iowa. Other modeling tools used for identifying CSAs include the Soil Moisture Distribution and Routing (SMDR) (Srinivasan et al. 2005), the Water Erosion Prediction Project (WEPP) (Pandey et al. 2009), the Kinematic runoff and erosion model (KINEROS) (Kalin et al. 2004), and the

Soil and Water Assessment Tool (SWAT) (Tripathi et al. 2003). SWAT is perhaps the most widely used tool (e.g., see Tripathi et al. 2003; Gitau et al. 2004; Srinivasan et al. 2005; White et al. 2009) for identifying CSAs and for evaluating effectiveness of BMPs in controlling NPS pollution.

These physically and semi-physically based modeling tools require spatial input datasets in the form of land use/ land cover (LULC), soil, topography, etc. to represent watershed conditions. Therefore, model simulation results are affected by the quality (accuracy, spatial resolution, age, etc.) of the input datasets used. Soils data is among the most commonly used data for identifying CSAs. The U.S. Department of Agriculture Natural Resources Conservation service (USDA-NRCS) provides two different types of soil datasets, the state level State Soil Geographic (STATSGO) dataset and the county level Soil Survey Geographic (SSURGO) dataset, at two different spatial resolutions. The SSURGO database is the most detailed soil dataset available for selected counties and areas throughout the United States and its territories. These are prepared by NRCS using field surveying. STATSGO is a more generalized soil dataset at the state level. Few studies have been conducted in the past to quantify the effect of soil data resolution on model performance. Wang and Melesse (2006) studied the difference in simulations for water, sediment, and nutrients, using STATSGO and SSURGO data as input to the SWAT model in the upper 45 percent of the Elm River watershed in eastern North Dakota. They concluded that while overall predictions using SSURGO data were better, simulations with STATSGO were more accurate in case of low flow conditions. Geza and McCray (2008) concluded from their SWAT modeling study in the Turkey Creek watershed located in Jefferson County, Colorado, that due to the differences in number of



hydrological response units (HRU), predicted stream flow was low for the STATSGO as compared to the SSURGO data. They also found higher sediment and sediment-attached nutrient yields with STATSGO-driven model simulations.

Although these studies have demonstrated that flow and water quality predictions are affected by the choice of soils data, they have not looked at how the locations of CSAs are affected by the choice of these soils datasets. Therefore, the objective of this study was to evaluate if the use of the STATSGO and SSURGO datasets can lead to differences in locations of CSAs of sediment. This information is critical for accurate and effective implementation of BMPs to control NPS pollution.

While SSURGO has a higher resolution and is becoming widely available, STATSGO is still widely utilized in watershed modeling. This is mainly due to the fact that many watershed models having GIS interfaces can automatically extract model parameters related to soil from STATSGO. Although the SWAT model developers have attempted to do so, to our knowledge, currently no model is equipped to do so with the SSURGO data. Thus, knowing how choice of the soil database affects CSA has practical implications. To our knowledge, this kind of analysis has not been done before.

### **3.3 Methodology**

#### **3.3.1 Study Area**

The study area used in this study is the Fish River watershed located in Baldwin County, Alabama, U.S.A with a drainage area of 398 km<sup>2</sup>, (Figure 1). The Fish River drains into the Weeks Bay which was designated as an *Outstanding National Resource Water* in 1992 by the Alabama Department of Environmental Management (ADEM).

This is the highest use designation for water bodies in Alabama, and point-discharges are not permitted to such water bodies. Weeks Bay is a small sub-estuary of the Mobile Bay receiving approximately 75% of its fresh water from the Fish River and 25% from the Magnolia River (Figure 1). The watersheds of the Weeks Bay consist of southern Pine Hills and coastal lowlands. Major LULC types in the Fish River watershed are pasture, agriculture, evergreen forest and urban. The LULC of the Fish River watershed has seen significant changes during the past decade, mainly due to urbanization. A major portion of the watershed is covered with sandy loam soil. Other portions of the watershed are covered with either sandy or loamy soil. The Weeks Bay Reserve (WBR) works with the local agencies to monitor and control NPS pollution in the Weeks Bay by implementing appropriate BMPs. In its most recent management plan, the WBR has listed reducing sedimentation as the first priority for minimizing NPS pollution in the Bay (Weeks Bay National Estuarine Research Reserve Management Plan, 2007).

### **3.3.2 Model Description**

The Soil and Water Assessment Tool (SWAT) is a watershed-scale hydrologic and water quality model developed by researchers at the USDA Agricultural Research Services (ARS). SWAT is a continuous simulation model that operates at daily time step. Accurate simulation of hydrology is the backbone of the SWAT model. In SWAT, simulation of hydrology of a watershed is carried in two phases: (1) the land phase of the hydrologic cycle that controls the amount of water, sediment, nutrient, and pesticide loadings to the reach in each subwatershed, and (2) the routing phase of the hydrologic

cycle that moves the water, sediment, nutrients, and pesticides through the stream network to the watershed outlet.

SWAT can use either the SCS curve number method (SCS 1972) or the Green-Ampt infiltration method (Green and Ampt 1911) for calculating surface runoff. For the Green-Ampt infiltration method, sub-daily precipitation (hourly) data is required. However, due to the unavailability of the sub-daily precipitation data for our study area, we used the SCS curve number approach. Potential evapotranspiration during the simulation period can be calculated using the Penman-Monteith (Monteith 1965; Allen 1986; Allen et al. 1989), the Priestley-Taylor (Priestly and Taylor 1972), or the Hargreaves (Hargreaves et al. 1985) method. Penman-Monteith method is used in this study. For routing stream flows, SWAT uses variable storage coefficient method (William 1969) or Muskingum routing method. We used the former.

SWAT calculates sediment yield using the Modified Universal Soil Loss Equation (MUSLE) (Williams 1975). MUSLE is the modified form of the Universal Soil Loss Equation (USLE). It uses a runoff factor in place of the rainfall factor for calculating sediment yield. USLE was developed by Wischmeier and Smith (1965, 1978). USLE calculates average annual soil loss from sheet or rill erosion on a single hillslope and does not consider deposition on the hillslope. MUSLE requires daily hydrologic simulations for calculating erosion. Other factors included in MUSLE are the soil erodibility factor, the cover and management factor, the support practice factor, the slope length factor, and the slope gradient factor. Deposition and degradation processes control the routing of sediment through the watershed channel. The amount of sediment passing through a reach is a function of the channel velocity. SWAT gives output for sediment yield in the

form of total sediment loadings and also as fractions of sand, silt and clay. SWAT also models transport and transformation of nutrients in the watershed. More detail on the processes simulated in the SWAT model can be found in Neitsch et al. (2005).

### **3.3.3 Input Data**

For this study we used ArcSWAT 2.1.6 which is a user-friendly GIS (Geographical Information Systems) interface for SWAT 2005 that provides a complete set of tools for delineating the watershed, defining and editing inputs, processing spatial data such as soils and land use, and running and calibrating the model. ArcSWAT requires input data in the forms of Digital elevation model (DEM), LULC, soil, and weather data. Details of input/output files being used in SWAT have been documented by Neitsch et al. (2005). National Elevation dataset with a 1/3 arc second resolution (10 m pixels) was downloaded from the Seamless Data Distribution System, National Center for Earth Resources Observation and Science (EROS), and USGS (<http://seamless.usgs.gov/index.php>) and processed with ArcGIS 9.2. National Land Cover Dataset (NLCD) for 1992 was used as an input for LULC data. NLCD 1992 was the first land cover mapping project to provide data for the 48 lower states including Alabama. Landsat TM data was the major source for developing this database for Multi Resolution Land Characteristics Consortium (MRLC) (Loveland and Shaw 1996).

Two types of soils data, STATSGO and SSURGO, were used for this study. The dominant soil in the STATSGO soils data was Greenville-Orangeburg-Malbis association (AL198), covering around 70% of the Fish River watershed. Other dominant STATSGO soils for the rest of the watershed were Dothan-Orangeburg-Troup (AL191) and Troup-

Plummer-Bayboro (AL 211) (Figure 2(a)). The SSURGO dataset has a much higher resolution than the STATSGO data. However, the SSURGO data cannot be directly used in ArcSWAT; to use this dataset, an ArcView extension that runs under AVSWAT was used to convert the data into the specified format. AVSWAT is the GIS interface for SWAT in ArcView 3.1 (Di Luzio et al. 2002). *SSURGO* 2.0 dataset pre-processor extension (Peschel et al. 2003) is used for making SSURGO soils data compatible with ArcSWAT. The Fish River watershed contains 106 different soil types (Figure 2(b)) based on SSURGO. Marlboro (very fine sandy loam, 0 to 2 percent slopes) and Lakeland (loamy fine sand, 0 to 5 percent slopes), each comprising about 10% of the whole watershed, are the two dominant SSURGO soils in the study watershed.

Rainfall data for this study was available from three climate stations, a USGS rain gauge at the USGS flow monitoring site and two NOAA stations, one each on the east and the west side of the USGS gauge (Figure 1). Thirty years of precipitation data were available from the NOAA stations, while precipitation data at the USGS station started in July, 1999. Temperature data was available only from one of the NOAA stations. Data were downloaded from National climatic data center (NCDC). Stream flow data was available only at the USGS gauge 02378500 (station name: Fish River near Silver Hill, AL; refer to Figure 1 for its location).

### **3.3.4 Model Setup**

The Fish River watershed was delineated with the aid of the GIS interface of the SWAT using the 10 m DEM and the predefined stream network obtained from the National Hydrography Dataset (NHD). The watershed was first sub-divided into

subwatersheds. The size and the number of the subwatersheds can be adjusted according to the need of the study by varying a threshold parameter. These subwatersheds are spatially related to each other (Neitsch et al. 2005). We delineated the watershed boundary using a threshold area of 250 hectares for the subwatersheds so that extracted channel network closely followed blue lines of the topographic maps. All the parameters related to subwatersheds were then calculated automatically by ArcSWAT.

The LULC data and the soils data were then clipped using the watershed boundary. Each layer was in the projected coordinate system “NAD 1983\_UTM\_Zone 16N”. Both SSURGO and STATSGO soils datasets were used independently. Land use and soil layers were connected to their respective databases using lookup tables. After reclassifying soil, LULC and slope layers, the layers were overlaid to form Hydrologic Response units (HRU). HRUs are the smallest units in SWAT. These are the combination of unique soil, LULC and slope type. SWAT provides the users with the option of defining HRUs by selecting the threshold levels for land use, soil and slope percentages; 10 percent was chosen as the standard for all three datasets. So any soil/land use/slope occupying less than 10% of the subwatershed area was eliminated, and the remaining soil/land uses/slopes were redistributed within the subwatersheds. In order to capture the effect of non point sources of pollution from urban areas, residential and commercial areas were not included in defining the threshold percentage for land use.

The number of subwatersheds resulting from the above described process was 99 for each of the soil datasets. But due to the difference in number of soil types for SSURGO and STATSGO datasets, the number of HRUs formed were 1635 and 827 for the SSURGO and the STATSGO datasets, respectively.

### 3.3.5 Model Calibration and Validation

Model was calibrated for flow for five years from 1990 to 1994 for both SSURGO and STATSGO data separately. Stream flow at the USGS gauge was calibrated first on the annual basis. Monthly and daily flow calibrations were subsequently done. For calibrating stream flows, it was separated into base flow and surface flow components using the web-based hydrograph separation program (WHAT) (Lim et al. 2005). Validation was carried out for four years from 1995 to 1998. Curve number (CN2), surface runoff lag coefficient (SURLAG), threshold depth of water (GWQMN), groundwater “revap” coefficient (GWREVAP), and ground water delay (GW\_DELAY) were the parameters that were adjusted during the flow calibration (Table 1).

Calibration was not performed for sediment due to two reasons. First, although some snapshot sediment concentration data were available through grab sampling at several tributaries of the Fish River, no corresponding flow data existed at those sites. Second, calibration can mask the information coming from each soil data set (Munkundan et al. 2010). Therefore, we used the model calibrated only for flow for locating the CSAs within the watershed.

Quantitative and qualitative measures were used to assess whether the stream flow simulated using the model accurately represent the observed flows. The performance of the model against the observed flows was evaluated using mass balance error ( $MBE = (\sum Sim - \sum Obs / \sum Obs) * 100$ ), coefficient of determination ( $R^2$ ) and Nash-Sutcliffe efficiency ( $E_N$ ) (Kalin and Hantush 2006).

### **3.3.6 Locating Critical Source Areas (CSAs) from STASGO and SSURGO Datasets**

Sedimentation adversely affects water quality of surface water bodies. To control erosion and subsequent transport of eroded sediment to surface water bodies, erosion and sediment control BMPs are implemented. However, often, monetary considerations limit the extent of implementation of management practices to CSAs. It is therefore important to locate CSAs responsible for high sediment loading.

In this study, SWAT in combination with the Tukey-Kramer test was used to identify potential subwatersheds and HRUs having statistically higher sediment yields. Two different models, one using the SSURGO data and the other using the STASGO data (both calibrated and validated for flow), were used to quantify sediment yield rates from the subwatersheds. Model simulations were performed separately at the annual time scale for 17 years from 1990 to 2007.

The Tukey-Kramer test (Kramer 1956, 1957; Tukey 1953) was used to identify and prioritize CSAs. The test compared the mean sediment yield of each subwatershed to the mean sediment yield of other subwatersheds to decide whether they are significantly different from each other. Confidence level used was 95%. The test was performed using the Statistical Analysis Software (SAS). After obtaining critical subwatersheds using the test, the same test was performed on the HRUs for the two different models (using STASGO and SSURGO data, respectively) to identify CSAs at HRU level.



## 3.4 Results and Discussion

### 3.4.1 Model Calibration and Validation

Monthly stream flow data from the USGS gauge within the watershed (Figure 1) for the period 1990-1994 was used to calibrate and 1995-1998 to validate the SWAT model. Two different model setups of the SWAT model, one using the STATSGO soil data and the other using the SSURGO soils data, were calibrated and validated. Figure 3 graphically displays calibration and validation results for surface runoff, baseflow and total streamflow. While the model underestimated surface runoff for both the SSURGO and the STATSGO data in few wet months, such as March 1990 and July 1997 (Figures 3a and 3b), it slightly overestimated baseflow when the STATSGO data was used (Figures 3c and 3d). Figures 3e and 3f show simulated flow using the STATSGO data also being slightly higher than both observed flow and the simulated flow obtained with SSURGO data. Model performance statistics showed that the model was able to represent flow conditions successfully at the USGS gauge for both soil datasets. The  $R^2$  and  $E_N$  values were higher than 0.75 for all of the simulations using both the STATSGO and the SSURGO data for calibration and validation periods. Although, monthly  $E_N$  values ranging from 0.78 to 0.87 suggest that flows were accurately simulated by the SWAT model using both soil datasets, mass balance error (MBE) for the STATSGO (MBE calibration = 8.5% and MBE validation = 14.7%) was higher than the SSURGO (MBE calibration = 1.1% and MBE validation = 8.5%) dataset for both calibration and validation periods.  $R^2$  and  $E_N$  values above 0.50 are usually considered acceptable (Srivastava et. al. 2006; Santhi et al. 2001).

### 3.4.2 Model Predicted Sediment Loadings

Model simulated average annual sediment yields for the entire Fish River watershed were 134,588 and 73,705 tons, for the period between 1990 to 2008 for the STATSGO and the SSURGO datasets, respectively. It must be noted that calibration was not performed for sediment, so these sediment loadings represent sediment loadings generated by the uncalibrated erosion and sediment transport models. The SSURGO dataset predicted less sediment loading as compared to the STATSGO data. This is similar to the results obtained by Geza and McCray (2008), where sediment yield obtained using the STATSGO dataset was higher as compared to the sediment yield obtained from the SSURGO dataset. As mentioned earlier, the number and sizes of HRUs were different for SSURGO and STATSGO soil datasets. Change in the number and size of HRUs affects various sediment yields parameters (Geza and McCray 2008) such as soil erodibility factor, slope length factor and slope gradient factor. The area weighted average soil erodibility factor calculated separately for the whole watershed with SSURGO and STATSGO datasets were 0.178 and 0.204 respectively. Thus, we found that STATSGO has a higher average soil erodibility factor than SSURGO, which can eventually contribute to higher sediment yield from STATSGO dataset. It was also found that, while STATSGO data produced more surface runoff at the CSAs as compared to SSURGO data, groundwater contribution was higher in case of SSURGO dataset. In certain CSAs surface runoff for STATSGO was as much as 73% higher than the surface runoff simulated using SSURGO dataset, which explains higher sediment loading in case of STATSGO dataset. This may be attributed to higher area weighted average curve number for the subwatersheds identified as CSAs while using STATSGO data. These two

factors eventually contribute to higher sediment yield from STATSGO dataset. Peschel et al. (2006) also found similar results from their study at Upper Sabinal River Watershed near Uvalde, Texas. They found that model using SSURGO dataset was producing lower surface runoff as compared to the model using STATSGO dataset in all the subwatersheds except one.

Figures 4a and 4b give percent sediment yields obtained from the corresponding watershed areas. These graphs were developed separately at the subwatershed and HRU levels. The graphs were based on the rankings of the subwatersheds and the HRUs in terms of their sediment yield per hectare. Therefore, subwatersheds and HRUs with higher sediment yields per hectare were ranked at the top. While the graph generated at the subwatershed level shows a rather gradual rise of sediment yield with the area of the watershed (Figure 4a), the graph at the HRU level (Figure 4b) shows that almost all the sediment yield obtained from the watershed is contributed by only 25% area of the watershed. These graphs highlight the importance of locating CSAs at the HRU level. The graphs also show a comparison between the SSURGO and the STASGO soil datasets in terms of sediment yield obtained from a particular area of the watershed at the subwatershed and HRU levels. Both at the subwatershed and the HRU levels, the difference between SSURGO and STATSGO data is higher for the areas that produce large sediment loads. This information can be used to decide upon the minimum land area that needs BMPs to reduce sediment yield by a given percentage.

Figures 5a and 5b, respectively, show the subwatersheds within the Fish River watershed, with graduated colors representing their respective sediment yield using the STATSGO and the SSURGO data. Areas with dark color represent the areas having

higher sediment yields. To represent the differences in sediment yield across the watershed, sediment yields were divided into different classes of equal interval. Subwatersheds within certain range of sediment yields were represented with the same colors. As can be noticed from the figures, among the subwatersheds falling under the class with the highest rate of sediment yield for the SSURGO and the STATSGO data, only one was common (subwatershed 40). The sediment yields from this subwatershed (area 0.46 km<sup>2</sup>) were 7.4 and 20.7 tons ha<sup>-1</sup> yr<sup>-1</sup>, respectively, for the SSURGO and the STATSGO data. The remaining subwatersheds in the highest sediment yield class were different. For the SSURGO data, those subwatersheds were subwatershed 30 (area of 0.03 km<sup>2</sup>) with a sediment yield of 8.8 tons ha<sup>-1</sup> yr<sup>-1</sup> and subwatershed 19 (area 3.42 km<sup>2</sup>) with sediment yield of 6.8 tons ha<sup>-1</sup> yr<sup>-1</sup>. For the STATSGO, it was subwatershed 49 (0.85 km<sup>2</sup>) with a sediment yield of 23.9 tons ha<sup>-1</sup> yr<sup>-1</sup>. This suggests that, in addition to the large differences in sediment sediment yields, the locations of CSAs in the watershed varied due to the use of different soil datasets. Figures 5a and 5b also give the distribution of subwatersheds based on their sediment yield (tons/ha/yr) for STATSGO and SSURGO data, respectively. The distribution depicts that there are relatively few subwatersheds with high sediment yield (tons/ha/yr). Hence, it becomes important to accurately identify those subwatersheds that have significantly higher sediment yields.

### **3.4.3 Locating Critical Source Areas (CSAs) from STASGO and SSURGO Datasets**

The Tukey-Kramer test was used twice, first to identify CSAs at the subwatershed level and second to identify CSAs at the HRU level. The statistical test, along with multiple comparisons between the means of sediment yield of the subwatersheds, also

arranged the subwatersheds in descending order of their average sediment yield per hectare. Subwatersheds that were at the bottom of the list had significantly lower sediment yields (tons/ha/yr). These subwatersheds were not considered as CSAs, and were removed from the analysis. As summarized in Table 2, while STATSGO data suggested that 35 subwatersheds covering 138.11 km<sup>2</sup> were contributing approximately 60% of the total sediment load, SSURGO data suggested that the number of critical subwatersheds having significantly different sediment yield were 45, covering about half of the watershed to yield 72.7% of the total sediment load. Figure 6a presents the details of the results from the Tukey-Kramer test in the form of box-plots for the critical subwatersheds along with their average annual sediment yields for the STATSGO data. Subwatersheds with similar average sediment yield at 95% confidence level are represented by the same alphabet in the figure. Note that the horizontal axis is truncated at 21 due to space. Based on the Tukey-Kramer test, subwatersheds 40 and 49 generate similar amounts of sediment, and they differ significantly from all other subwatersheds. The next 6 subwatersheds contribute similar sediment yield. Details of the results from Tukey-Kramer test with critical subwatersheds and their average sediment yield for the SSURGO data are presented in Figure 6b. Subwatersheds 30 and 40 have the highest sediment yields for SSURGO data. Sediment yield from subwatershed 40 is similar to the sediment yield from subwatershed 19. Note that the top sediment generating subwatersheds are not the same. Considering the labor and monetary constraints in applying management practices to large areas covered by subwatersheds, it is often necessary to identify the potential CSAs at the HRU level. So, it was important to proceed with the second Tukey-Kramer test to identify the critical areas at a higher

resolution, i.e. at the HRU level. Table 3 presents a summary of the number and area of HRUs formed using STATSGO and SSURGO data.

Three HRUs with the highest sediment yield rates (tons/ha/yr) for the STATSGO and the SSURGO are marked within their subwatersheds in Figures 5a and 5b, respectively. For the STATSGO data, the subwatersheds containing these critical HRUs were 8 and 59, while for the SSURGO data the subwatersheds were 6, 73 and 78. The change in soil type, thus resulted in varying locations of CSAs. The weighted average clay, silt, sand and rock percentages for the whole watershed were 10.1%, 13.4%, 73.7%, 2.8% and 8.8%, 15.4%, 58.6%, 17.2% for STATSGO and SSURGO soil datasets, respectively. Note the high rock percentage in SSURGO, which do not contribute to sediment yield. Further, CSAs for both soil datasets represented a unique combination of land use, soil type and slope. All the CSAs are located in urban areas with the soil having relatively higher percentage of silt (greater than or equal to 19.6%) and slope higher than 10%. It is also interesting to note that the subwatersheds containing the CSAs were different from those obtained earlier on the basis of the sediment yield per hectare at the subwatershed level (Figures 5a and 5b). Similar to the selection procedure for the subwatersheds, those HRUs which had significantly lower total sediment yield were eliminated. The HRUs that were selected after the Tukey-Kramer test having significantly higher sediment yield were considered as CSAs for the watershed at the HRU level. Results, presented in summarized form in Table 4, suggest that when the STATSGO data was used, about 0.66% of the whole watershed was contributing to about 15.4% of the total sediment yield. Similar results were obtained using the SSURGO data, where 5.2% of the total sediment yield was coming from only 0.14% of

the watershed area. Details of the sediment yields (tons/ha/yr) obtained from CSAs at the HRU level are presented in Figures 7a and 7b for the STATSGO and the SSURGO data, respectively.

Comparison of the results obtained using the STATSGO and the SSURGO datasets in terms of number of HRUs and the percentage of the watershed area responsible for a given percentage of the total sediment yield are shown in Table 5. While the number of HRUs at each step of the table for the SSURGO data was twice that of the STATSGO data, the percentage contributing area for any particular percentage sediment yield was about the same. As shown in the table, half of the total sediment yield obtained for the whole watershed is coming from 6.75% of the watershed for the STATSGO data and 7.23% for the SSURGO data.

### **3.5 Summary and Conclusions**

Critical Source Areas (CSAs) of pollution in a watershed are often identified using watershed models. One of the main inputs to these models is the soil data. Two often used soils datasets are the STATSGO and the SSURGO data. The objective of this study was to evaluate if the use of the STATSGO and the SSURGO dataset can lead to differences in locations of CSAs of sediment. The study was carried out in the Fish River watershed in coastal Alabama. Two different SWAT model setups for the Fish River watershed were used; one using the STATSGO data and the other using the SSURGO data. The Tukey-Kramer statistical test was then used to identify CSAs of sediment at subwatershed and HRU levels.

Results showed that total sediment yield obtained through the use of the STATSGO data were much higher than those obtained using the SSURGO data. This was attributed to the combined effect of higher soil erodibility factor and higher surface runoff in CSAs using STATSGO data. As expected, at the subwatershed-level, a relatively larger area was identified as CSA of sediment. At the HRU level the CSAs covered a much smaller fraction of the watershed. Overall, at the HRU level, around 7% of the watershed was identified as contributing to almost half of the entire sediment yield from the watershed. At the subwatershed level, around 27% of the watershed area was contributing to half of the total sediment yield. Since the total area of the watershed that needs BMP affects the cost of implementation and maintenance of BMPs, the HRU level approach should be used for identifying CSAs. Further, it was found that the locations of CSAs were different at the subwatershed and HRU levels, when different soils datasets (SSURGO vs. STATSGO) were used. The top CSAs were characterized by their combination of urban lands use, high silt content of the soil and higher slopes (>10%). This suggests that the order of CSAs might change depending on the resolution of the input data used. Therefore, a careful selection of soil input dataset is necessary for identification of CSAs within a watershed.



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Table 3. Flow calibration parameters for STATSGO and SSURGO dataset

<b>Parameters</b>	<b>STATSGO</b>	<b>SSURGO</b>	<b>DEFAULT</b>
CN2	-15%	-10%	0*
SURLAG	0.8	1.5	4 <sup>+</sup>
GWQMN	0	4	0 <sup>+</sup>
GWREVAP	0.06	0.2	0.02 <sup>+</sup>
GW_DELAY	150	150	31 <sup>+</sup>

\* represents percentage change

<sup>+</sup> represents final values after adjustments

CN2 = Curve number, SURLAG = Surface runoff lag coefficient, GWQMN = Threshold depth of water in shallow aquifer, GWREVAP= Groundwater “revap” coefficient, GW\_DELAY = Ground water delay

Table 4. Summary of CSAs at subwatershed level based on Tukey-Kramer test

<b>Soil data type</b>	<b>Number of critical subwatersheds</b>	<b>Cumulative area (km<sup>2</sup>)</b>	<b>% watershed area</b>	<b>% Sediment erosion</b>	<b>Total Sediment (ton/yr)</b>	<b>Sediment yield (ton/ha/yr)</b>
<b>STATSGO</b>	35	138.11	34.7	59.92	80640	5.8
<b>SSURGO</b>	45	200.23	50.3	72.71	53588	2.7

Table 5. Comparison of HRUs based on STATSGO and SSURGO dataset

	<b>Number of HRUS</b>	<b>Minimum Area of HRU (ha)</b>	<b>Maximum Area of HRU (ha)</b>	<b>Average Area of HRU (ha)</b>	<b>Standard Deviation (ha)</b>
<b>STATSGO</b>	827	0.011	940	48.1	91.0
<b>SSURGO</b>	1635	0.009	751	24.3	53.2

Table 6. Summary of CSAs at HRU level based on Tukey-Kramer test

<b>Soil data type</b>	<b>Number of CSAs</b>	<b>Cumulative area (km<sup>2</sup>)</b>	<b>% watershed area</b>	<b>% Sediment erosion</b>	<b>Total Sediment (ton)</b>	<b>Sediment yield (ton/ha/yr)</b>
<b>STATSGO</b>	35	2.61	0.66	15.4	20695	79.3
<b>SSURGO</b>	30	0.59	0.14	5.2	3823	64.8

Table 7. Comparison of the % sediment yield obtained using STATSGO and SSURGO data

<b>Sediment yield (%)</b>	<b>Number of HRUs</b>		<b>% Area of watershed</b>	
	STATSGO	SSURGO	STATSGO	SSURGO
<b>5</b>	15	29	0.20	0.14
<b>10</b>	21	96	0.43	0.49
<b>25</b>	90	201	1.98	2.28
<b>50</b>	142	284	6.75	7.23



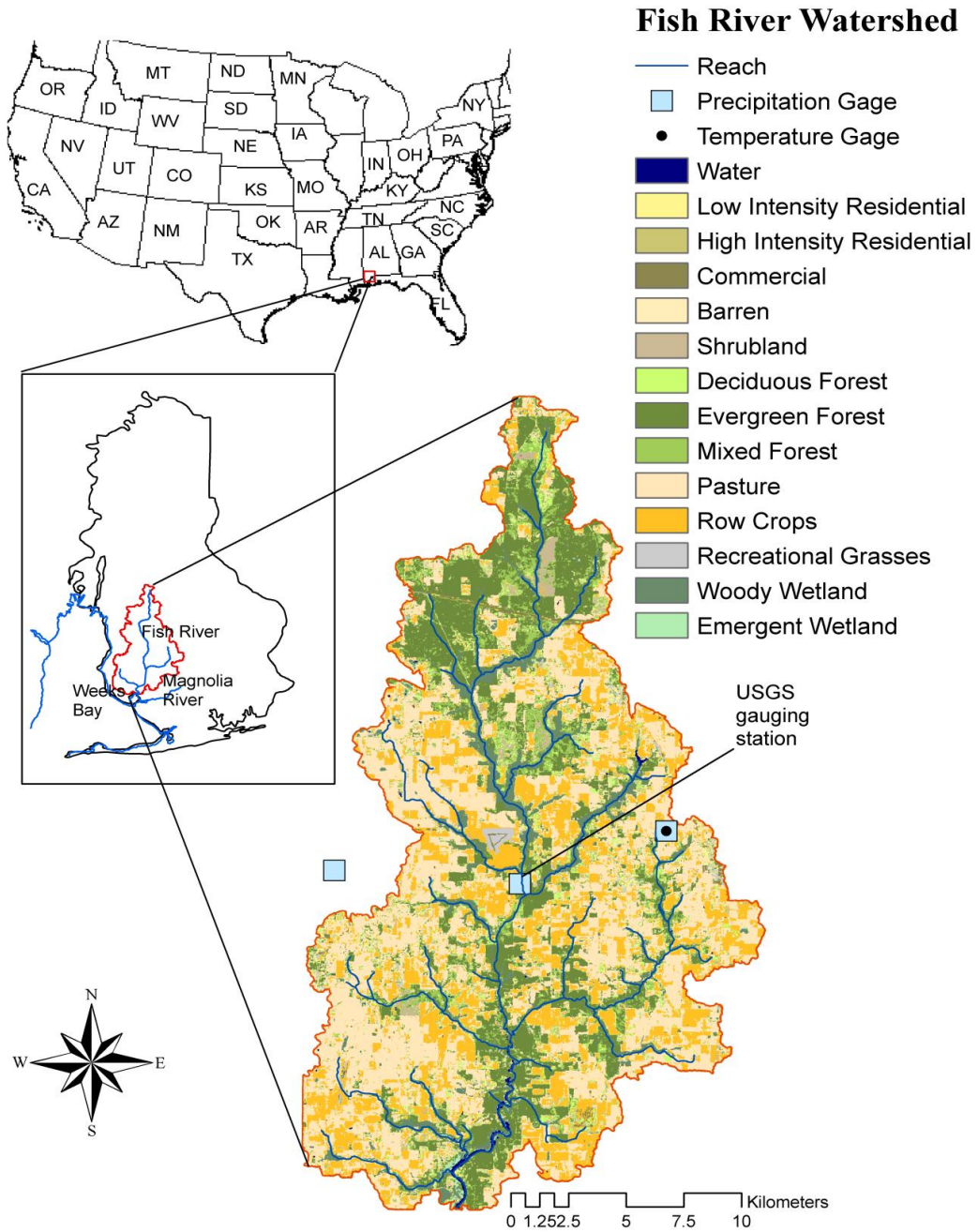


Figure 11. Location of the Fish River watershed in Alabama along with its land use distribution obtained using 1992 LULC data. Locations of the precipitation and the temperature gauges are also shown.

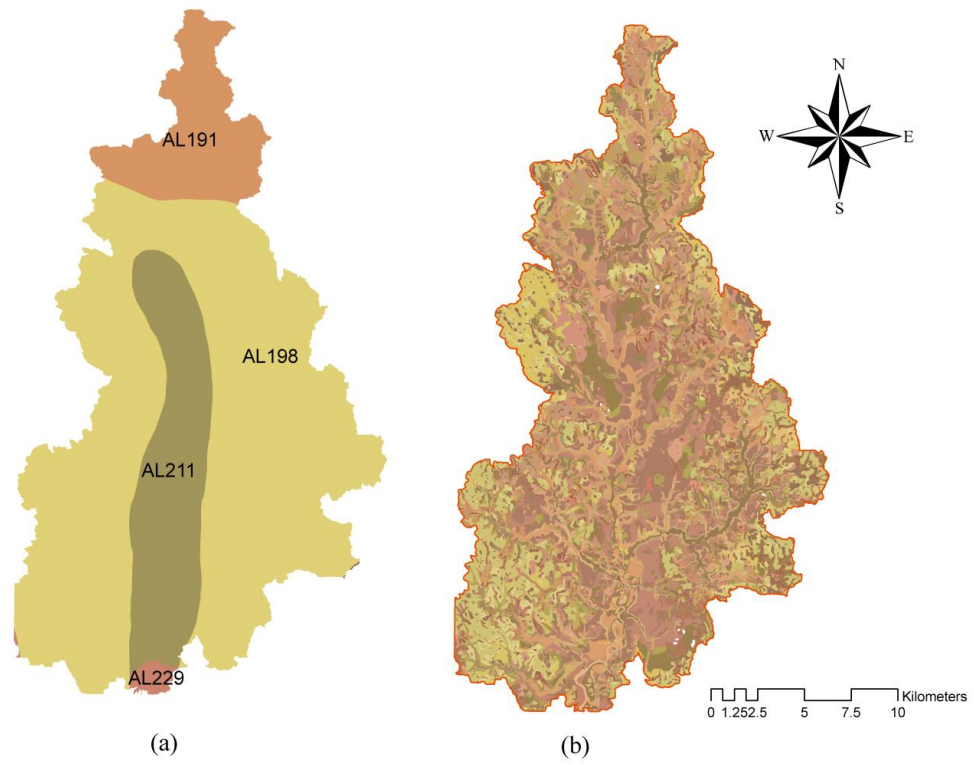


Figure 12. Soil data distribution within the Fish River watershed as depicted by the (a) STATSGO and (b) SSURGO datasets.

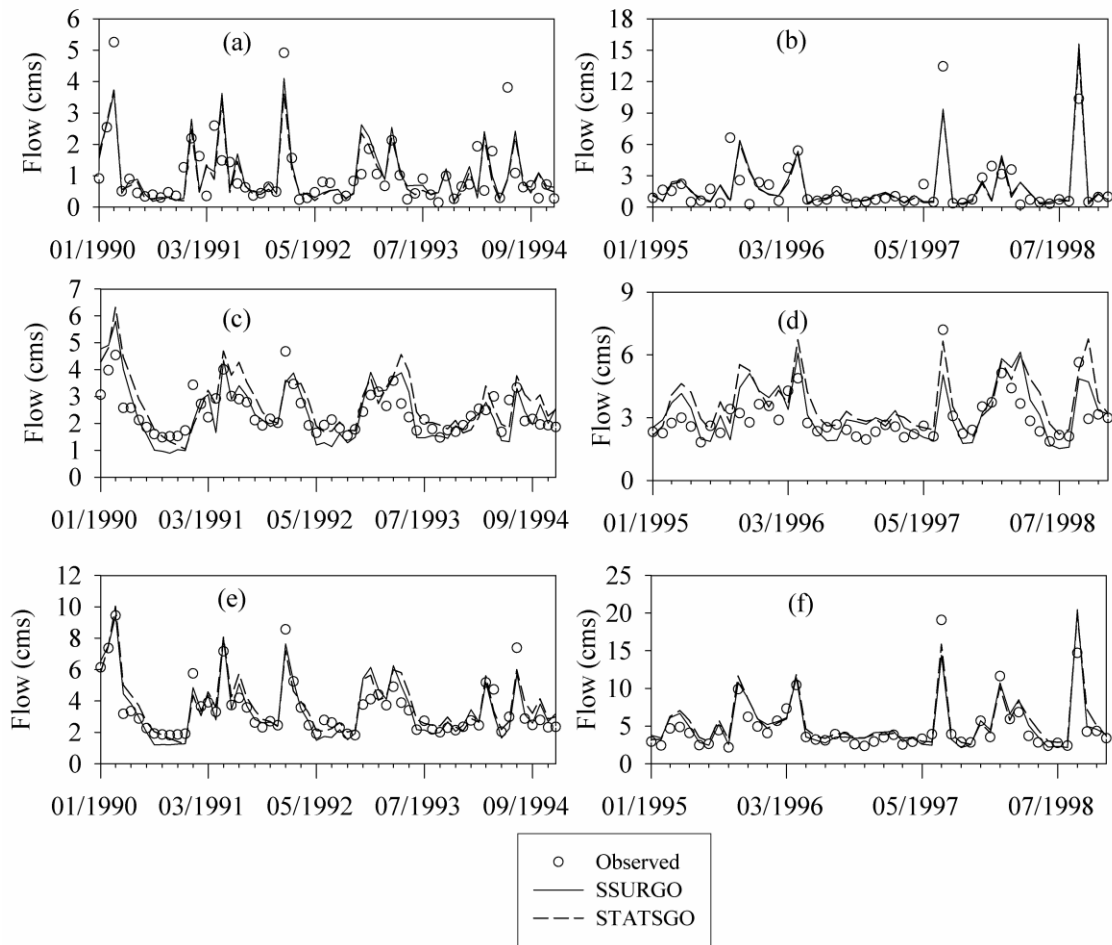


Figure 13. Comparison of observed and simulated monthly flows at the USGS gauging station for the (a) Surface Runoff (calibration period), (b) Surface Runoff (validation period), (c) Baseflow (calibration period), (d) Baseflow (validation period), (e) Streamflow (calibration period), and (f) Streamflow (validation period).

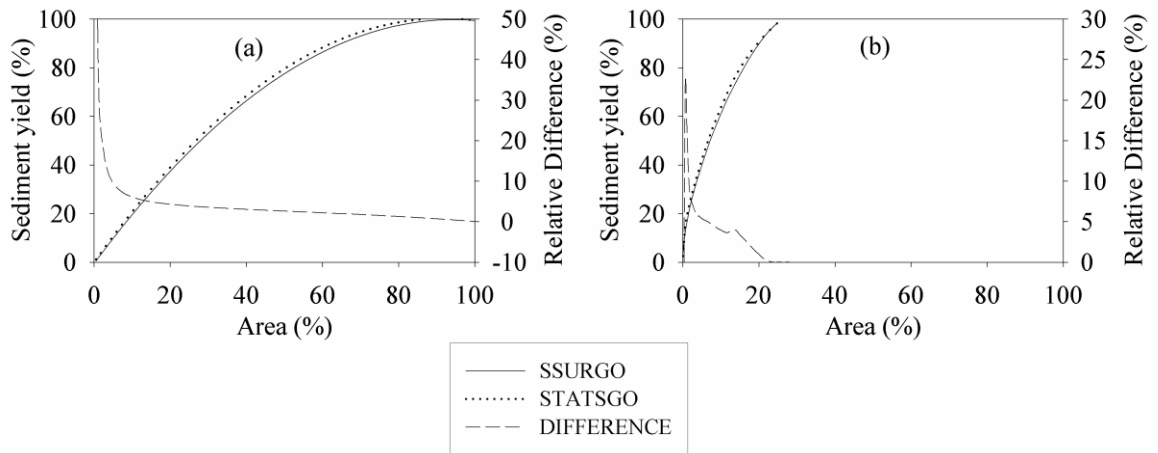


Figure 14. Percentage sediment yield generated from the whole watershed for the SSURGO and the STATS GO datasets based on (a) sub-watershed rankings and (b) HRU rankings. Also shown are the relative differences in the sediment yield from the two soil datasets.

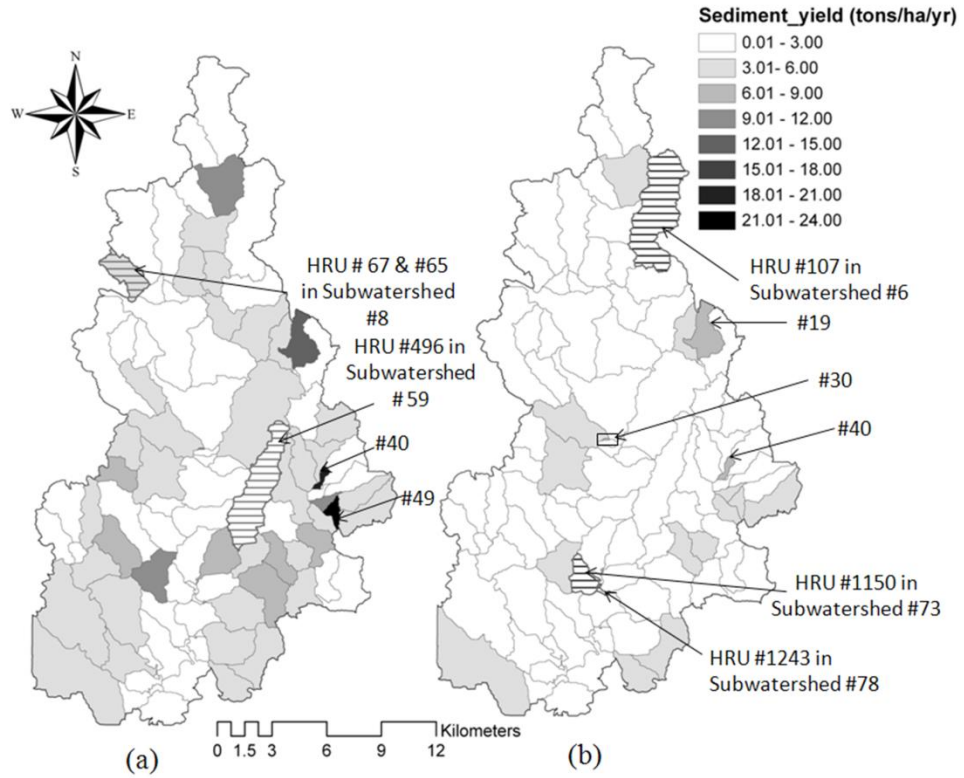


Figure 15. Sediment yield from various sub-watersheds of the Fish River watershed obtained using the (a) STATSGO and (b) SSURGO soil datasets. Also shown are the locations of the sub-watersheds having HRUs with the highest sediment yield.

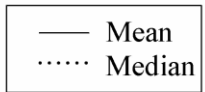
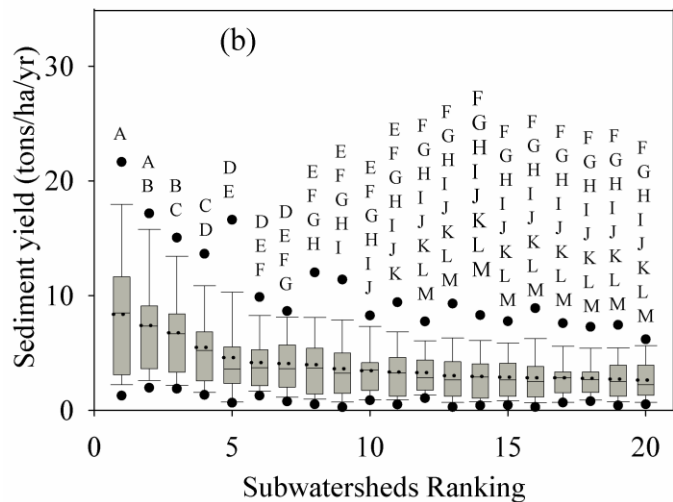
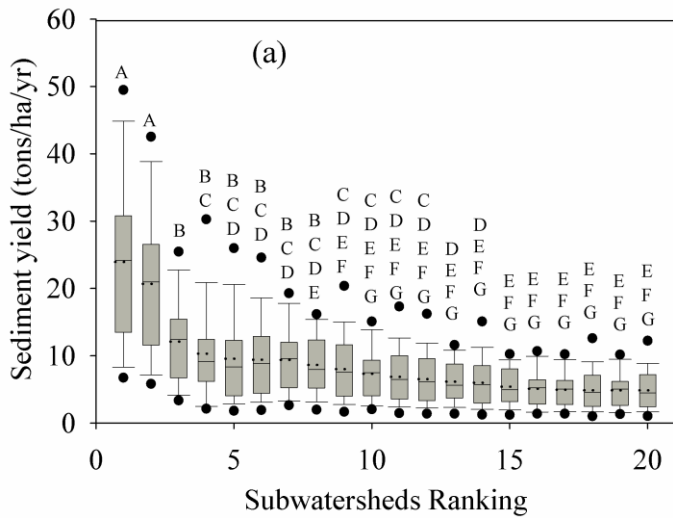


Figure 16. Sediment yield from various sub-watersheds of the Fish River watershed obtained using the (a) STATSGO and (b) SSURGO soil datasets. The figures also show the results obtained from the Tukey-Kramer test. The sub-watersheds with similar alphabets have similar sediment yields.

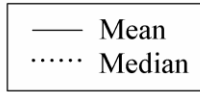
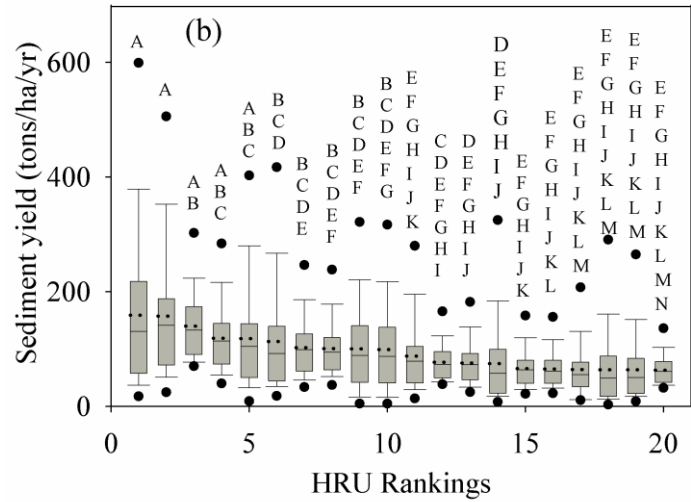
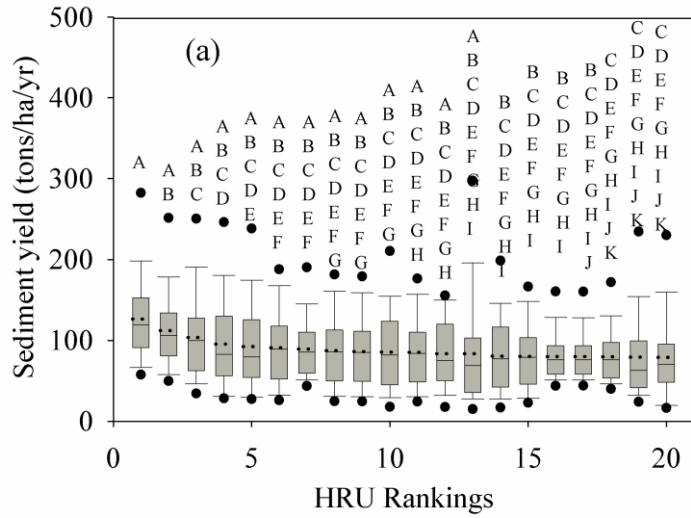


Figure 17. Sediment yield from various HRU of the Fish River watershed obtained using the (a) STATSGO and (b) SSURGO soil datasets. The figures also show the results obtained from the Tukey-Kramer test. The sub-watersheds with similar alphabets have similar sediment yields.

## **CHAPTER 4**

### **4. Summary and Conclusions**

#### **4.1 Synthesis**

Land use/cover (LULC) changes can affect the quantity and quality of water. Watershed models are efficient and cost effective tools to study the impact of changes in LULC on water quantity and quality. However, the credibility and reliability of the predictive power of watershed models are seldom tested. This study assessed the SWAT model in predicting the impacts of changes in LULC over time in the Fish River watershed, which is the main freshwater source of Weeks Bay, Alabama. Observed flow and water quality (TSS,  $\text{NO}_3^-$  and TP) data were compared against the model simulations at several sampling sites within the Fish River watershed. SWAT was first calibrated for flow, but only at the USGS gauge, which is located approximately in the middle of the watershed. Observed flow data was not available for other sites during the period of water quality data collection from 1994 to 1998. It was assumed that the model, once calibrated at the USGS site for flow, should work satisfactorily at the other locations as well. The model was then calibrated and validated directly for water quality parameters at the sampling sites. During both flow and water quality calibration, 1992 NLCD data was used as the LULC input. The model was then run with 2008 LULC and model simulations were compared to observed flow and water quality data during 2008 – 2010.



Model performances at both time periods (1994-1998 and 2008-2010) were evaluated through visual comparison of time series graphs and through the use of statistical performance measures  $R^2$ ,  $E_N$  and MBE.

Graphs and performance measures ( $R^2$ ,  $E_N$ , MBE) showed that the SWAT model was able to simulate flow and water quality during calibration, validation and prediction periods (2008 - 2010) for most of the sampling sites. Model performance was best for flow and weakest for  $\text{NO}_3^-$ . It was observed that model simulations systematically underestimated TSS loadings at various sites during extreme events. TSS loading estimates in SWAT constitute silt and clay particles. During large storms TSS data may contain particles larger and heavier than silt and clay particles, resulting in high observed TSS loadings. Although, there seems to be a slight over prediction during high flows, overall, the model satisfactorily predicted Org-P loadings at the monthly time scale. This establishes SWAT as a reliable tool in predicting the effect of LULC changes. As an exercise, 1992 LULC was also tested, to predict flow at the USGS gauge and water quality at the sampling sites during Oct'2008 – Jan'2010. Although flow simulations were acceptable from the modeling standpoint, they were not as good as the results obtained from running the model using the 2008 LULC. This finding highlights the importance of using most accurate and updated LULC for modeling.

Often it is not satisfactory to know that changes in LULC will cause a certain amount of increase or decrease of a particular or group of water quality constituents. In case of undesired increases locating the critical source areas (CSA) of pollutants has practical implications from management perspective. Process-based, distributed watershed models are often used for identifying CSAs of pollutants from watersheds.

However, model simulations are highly sensitive to the quality (accuracy, spatial resolution, etc.) of the input datasets. Soils data are among the most important data for identifying CSAs. Therefore, the second objective of this study was to evaluate if the use of the STATSGO and the SSURGO soil datasets can lead to differences in locations of CSAs of sediment in the Fish River watershed, where sediment is identified as one of the major water quality problems. Two different SWAT model setups for the Fish River watershed were used; one using the STATSGO data and the other using the SSURGO data. The Tukey-Kramer test was then used to identify CSAs of sediment at sub-watershed and HRU levels.

It was found that the total sediment yield obtained through the use of the STATSGO data were much higher than those obtained using the SSURGO data. This was attributed to the higher surface runoff and higher erodibility factor for STATSGO data. As expected, at the subwatershed-level, a relatively larger area was identified as CSA of sediment; at the HRU level, the CSA was much smaller. Further, it was found that the locations of CSAs were different at the sub-watershed and HRU levels, when different soils datasets (SSURGO vs. STATSGO) were used. This suggests that CSA prioritization might change with the resolution of the input data used. Therefore, a careful selection of soil input dataset is necessary for identification of CSAs within a watershed.

## **4.2 Future Research**

Chapter 2 focused on calibration and validation of the SWAT model for flow and water quality. During the calibration process various SWAT parameters were systematically adjusted for the entire watershed. In other words, model parameters were

not calibrated at subwatershed level. Future research may be conducted involving calibration of model parameters at subwatershed level. This could help in fine tuning the model and also present a better understanding of the model processes at subwatershed level.

Three climate stations were used as the precipitation and temperature data source for the SWAT model. There were substantial variations in precipitation data from these stations pointing out to high degree of spatial variation.. The use of radar technology, such as NEXRAD data, for precipitation could improve capturing of this spatial variation.

Chapter 3 explored the effect of using soil databases of different resolutions on identifying CSAs. Soil database is one of the several input datasets required by the SWAT model. It would be interesting to study the effect of various other input datasets on the identification of CSAs. For example, it would be worth exploring how DEM data of different resolutions, or LULC datasets from different sources, affect locations of CSAs.

Studies exist which explore, through watershed models, the effect of BMPs on water quantity and quality. Almost none of those studies used observed data to verify their results. Therefore, future research can be conducted to assess the effectiveness of BMPs using SWAT or any other watershed model. Water quality data collected before and after the implementation of BMPs may be compared with the model simulations to evaluate the credibility of the model in capturing the effectiveness of BMPs.

In this study only past and current LULC data were used. SWAT can also be used to study various “what-if” scenarios, in terms of LULC changes. For instance, it would be interesting to see the changes in water quantity and quality if urban areas classified as

“low density residential areas” are converted into “medium density residential areas.” Similarly, other scenario analysis can be carried out during the future studies for Fish River watershed.