Updating Soil Hydraulic Properties under Changing Land Use/Cover for Improved Hydrologic Predictions

by

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Abstract

Land use/cover (LULC) change, especially forest to urban transition, can alter the soil hydraulic properties, including soil hydraulic conductivity, even though the soil texture and series may remain the same. Soil hydraulic properties have a big influence on hydrologic processes. Watershed models are commonly used to project the potential alterations in the hydrologic regime of streams in response to ongoing or expected LULC changes. Soil related hydrologic parameters (such as hydraulic conductivity) required by these models are typically derived from soil databases. Unfortunately, when LULC changes, these soil parameters are often retained at their existing values. This is because of the lack of knowledge in quantifying changes in values of these parameters under different LULC conditions. Analyzing these soil parameters either in the field or in the laboratory is time consuming and costly. Further, scaling up from such small scales is not easy. Alternatively, pedotransfer functions, which are algorithms that describe soil-water relationships based on basic soil properties, can be used to analyze existing databases of measured soil hydraulic data. Soil hydraulic properties are seldom investigated directly under LULC changes; however some information on changes in bulk density is available. Changes in bulk density can be used as an input parameter for pedotransfer functions to derive changes in soil hydraulic conductivity to be used in watershed modeling. In practice, these functions often prove to be good predictors for updating soil hydraulic properties. This study aims to overcome this challenge using pedotransfer functions for updating soil hydraulic parameters under changing LULC by making use of soil maps in conjunction with historic aerial photos. The methodology was tested in two watersheds in Northwest Georgia with the Soil and Water Assessment Tool (SWAT). Both watersheds have seen significant urbanization (formerly forest dominated) over the past two decades. Sensitivity analysis revealed that curve number and soil properties were the most sensitive parameters on flow generation. The model performance was evaluated by defining two periods which are describes as reference and testing periods. The results showed that changes in LULC and its alteration to soil properties affect model performances. Overall discharge simulations of the watersheds were similar, but improvement was observed in high flows when changed soil parameters were used.

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CHAPTER I: INTRODUCTION

1.1 BACKGROUND

Land use/cover (LULC) change can be defined as the human modification of the earth's terrestrial surface (Beilfuss *et al.,* 2000; Nie *et al.,* 2011; Dube *et al.,* 2014). In recent decades, LULC in the United States has changed rapidly - agriculture and forested areas have been decreasing while urban, transportation and recreation areas have been steadily increasing (Alig *et al.,* 2010; USDA-NRCS, 2007). Since the 17th century, the Southeastern United States especially has seen rapid changes in LULC (Delcourt and Harris, 1980; Sleeter *et al.,* 2012; Zhao *et al.,* 2013; Hansen *et al.,* 2010). During the early periods, many forested areas have been lost to agricultural fields. Later, forest recovered because many agricultural fields were abondoned either due to loss of soil fertility or lack of free/cheap labor. The latest LULC change trend in the region is urbanization. Forests, agricultural fields and pastures are converted to urban areas. Since rivers, lakes and streams receive water from watersheds, transition in LULC to urban can lead to natural ecosystem deterioration and degradation of catchments (Fohrer *et al.,* 2001; Mango *et al.,* 2011). LULC is also tightly linked to various hydrological processes, such as evapotranspiration, interception, infiltration, and ultimately runoff generation which affects loss of nutrients from the soil. Forest conversion to agriculture or urban land use causes increased discharge, peak flow, and velocity of streams (Lockaby *et al.,* 2011).

The influence of LULC change on catchment water balance is a highly studied topic. Understanding the role and impacts of LULC change in a watershed could play an important role in developing strategies and future development plans to reduce or mitigate flooding problems, erosion/sedimentation and nutrient loadings. However, changes in LULC can also have significant impacts on soil conditions and microbial communities which are likely to respond to these changes. The effects of LULC alteration on the physical and chemical properties of soils have been well studied (Zimmermann *et al.,* 2006; Hu *et al.,* 2009; Price *et al.,* 2010; Chen *et al.,* 2014). LULC change can create variations in surface roughness, soil aggregate structure,soil organic content and nutrients, and pH (Hörmann *et al.,* 2005; Post and Mann, 1990; Murty *et al.,* 2002; Chen *et al.,* 2014). Unfortunately, most studies modeling the effects of LULC on water resources often perform simulations without considering the changes in the soil properties. Soils play an essential role in the development and sustainability of ecosystems. Therefore, soil data comprise a key input for hydrologic models (Mednick *et al.,* 2008), and such models are extremely sensitive to soil related parameters (Romanowicz *et al.,* 2005; Peschel *et al.,* 2006; Geza and McCray, 2008). Additionally, many environmental modeling and land management applications require detailed soil spatial and attribute data (Zhu *et al.,* 2001). Conventional soil surveys, such as the STATSGO and SSURGO databases in the U.S, are the primary sources of soil spatial data for modeling and other management applications, although they were not produced to provide the detailed soil information required by most environmental models (Band and Moore, 1995; Zhu, 1999).

Surface properties of a soil can be altered by natural and anthropogenic processes (Effland and Pouyat, 1997; Tugel *et al.,* 2008). Thus, soil hydraulic properties, especially soil hydraulic conductivity, may be altered as a result of anthropogenic or natural disturbances (Heddadj and Gascuel-Odoux, 1999). Soil hydraulic conductivity is one of the most dynamic soil properties (Lin *et al.,* 2005), because physical, chemical and biotic factors that affect hydraulic conductivity can vary widely in both space and time (Starr, 1990).

Important soil physical properties include texture, particle size, bulk density, porosity, water content, and unsaturated/saturated conductivity (Khaleel *et al.,* 1981; Huisman *et al.,* 2004; Li and Shao, 2006; Price *et al.,* 2010). Soil physical properties which change with the variation in soil structure include bulk density, total porosity, and aggregate stability, consequently affecting soil hydraulic properties such as saturated hydraulic conductivity (Gill, 2012). Surface soil texture controls many important ecological, hydrological, and geomorphic processes (Scull *et al.,* 2008). Movement of water and nutrients in soils is controlled by properties such as bulk density and hydraulic conductivity which affect processes such as infiltration and nutrient transport. Bulk density and hydraulic conductivity control the proportion of precipitation entering the soil, its retention in subsurface storage and the water transmission rates to stream networks. Therefore, both surface flow production and baseflow maintenance are influenced by soil properties (Hewlett, 1961; Zimmerman *et al.,* 2006; Tetzlaf *et al.,* 2007). Many watershed models assume incorrectly that soil surface characteristics (0-20 cm) are time invariant (Hu *et al.,* 2009). Therefore, there is a need for developing methods to update soil hydraulic parameters under changing LULC.

Watershed models are widely used to understand the impacts of various anthropogenic activities and natural processes on water flow and associated transport of sediment, chemicals, nutrients, and microbial organisms within a watershed. Understanding such impacts are needed for water resource management purposes such as estimating water availability over time, providing a better understanding of LULC change impacts on water resources, and quantifying the temporal and spatial alterations in aquifer recharge throughout a watershed (Pedraza and Ockerman, 2012). Specifically, process-based models can handle many components of the hydrologic cycle using multiple data such as climate, soil, topography, vegetation, and land management practices occurring in a watershed. Selection of an appropriate model depends on the project objectives and the characteristics of the watershed that is being studied. The Soil and Water Assessment Tool (SWAT) is one of the most widely used watershed models to study land management, LULC, and climate changes impacts on water quantity and quality.

SWAT has been widely used to study LULC change impacts. A quick search on the SWAT literature database (https://www.card.iastate.edu/swat_articles) shows 133 journal articles on this topic (accessed September 25th, 2015). These studies mostly ignored changes in soil hydraulic parameteres under changes LULC. Romanowicz *et al.* (2005) studied the sensitivity of the semi-distributed hydrological SWAT model to the pre-processing of soil and land use data for modeling rainfall-runoff processes in a catchment in Belgium. They evaluated and generated 32 different soil and land use parameterization scheme to analyze the sensitivity of the model outputs. Two distinct scales of soil maps were combined and generalized with a detailed land use map. Their results indicated that the SWAT model is extremely sensitive to the quality of the soil and land use data and the adopted pre-processing procedures of the geographically distributed data.

The traditional way in modeling LULC changes with SWAT is through changing some vegetation related parameters and the SCS curve number (CN), which reflects both soil and LULC characteristics of the watershed (Tadesse *et al.,* 2015; Githui *et al.,* 2009; Babar and Ramesh, 2015; Brook *et al.,* 2011; Homdee *et al.,* 2011; Costa *et al.,* 2003; Zhang *et al.,* 2011; Sang *et al.,* 2010; Wang *et al.,* 2012; Fang *et al.,* 2013; Nie *et al.,* 2011; Hartcher and Post, 2008). However, the CN does not fully capture the changes in soil characteristics. Porosity, bulk density and saturated/unsaturated hydraulic conductivity influence hydrology as well (consider subsurface flow, recharge, etc.) while CN does not take into account these soil characteristics.

Soil data are among the most important inputs for hydrological models. While site-specific data are always preferred, the two U.S. Department of Agriculture (USDA) soil databases, the state-level State Soil Geographic (STATSGO) dataset and the county-level Soil Survey Geographic (SSURGO) dataset, are often the best options for watershed modelers in the United States where site-specific soil data are unavailable. These databases are publicly available for the United States and are intended to provide information that is sufficient for general watershed scale studies. The STATSGO database contains basic attributes for the continuous coverage of soils across the United States. Compared to STATSGO, SSURGO has a higher resolution and provides more detailed information on the soils. Additionally, many studies have demonstrated that the SSURGO dataset yields overall better performance on hydrologic simulation (predicting sediment, nutrient, agricultural chemical yields, runoff, and streamflow) than STATSGO dataset (Anderson *et al.,* 2006; Sheshukov *et al.,* 2011; Zhang *et al.,* 2012; Bosch *et al.,* 2004; Di Luzio *et al.,* 2004; Singh *et al.,* 2015).

Depending on the soil types and characteristics and land use management approaches, soil hydraulic conductivity can be greater, lower, or could remain the same. Hence, it can be expected that soil hydraulic conductivity may vary in time. Estimation of the soil hydraulic properties across the landscape is also a requirement for hydrologic modeling purposes. Unfortunately, in most cases where hydrologic modeling is needed, there is little field data on soil hydraulic properties. Therefore, modelers often rely on publicly available soil databases such as SSURGO and STATSGO. Therefore, a methodology is needed to estimate the changes in soil hydraulic properties from available information. These properties can be estimated using relationships based upon more routinely and more frequently collected soil property measurements.

Pedotransfer functions (PTFs), which are regression equations expressing relationships between soil properties, are often used to estimate certain soil properties that are difficult and costly to measure from more easily available soil data. Although many PTFs have been proposed in the literature to calculate soil hydraulic properties (e.g. Cosby *et al.,* 1984; Saxton *et al.,* 1986; Jabro, 1992; Rawls and Brakensiek, 1985; Risse *et al.,* 1995; Wösten *et al.,* 1999), only a handful of studies applied PTFs to improve the watershed models predictions (Holvoot *et al.,* 2004; Bouraoui *et al.,* 2005; Bormann *et al.,* 2007; Schuol *et al.,* 2008; Rouhani *et al.,* 2009).

1.2 LITERATURE REVIEW

Below is a review of the literature relevant to soil hydraulic properties and methods for determining surface soil hydraulic properties based on land use land cover changes.

1.2.1 Watershed Modeling and Soil Data

Soils play key role in ecosystem development and sustainability. They also affect several hydrologic processes in the ecosystem. Soil attributes such as texture, bulk density, and hydraulic properties have significant impacts on hydrologic processes, including infiltration, evaporation, and surface runoff. Therefore, watershed models require soil related parameters along with climatic data and other model parameters. The SSURGO and STATSGO data are the two datasets developed by the USDA-NRCS to provide general soil data for the entire US and are widely used in watershed modeling to obtain soil parameters.

Even though numerous studies reported differences in simulated streamflow calculated based on STATSGO and SSURGO, no definitive conclusions have been drawn concerning the accuracy of simulated flows (Levick *et al.,* 2004; Peschel *et al.,* 2006; Kumar and Merwade, 2009). Other studies showed that soil data with varying resolution had a limited impact on streamflow predictions (Chaplot, 2005; Moriasi and Starks, 2010; Mukundan *et al.,* 2010). Di Luzio *et al.*

(2005) examined the potential impacts of the input variables of the SWAT model, including the digital elevation model (DEM), land use, and soil data, on streamflow simulation. They found that DEM data and land use maps had a considerable influence on the results affecting the water yield prediction. Interestingly, soil maps had limited impact on the model results. Similarly, Mukundan (2008) concluded that SSURGO data improved model predictions with SWAT only slightly compared to STATSGO, and the difference between predicted and observed daily streamflow and sediment load in the North Fork Broad River watershed, Georgia (GA) were not statistically significant. Geza and McCray (2008) applied SWAT using both STATSGO and SSURGO to predict streamflow, nutrient and sediment loads in Turkey Creek watershed, Denver, Colorado. They used the same number of sub-basins; however, the number of hydrologic response units (HRUs) varied. The number of HRUs with STATSGO and SSURGO were 261 and 1301, respectively. Consequently, differences in soil type and size of HRUs affected the predicted streamflow. Predicted streamflow was higher when SSURGO was used. Additionally, SSURGO predicted less stream loading than STATSGO in terms of sediment and sediment-attached nutrient components.

Like most other watershed scale hydrologic models, SWAT requires a number of parameters for a particular application. Determining the values for these parameters, in reality, based on field and laboratory test is the best option, yet due to cost and time limitations, several studies estimated the initial values from the available database and adjusted these values (also called model calibration) to make the model generated streamflow match the observed streamflow (e.g. Srinivasan and Arnold, 1994; Bingner, 1996; Peterson and Hamlett, 1998; Sophocleous *et al.,* 1999; Weber *et al.,* 2001; Gitau *et al.,* 2002; Van Liew and Garbrecht, 2003; Chu and Shirmohammadi, 2004). Most SWAT modeling studies within the US lately rely on SSURGO for soil parameters (Huismann *et al.,* 2004; Anderson *et al.,* 2006; Bormann *et al.,* 2007; Peschel *et al.,* 2006; Nisar and Lone, 2013); however, the accuracy or representativeness of those data have not been sufficiently discussed with respect to actual field data. To our knowledge, soil hydraulic properties in SSURGO are infrequently updated (USDA-NRCS, Personal communication, 2015). Further, in LULC change studies, same soil parameter values are often used even if the LULC changes. In that sense, this study can contribute to the general understanding of advantages and disadvantages of using soils with updated values in SWAT modeling. It is hypothesized that the use of updated soil properties under LULC change should result in improved streamflow prediction accuracy.

1.2.2 Soil Physical and Hydraulic Properties

Soils are characterized by specific physical and hydrological properties containing texture, structure, water retention and transmission (Lorenz and Lal, 2012). Soil properties such as texture, bulk density, and water retention play significant roles in soil behavior. Soil texture is one of the most important soil characteristics since it influences many other properties significant to land use and management (Brown, 1990) and it can control many important ecological, hydrological, and geomorphic processes (Scull *et al.,* 2008). The quantification of soil physical and hydraulic properties begins with the determination of bulk density and soil texture (Avril and Barten, 2007). The soil bulk density is important as a measure of both porosity and soil strength. Bulk density, defined as the mass per unit volume and expressed as g/cm^3 or Mg/m^3, is the most common measure of soil compaction. Bulk density can easily be altered by soil disturbing activities such as agricultural and urban development. In turn, physical, chemical and biological properties of the soil can be modified by the changes in compaction of the soil (Hakansson *et al.,* 1988). Because pores within the soil can contain water, altering the bulk density of the soil can have adverse effects on the soil–water relationship.

Soil hydraulic properties, i.e. the soil water retention characteristics and hydraulic conductivities, are physical properties that determine the ability of soil to transport and retain water (Hussen and Warrick, 1995). Soil water storage and transport largely depend on soil hydraulic properties. The entry of water into the soil, movement of water in the soil profile, flow of water to drains, and evaporation from the soil surface are examples to processes affected by soil hydraulic properties. They are fundamental in partitioning water inputs at ground surface as well as in determining the availability of soil water for extraction by plants. The quantification of soil hydraulic properties serves as the basis for the calculation of surface hydrological processes. These properties are influenced by several factors, including soil structure, texture, bulk density, and organic carbon content. Hydraulic properties can be estimated from morphological properties which include texture, initial moisture state, macroporosity and root density (Lin *et al.,* 1999).

Soil water retention is a hydraulic property that governs soil function and has a strong impact on soil management (Rawls *et al.,* 2003). Soil water retention is dependent on soil physical properties such as texture, structure and bulk density (Babalola, 1978; Rawls *et al.,* 1991; Minasny *et al.,* 1999). Measured data are often used in theoretical models to estimate hydraulic properties (e.g., unsaturated hydraulic conductivity) and to develop Water Retention Curves (WRCs) that characterize the energy status of soil water (Simunek, 2008). Since soil organic matter (SOM) affects soil structure and related properties, Rawls *et al*. (2003) found that water retention is affected by differences in SOM content. Soil porosity also affects water retention.

Soil saturated hydraulic conductivity is a critical hydraulic property (Rawls *et al.,* 1998). Hydraulic conductivity controls water infiltration, surface runoff, leaching of pesticides, and migration of pollutants, and is highly dependent on soil texture and structure (Bagarello and Sgroi, 2004). The saturated hydraulic conductivity directly affects the amount of runoff and eroded surface soil that are transported to local waterways, thereby affecting both in-field soil and in-stream water quality (Papanicolaou and Abaci, 2008; Elhakeem and Papanicolaou, 2009). Prieksat *et al*. (1994) showed that saturated hydraulic conductivity exhibited temporal variability due to land use, tillage, and dynamics of plant roots. McKeague *et al*. (1982) concluded that soil management and land use have major effects on soil structure, porosity, and density, which subsequently affect saturated hydraulic conductivity. SOM influenced saturated hydraulic conductivity through increased aggregation and microbial activity, while bulk density effects were related to porosity. A study by Rachman *et al*. (2004) analyzed soil hydraulic properties for a grass hedge system 10-years after establishment. They indicated that the most significant factors affecting saturated hydraulic conductivity (K_{sat}) were bulk density and macroporosity. They found that K_{sat} declined with depth of the grass hedge position with the lowest values found at the 20-40 cm depth.

The surface soil is the interface between the external environment and the soil. Hydraulic properties of surface soils influence the partition of rainfall, snowmelt and irrigation water into runoff and soil water storage, and thus knowledge of surface soil hydraulic properties is essential for efficient land and water management. This study concentrated only on the saturated hydraulic conductivity and bulk density of the surface soil hydraulic properties.

1.2.3 Effects of LULC Change on Soil Physical and Hydraulic Properties

Soil chemical, physical, and biological properties can be significantly affected by LULC changes (Shukla *et al.,* 2003). Zimmermann *et al.* (2006) examined soil hydraulic properties of a variety of land uses (i.e., forest, forested pasture, and pasture) using a hood infiltrometer in Brazil and concluded that water infiltrability and hydraulic conductivity at soil surface (20 cm depth) increased from pasture to forest land uses. Hydraulic conductivity and field capacity were found to be 50 to 75% less in cultivated lands than forest lands (Wahren *et al.,* 2009).

Nisar and Lone (2013) found that the change in LULC, in Sindh catchment of Kashmir Himalayan region, has effects on certain soil properties. The LULC change over a period of 15 years was investigated through remote sensing which was used to detect LULC changes. Also, soil samples at 0-20 cm depth were collected from four different LULC types, including forests, pastures, cultivated land, and urbanized areas to be analyzed for various parameters, namely organic matter, water holding capacity, soil pH, electrical conductivity, and available nutrients. They concluded that change in LULC significantly influenced most soil properties of the catchment. The pH of cultivated soils was significantly higher than forest and pastural soils. Cultivated soils were found to have the lowest organic matter content while pasture soils were found to have the highest. Forests had significantly higher water holding capacity than pasture and cultivated land.

Borman *et al*. (2007) evaluated the effects of LULC changes on catchment water balances with three different hydrological models within the Land Use Change on Hydrology Ensemble Modeling framework. They claimed that land use alterations may lead to changes in soil chemical and physical properties such as bulk density. Differences in bulk density can be used as an input for pedotransfer functions to derive changes in soil hydraulic model parameters. They concluded that different models presented a different sensitivity to the change in soil parameterization even though the extent of absolute changes in simulated evapotranspiration and discharge was similar.

Human activities have been shown to alter soil physical properties of bulk density, saturated hydraulic conductivity, and moisture retention, through erosion, compaction, and pore structure evolution. Price *et al.* (2010) compared these soil physical properties under different land use types (forest, pasture, and managed lawn) and across two parent materials (alluvium and saprolite) in Macon and Jackson counties in southwestern North Carolina. In the study area, 90 points were sampled (30 in each land use) which had a long-term consistent LULC. Soil properties did not significantly differ between pasture and lawn. They found that forest soils had a tendency to have notably higher infiltration rates and water holding capacities, and lower bulk densities than lawn and pasture soils. However, several studies have demonstrated no significant differences between the water holding capacity at field capacity of disturbed and undisturbed soils (Jusoff, 1989).

Kelishadi *et al.* (2013) investigated how near-saturated soil hydraulic properties are affected by different LULC and management practices. They found that unsaturated/saturated hydraulic conductivity values were not significantly affected by soil textural classes; however, LULC significantly affected soil hydraulic parameters. Similarly, Zhou e*t al.* (2008) studied the differences in surface soil hydraulic properties under varying LULC for a given soil series and their temporal dynamics by using tension infiltrometers. They investigated the soil textures, structures, and parent materials for four soil series under four common LULC (woodland, cropland, pasture, and urban). They stated that the differences in LULC and soil types altered surface soil hydraulic properties (including field-saturated and near-saturated hydraulic conductivities). However, temporal variation of surface soil hydraulic properties was found to be greater than their spatial variation caused by LULC. Consequently, soil hydraulic conductivity was greater in the forest compared to other LULC, which was associated with the higher organic matter content, lower bulk density and low disturbance by anthropogenic activities in forest soils.

Ossola *et al.* (2014) studied how vegetation management practices and structural complexity affected soil properties and processes in urban green spaces in the south-eastern Melbourne metropolitan area, Australia. They selected a network of 30 research plots on sandy soils from three different types of urban green spaces. Bulk density, aggregate structure, soil organic matter, infiltration rates and water holding capacity were measured as soil properties and processes. They concluded that the above-ground structure of urban green space affected soil and litter properties and processes. Saturated hydraulic conductivity was ten times lower in low complexity parks compared to high complexity parks. Nonetheless, bulk density and soil organic matter were similar.

Huisman *et al*. (2004) studied the sensitivity of SWAT-G (modified SWAT model for Germany) simulations toward changes in soil properties due to LULC change in an artificial study catchment in Germany. They performed a model sensitivity analysis to investigate the impact of changes in bulk density, saturated hydraulic conductivity and available water content at the depth of the top soil layer on several simulated hydrological fluxes since there was little information on the soil-vegetation interactions. The study results indicated that the changes in soil properties due to LULC transition from cropland to pasture only had a minor impact on the simulated runoff and actual evapotranspiration.

1.2.4 Problem Statement

Hydraulic conductivity is one of the most important soil properties used to predict soil behavior, and suitability for a variety uses (West *et al.,* 2008). Hydraulic conductivity displays spatial and temporal variability at both small and large watersheds. It is significantly influenced by various combinations of the external factors (e.g. land use, vegetation, and precipitation) and intrinsic soil properties (e.g., bulk density, texture) (Gupta *et al.,* 2006; West *et al.,* 2008;

Papanicolaou *et al.,* 2008; Deb and Shukla, 2012). Spatial variability of hydraulic conductivity due to regional differences is controlled by intrinsic soil properties, while the added seasonal variability of hydraulic conductivity within a region is due to external factors (Elhakeem *et al.,* 2014). Most of the hydraulic conductivity values presented in the SSURGO and STATSGO databases are based on intrinsic soil properties, and the direct use of these data without correction for the external factors should be resolved. While the spatial variability of hydraulic conductivity at a specific site can be captured only via detailed field measurements, temporal variability at a given site requires continuous measurements over extended periods of time (Papanicolaou *et al.,* 2009). Direct measurements of hydraulic conductivity at a specific site by standard instruments such as the double ring infiltrometer provide representative values for hydraulic conductivity. However, in-situ measurements of saturated hydraulic conductivity are often expensive, labor-intensive and typically have a sparse spatial resolution. Because of these limitations, most of the models use existing soil databases.

Most studies analyze the effect of land use change on the watershed flow without considering that a change in LULC may also cause a change in other associated landscape characteristics such as soil properties. For hydrologic modeling, rapid but robust methods for hydraulic conductivity prediction are still needed, where in-situ measurements may not be practical. Indirect methods for hydraulic conductivity prediction, which involve, for example, pedotransfer functions, can potentially address the problem. This thesis mainly focuses on the comparison of SWAT model predictions of streamflow using the standard SSURGO soil dataset and an updated SSURGO soil database where soil hydraulic conductivity parameters are calculated by PTF algorithm approach in two watersheds, which have experienced significant LULC changes, in the state of GA, USA.

1.3 STUDY OBJECTIVES

The overarching goal of this research is to come up with a blueprint to update certain soil hydraulic parameters using pedotransfer functions under changing LULC for improved hydrologic predictions. Because of the dynamic nature of watersheds, there is a need for a systematic approach in updating soil hydraulic properties under changing LULC, which are mostly derived from readily available soil databases in the US, in order to improve streamflow predictions by watershed models. In this study, a pedotransfer function based method is proposed for updating key soil hydraulic parameters. The proposed approach was tested with the SWAT model in two urban watersheds in Southeastern USA that underwent forest to urban transition. The improvement in model performance as a result of this new strategy was assessed.

The specific objectives of this study are to

i. Develop a methodology for modifying soil hydraulic parameters of bulk density and hydraulic conductivity under changing land use. The proposed functional relationships are based on pedotransfer functions (PTFs).

ii. Test the proposed methodology in two urbanized watersheds within the metropolitan Atlanta area in GA, USA. SWAT model was calibrated and validated for the periods when both watersheds were heavily forested. The calibrated model was tested during the urbanized periods after properly updating the relevant model parameters.

In chapter II, the PTFs used in updating soil hydraulic parameters are discussed first, followed by a brief summary of the SWAT model. After describing the study area, the steps followed in model calibration, validation and testing stages are presented. Results are presented in chapter III.

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CHAPTER II: METHODOLOGY

This chapter describes the use of PTFs to update soil hydraulic parameters when there is a change in LULC. Then, an application of this soil parameter updating is presented in two watersheds in the Piedmont Region of GA. Both watersheds were heavily forested in the 1980s, but have since urbanized. SWAT model was used to model the urbanization impacts on the streamflow in both watersheds and results were compared to USGS streamflow data. A detailed description of the study area along with the soil characteristics of the Piedmont physiographic region is followed by a brief summary of the SWAT model and the input data used to simulate streamflow in these two watersheds. The SWAT model was calibrated and validated for the period where watersheds were forested. The calibrated and validated model was then used to test the SWAT model's ability to predict streamflow during the urbanized period, during which soil hydraulic parameters were updated to reflect the effect of forest to urban transition. Results and Discussion are presented in next chapter.

2.1 PEDOTRANSFER FUNCTIONS (PTFs)

Direct measurement of soil hydraulic properties is time-consuming and costly. Therefore, scientists have developed methodologies for indirect estimation of hydraulic conductivity and other soil hydraulic parameters. Pedotransfer functions (PTFs) are among such tools used for predicting soil hydraulic properties such as unsaturated and saturated hydraulic conductivity (Wösten *et al.,* 2001). The PTFs, as initially introduced by Bouma and Lanen (1987), are described as tools that allow for a translation of data from what is presently unavailable into some useful type of data. At present, most PTFs use a combination of readily available soil properties such as textural class, particle size distribution, bulk density, and organic matter as predictor variables (Tietje and Hennings, 1996). A large amount of qualitative data in soil surveys also makes PTFs desirable as a way to predict soil hydraulic properties.

In the literature, a considerable number of PTFs differing in data requirements and modeling principles have been proposed (Cosby *et al.,* 1984; Rawls and Brakensiek 1985; Saxton and Rawls 2006; Wösten *et al.,* 2001). Most PTFs predict saturated hydraulic conductivity using percentages of sand, silt, clay, and bulk density (Wösten *et al.,* 2001, Pachepsky and Rawls, 2004; and Shein and Arkhangel'skaya, 2006). PTFs can be obtained by various mathematical methods and algorithms. Although the temporal and spatial variability of hydraulic characteristics can have significant effects on model results, Wösten *et al.* (2001) stated that valid predictions rather than direct measurements are satisfactory for many applications. Lin *et al.* (1999) also found that PTFs using morphological features resulted in predictions comparable to continuous PTFs constructed from measured physical properties. Because PTFs predict properties from available basic soil data, they are advantageous due to their relative inexpensiveness and ease of derivation and use. However, for an application at a specific point, use of a PTF may be inadequate and direct measurement may be the only option (Wösten *et al.,* 2001).

Although various PTFs have been compared and evaluated in several studies (Tietje and Tapkenhinrichs, 1993; Wösten *et al.,* 2001; Jarvis *et al.,* 2002; Pachepsky and Rawls, 2004), the PTFs proposed by Rawls and Brakensiek (1985) are the most commonly used ones in the literature (Wagner *et al.,* 2001; Cornelis *et al.,* 2001; Cronican and Gribb, 2004; Bormann *et al.,* 2007; Elhakeem *et al.,* 2014). Therefore, it was selected for this study too to estimate saturated hydraulic conductivity.

2.1.1 Estimating Soil Hydraulic Conductivity from PTFs

LULC change may alter the soil hydraulic properties, yet this has not been commonly studied in the past (Texeira, 2001). Most of the watershed modeling studies focused on the impacts of LULC changes on hydrological fluxes in catchments without considering the alteration in soil hydraulic properties due to LULC change (Baker and Miller, 2013). Moreover, direct field measurements of soil hydraulic parameters including the saturated hydraulic conductivity are technically difficult, making use of PTFs key for their estimation. Thus, an approach is needed to assess the changes in soil hydraulic properties from available information. PTFs can potentially address this problem. Using PTFs, one can derive soil hydraulic properties (e.g. saturated hydraulic conductivity) from readily available soil data such as soil texture, porosity, and bulk density (Jabro 1992; Rawls et al. 1982; Rawls et al. 1998; Saxton and Rawls 2006; Saxton et al 1986). Bulk density can easily be altered by soil disturbing activities such as agricultural and urban development. The porosity of a soil indicates its ability to store and transmit water. Soil texture may be used as the first estimator of hydraulic conductivity because texture affects the pore space available for water movement. Also, soil texture is easy to measure and often available for an area of interest.

Porosity is a critical input into the Rawls and Brakensiek (1985) PTF calculation (Table 2.1). In this study, bulk density is used to calculate porosity. Porosity values required in the Rawls and Brakensiek PTF were derived from published bulk density values (Table 2.2 and 2.3). In the porosity formula, soil minerals were assumed to have a density of 2.65 g/cm^3. Estimating the changes in soil hydraulic properties using bulk density has the advantage that bulk density is an easy to measure parameter and changes in bulk density due to LULC change have been reported in the literature (e.g. Pouyat *et al.,* 2002; Bewket *et al.,* 2003; Price *et al.,* 2010; also see Table 2.2

and 2.3). Other required data such as clay and sand content were assumed to remain constant under LULC changes. Available water content (AWC), wet bulk density (ρ_b^w), clay % and sand % were derived from SSURGO database. AWC was also assumed to remain constant when LULC changes, and wet bulk density values were converted to dry bulk densities to calculate porosity (Table 2.1). The formula used in calculation of dry bulk density from wet bulk density was borrowed from the SWAT model (Neitsch *et al.,* 2009), which requires field capacity (FC) and wilting point (WP). According to the literature review, bulk density increases approximately 30% when a forested soil is converted to urban soil. Soil hydraulic conductivity was eventually calculated based on soil texture, bulk density, and porosity using the PTF of Rawls and Brakensiek (1985) (Table 2.1). The approach followed in calculating new K_{sat} values of SSURGO dataset is explained below.

K_{sat} values were first calculated using the PTF without considering any changes in bulk density and porosity to demonstrate the reference conditions. K_{sat} values were also calculated using PTF after allowing for changes in porosity and bulk densit4y due to transition of LULC from forest to urban. The percent decrease in K_{sat} values due to forest to urban transition were determined based on these two calculated K_{sat} values. The percent reductions were then applied to SSURGO derived K_{sat} values to estimate new K_{sat} values for urban soils. The new K_{sat} values were updated using ArcSWAT in the both Big and Suwanee Creek Watersheds. Changes in K_{sat} and bulk densities of the soils in our study watersheds are given in Appendix A and B.

Forest Soil Bulk Densities

A forest soil is a natural and only slightly disturbed or undisturbed material that developed under permanent forest cover. Forest soils are characterized by being more porous and having lower bulk density than cultivated soils. In addition to this, because forest soils have significantly lower bulk density, they have higher hydraulic conductivities than urban or agricultural soils (Price *et al.,* 2009). The bulk density of soils varies due to organic matter content, texture, and compaction. Because of the lower particle density of organic matter and its tendency to improve soil aggregation, soils high in organic matter, like forest soils, tend to have lower bulk densities than soils with lower organic matter contents.

Approximate bulk densities for a variety of soils and soil materials such as organic soils, pine wood, and forest loamy A-horizons were given as 0.1-0.7, 0.7 and 0.7-1.2 g/cm^3, respectively by the USDA Soil Indicator Program (O'Neill *et al.,* 2005 adapted from Brady and Weil, 1996). Neil *et al.* (1997) found average values in the Brazilian Amazon Basin state of Rondonia, ranging from 0.59 to 1.37g/cm^3. The bulk density of surface soils in forests was found in the literature to range from 0.1 to 1.37 g/cm^3 (Table 2.2).

Urban Soil Bulk Densities

Urban soils are usually compacted moderately to severely from the use of heavy equipment on the soil during construction, vehicle parking, and maintenance equipment (Scharenbroch *et al.,* 2005). Soil compaction is the physical consolidation of the soil by an applied force that destroys soil structure, compresses soil volume, increases bulk density, reduces porosity, and limits water and air movement (Osman, 2013). Urban soil compaction also reduces water infiltration, thus increasing stormwater runoff. Urban soils are particularly characterized by high variability in bulk density and saturated hydraulic conductivity (Mullins, 1991). Increases in bulk density, however, may not be confined to the topsoil but penetrate to a considerable depth and decrease soil porosity in the subsoil (Lorenz and Kandeler, 2005; and Lehmann and Stahr, 2007). Generally, the bulk density of surface soil in urban ecosystems may be high due to physical soil modification (Scharenbroch *et al.,* 2005).

Short *et al*. (1986) measured bulk densities of 1.25-1.85 g/cm^3 (average=1.61 g/cm^3) of the surface horizon and bulk densities of 1.4-2.3 g/cm^3 (average=1.74 g/cm^3) at 30 cm depth for open parkland in the Mall of Washington, DC. Similar finding were reported by Patterson *et al*. (1976) in Washington, DC; average values of urban bulk density were ranging from 1.81 to 2.18 g/cm^3 (average =2.02 g/cm^3). Craul *et al*. (1985) found values of 1.52-1.96 g/cm^3 (average=1.73 g/cm^3) for subsoils in Central Park, New York City. These are large values in comparison to most grassland areas and forest, but comparable values may well be found in many urban parks (Bullock and Gregory, 1991). Hiller (2000) found that soils in abandoned shunting yards in the Ruhr area, Germany, had bulk densities ranging from 1.0 to 2.1 g/cm^3 (average=1.67 g/cm^3) depending upon the site and depth of soil where the measurements were taken. Gbadegesin and Olabode (2000) reported that bulk density of urban soils ranging from 1.05 to 2.18 g/cm^3, with a mean of 1.62 g/cm^3 in Ibadan.

Other studies showed that an increase in soil bulk density decreases hydraulic conductivity due to the reduction of larger pores (Franzluebbers, 2002; Zacharias and Wessolek, 2007). Additionally, soil bulk density and porosity are good indicators for soil compaction implying a destruction of soil structure impacting infiltration through soil (Logsdon and Karlen 2004). Bulk densities of surface soils in urban areas are presented below (Table 2.3).

According to the literature review, the average values for bulk densities in the forest and urban land uses are approximately 1.07±0.09 g/cm^3 and 1.39±0.28 g/cm^3, respectively (Table 2.2 and 2.3). To compile soil hydraulic conductivity values, several studies that focused on soil bulk densities under different LULC were reviewed. The final studies used in our analyzes was comprised of 10 studies representing urban land uses and 12 studies representing forest land uses around the Piedmont Physiographic Region, which is where the two study watersheds are located.

2.2 STUDY AREA

The proposed approach was tested at two watersheds having a history of LULC change from forest to urban use. A five-county study area (i.e. Fulton, Forsyth, Cherokee, Gwinnett, and Hall) was surveyed in the Atlanta metropolitan area in the Piedmont physiographic region of Georgia, USA. The selected study watersheds were the Suwanee Creek watershed located in Gwinnett County and Hall County, and the Big Creek watershed located in Fulton, Forsyth, and Cherokee counties (Figure 2.1, Table 2.4). Both watersheds are within the Metropolitan Atlanta, GA. They were selected based on maximum LULC change (forest to urban transition) percentage (Table 2.5) and having long-term daily streamflow data with no data gaps. Having streamflow data covering the forested and urban periods was important to compare the simulated streamflow to observed data in both periods.

The Southern Piedmont physiographic province begins in central Alabama and passes through northern Georgia and continues northeast to the northern tip of Virginia. The Piedmont Plateau province is a wide area extending from the foothills of the Appalachian Mountains to the Coastal Plain. Comprising approximately 30% of the land in Georgia, the Piedmont covers ± 4,606.139 ha (Turner, 1987) and is an upland sloping region with gently rolling hills. Elevation ranges from near 366 meter in the north to less than 152 meter in the south. Mean annual rainfall is 112 to 142 cm while mean annual temperature ranges between 15.0 and 17.8 °C. Major forest types are loblolly-shortleaf pine and oak-pine. The Georgia Piedmont consists of foothills underlain by acid crystalline and metamorphic rock. Being Georgia's most densely populated region, most cities are located in the Piedmont (Usery, 2015). The Piedmont region stretches some 1200 km by 200 km wide (Mayne *et al.,* 2003) from New Jersey in the north to Alabama in the south (Coleman, 2008). The topological, geological, and physiological features of the Piedmont region in Georgia are similar to those features found in the other states; thus the results from studies in Georgia or other states can possibly be extrapolated to other areas. Several major LULC transformations have occurred in the Piedmont over the past 200 years, from forest to cropland, then back to pine and hardwood woodlands, and recently urbanization and suburbanization as the major driver for LULC change in the region.

The City of Atlanta, GA is in the Southeastern Piedmont Province of the USA. The region is an expanding, urbanized and suburbanized complex in which the population has increased from 1.8 million in 1980 to 4.2 million people in 2013 (Atlanta Regional Commission, 2013). The metropolitan Atlanta area has been experiencing a period of rapid growth and development. With increasing population, there has been a change in LULC. As a result of population growth, residential, commercial, and other urban land uses more than tripled during this period.

Both of the study watersheds have experienced urban growth, and in the last decade, that has caused a rapid decrease of farmland and forest. This extensive development and other land use activities have caused severe alterations on Georgia's streams (Schoonover *et al.,* 2006). These changes in LULC have occurred mostly with the conversion of forest, cropland, and wet area to urban land use. The developed areas have been mostly residential. Table 2.5 depicts the major LULC changes from 1992 to 2011 in both watersheds. A large fraction of both watersheds was covered with forest in the early 1990s, which has since been gradually converted into urban areas due to population growth. The LULC change (forest to urban transition) in the Big Creek watershed and Suwanee Creek watershed was 36.9 % and 45.3 %, respectively. Streamflow has been continuously monitored in both watersheds by USGS since 1985.

Soils in the Piedmont

The dominant soil types in the Southern Piedmont area are Ultisols. These soils are extensively found in humid-warm temperate or humid-tropical climates. Most have developed under forest vegetation and include either a kandic horizon or an argillic. Cecil soil is the most common local soil in the Piedmont Georgia (Soil Survey Division Staff, 1993) and in the southeastern United States (West *et al.,* 1998). Other minor soils in the Georgia Piedmont are Entisols, Inceptisols, and Alfisols (West *et al.,* 1998; Bandaratillake, 1985). The soils in this region are also Saprolitic, formed from the in-place weathering of the bedrock. The upper portion of the soil is typically classified as silty-fine sand or low plasticity silt with less frequent occurrences of clayey sand, sandy clay and plastic sandy silt (Finke *et al.* 2001).

2.3 SOIL AND WATER ASSESSMENT TOOL (SWAT)

SWAT is a process-based, watershed scale, continuous time, semi-distributed hydrological model that uses spatially distributed data on topography, LULC, soil, and weather for simulating streamflow and water quality (Arnold and Allen, 1996; Arnold *et al.,* 1998). The SWAT model was developed in the early 1990s and represents over twenty five years of model improvement within the U.S. Department of Agriculture's Agricultural Research Service (USDA-ARS). It was created to predict the impacts of land management practices on water, sediment, and agro-chemical yields in large and complex watersheds with varying soils, LULC, and management conditions over long periods of time (Vazquez-Amabile and Engel, 2005). The subsequent implementation of a geographical information system (GIS) interface for SWAT (ArcSWAT) allows extraction of parameter information from various digital spatial datasets to be used for watershed modeling efforts (Di Luzio *et al.,* 2002). Additionally, the SWAT model application, supported by GIS technology, proved to be flexible and reliable tool for decision makers (Pisinaras *et al.,* 2010).

SWAT has been widely used around the world (Tuppad *et al.,* 2011; Singh *et al.,* 2015; Erturk *et al.,* 2015; Liu *et al.,* 2015; Brauer *et al.,* 2015; White *et al.,* 2015).

SWAT model operations take several steps. This involves the creation of the stream network, the watershed area, and the sub-catchments. In SWAT, the watershed is divided into sub-watersheds. Then sub-watersheds are subdivided into series of hydrological response units (HRUs) based on the combination of unique soil, land use, and slope characteristics. An HRU is an area of homogenous hydrologic characteristics determined by the spatial overlay of datasets such as elevation, land use, and soil type. Flow generation, sediment yield, and nonpoint source loadings from each HRU in a sub-watershed are summed, and the resulting loads are routed through channels, ponds, or reservoirs to the watershed outlet. SWAT2012 provides several options when simulating the hydrological process, which can be chosen by the user depending on the available data. The SWAT model uses either the SCS curve number method (SCS, 1972) or the Green & Ampt infiltration method (1911) to calculate losses and the resulting surface runoff. The Green & Ampt infiltration method requires sub-daily data, but due to the unavailability of sub-daily rainfall data for the study area, the SCS curve number method was chosen for surface runoff calculations. SWAT also provides the option of using Penman-Monteith, Priestley-Taylor, or Hargreaves method for estimating potential evapotranspiration (PET) for the model run. In our study, Penman-Monteith method was used to estimate PET. The hydrological processes are simulated based on the water balance equation which can be represented as:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})$$

where, SW_t is the final soil-water content (mm), SW_0 is the initial soil water content on day *i* (mm), *t* is the time (days), R_{day} is the amount of precipitation on day *i* (mm), Q_{surf} is the amount of surface runoff on day *i* (mm), E_a is the amount of evapotranspiration on day *i* (mm), W_{seep} is the amount of percolation and bypass flow exiting the soil profile bottom on day *i*, and Q_{gw} is the amount of return flow on day *i* (mm) (Neitsch *et al.,* 2009). Other than the soil water that is taken up by plants or 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. Details and the theoretical background of the SWAT are described in Neitsch *et al.* (2009).

2.4 INPUT DATA

Basic input data required to set up a SWAT model with ArcSWAT are digital elevation model (DEM), weather, land use, and soil data. Required data were compiled using databases from various state and federal governmental agencies. It is known that the quality of the DEM has a strong influence on the final output of the hydrological model (Defourny *et. al.,* 1999). Therefore, to delineate watershed areas, 10-meter resolution DEM was downloaded from USDA Geospatial Data Gateway website (https://gdg.sc.egov.usda.gov). Additionally, in ArcSWAT, the watershed was divided into multiple sub-basins based on topographic features of the watershed calculated using DEM data. DEM helps in understanding the flow behavior and flow pattern. For SWAT, the topographic attributes of the sub-basins, such as area, slope, and field slope length, were derived from the DEM. Weather data (daily precipitation, minimum and maximum temperature, solar radiation, relative humidity, and wind) were obtained for the period 1985-2013 from North American Land Data Assimilation System website (http://ldas.gsfc.nasa.gov/nldas) and Climate Forecast System Reanalysis website (http://rda.ucar.edu/pub/cfsr.html). LULC data is publicly available at a sufficient resolution to determine the LULC change between 1992 and 2011. The National Land Cover Database 1992 (NLCD 1992) is a consistent, generalized, 30 meter resolution LULC dataset for the contiguous US. Also, The National Land Cover Database 2011 (NLCD

2011) dataset is the most recent national land cover product for the United States (http://www.mrlc.gov/finddata.php). After obtaining NLCD 1992 and NLCD 2011 maps, LULC change maps were produced using ArcMap 10 to demonstrate the LULC transition in both watersheds. Over the 19 years, the LULC has significantly changed in both watersheds as can be seen in Figure 2.2 and 2.3. National Hydrography Dataset (NHD) was obtained from the USGS website (http://nhd.usgs.gov/data.html) and was used as a burn in shapefile to produce an improved stream network. Moreover, the soils of the watersheds have been mapped at a scale of 1:24,000 and released as SSURGO certified database by the United States Department of Agriculture Natural Resources Conservation Service (USDA-NRCS) (https://gdg.sc.egov.usda.gov/). The county level SSURGO dataset was used in deriving soil parameters.

Both study watersheds were delineated using required data by ArcSWAT 2012. To create HRUs, dominant land use, soil, and slope options were used. Big Creek watershed and Suwanee Creek watershed had 103 and 109 HRUs, respectively. In the Big Creek watershed, 40 HRUs were converted into urban land use from forest area and in the Suwanee Creek watershed, 55 HRUs were converted into urban land use from forest area. The Big Creek watershed contained 136 different SSURGO soil types while Suwanee Creek watershed contained 75 different SSURGO soil types. Dominant SSURGO soil types for Big Creek watershed consisted of Cecil (sandy loam, eroded very gently sloping phase and clay loam, severely eroded sloping phase). Dominant SSURGO soil types for Suwanee Creek watershed included Madison (sandy clay loam, 15 to 45 percent slopes and sandy clay loam, 10 to 15 percent slopes) and Appling (sandy loam, 6 to 10 percent slopes).

2.4.1 Soil Survey Geographic Database (SSURGO)

The USDA-NRCS designed the SSURGO database primarily for small scale applications (e.g. parcel, town-ship, or county scale) and it includes the most detailed level of available information. SSURGO maps are available at a range of scales between 1:12,000 and 1:63,360 and the smallest soil map unit represented in SSURGO database is about 0.02 km^2 (Geza and McCray, 2008). To generate the SSURGO maps, soil scientists used aerial photographs as base maps. Surveyors observed soils along delineation boundaries and used field traverses and transects to determine map unit composition (USDA, 1995). SSURGO was organized in ESRI shapefiles and text files for attribute data of soil properties, and it is publicly available.

SSURGO is an improved version of the State Soil Geographic Database (STATSGO) which is a generalized soil map at a scale of 1:250,000. STATSGO and SSURGO share similar data structures and formats. Typical spatial resolution of the SSURGO database is 10 to 20 times higher than STATSGO. This makes the use of SSURGO soils preferable for smaller scale projects, such as modeling small watersheds, catchments, or even individual fields (Sheshukov *et al.,* 2009). Modeling at the county level and below with higher resolution is essential for understanding ecological processes at smaller spatial scales.

SSURGO is still under development and does not cover the entire United States (Luo *et al.*, 2012). However, SSURGO has been widely used in hydrologic models such as the Agricultural Nonpoint Source (AnnAGNPS) model (Polyakov *et al.,* 2007), the Hydrology Laboratory Research Modeling System (HLRMS) (Koren *et al.,* 2004; Zhang *et al.,* 2006), the Watershed Characterization System- Sediment Tool by the Tetra Tech. Inc. (WCS-SED) (Bolstad, 2006), the Topography-based hydrological model (TOPMODEL) (Williamson and Odom, 2007), the European Hydrological System (MIKE SHE) (Sahoo *et al.,* 2006), and the Soil and Water

Assessment Tool (SWAT) (Geza *et al.,* 2009; Santhi *et al.,* 2006; Wu and Johnston, 2007). Most existing studies only focused on soil data extraction from SSURGO (Peschel *et al.,* 2003, 2006; Sheshukov *et al.,* 2009); however, the representativeness or accuracy of soil hydraulic parameters or others parameters have not been sufficiently examined before.

From communications with Natural Resources Conservation Service (NRCS) soil scientists, it is clear that the original field work was done during the period of 1970s, and there is hardly any field work after that. The soil properties represent the conditions of mid to late 1970's. The SSURGO database is populated with a combination of laboratory data and calculations. Lab data is used whenever possible, but in situations where NRCS did not have adequate data, which was most of the time the case, PTFs were used. The database is constantly updated when further lab or field data becomes available. However, most updates come from existing manuscript reports. Map units in the GA counties were updated between the years of 2013-2014 while Soil Data Join Recorrelation (SDJR) maps were created. Although these map units were updated, this does not necessarily mean that the soil properties (texture, soil hydraulic conductivity, bulk density) have been updated.

2.5 MODEL CALIBRATION, VALIDATION AND TESTING

To test whether updating the soil hydraulic parameters using PTFs can help better predict streamflow under changing LULC, the SWAT model was applied to the two watersheds described earlier. Traditionally, studies predicting the urbanization effects on streamflow with SWAT typically calibrate and validate the SWAT model for the pre-urbanization period and then apply the same model to predict the streamflow during the urbanized period (Singh *et al.,* 2015; Jeong *et al.,* 2014; Dixon and Earls, 2012; Kim *et al.,*2011; Zhou *et al.,* 2013). They only change the LULC map input to ArcSWAT for this. Since certain model parameters are associated with LULC (e.g. CN, maximum leaf area index, etc.) when LULC distribution in the watershed changes, the model reflects these changes on the predicted output. However, changes in parameters like saturated hydraulic conductivity, and porosity are generally ignored. In this study, the traditional approach was followed with the added improvement of further updating certain soil hydraulic parameters. A flow chart describing the modeling approach followed in this study is demonstrated in Figure 2.4 and is briefly described below.

SWAT was first calibrated and validated for streamflow in each watershed using the streamflow data collected from 1/1/1988 to 12/31/2000 (reference period). The LULC and soil data for this period came from the 1992 NLCD map and the SSURGO. The first 8 years of this period served as the calibration period and the remaining 5 years served as validation period. During both calibration and validation runs, model started 3 years before the actual period to warm up the model (i.e. spin up period). The calibrated and validated model was then used to explore whether SWAT can successfully predict streamflow during 1/1/2005-12/31/2013 (testing period), during which the LULC in both watersheds were dominantly urban. A three year warm up period was again used. This time, the 2011 NLCD map served as the base LULC map. For soil, two separate sources were used. In the first approach the SSURGO soil dataset was used to derive soil data and the model was run in the traditional approach as described earlier. In the second approach, the soil properties K_{sat} and ρ_b were updated using the PTF approach in areas where LULC has changed from forest to urban. To be able to do this the dominant soil type option was used in creating HRUs in SWAT. However, to minimize the loss of detail sub-watershed delineation was performed at very high detail (Figure 2.5 and Figure 2.6).

2.5.1 SWAT Calibration and Uncertainty Programs (SWAT-CUP)

The model calibration in this study has been carried out with SWAT-CUP, which is an interface developed for calibration of SWAT as well as for sensitivity and uncertainty analysis (Abbaspour *et al.,* 2007). The program contains five different calibration procedures: Sequential Uncertainty Fitting version 2 (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov chain Monte Carlo (MCMC). It also includes functionalities for validation and sensitivity analysis as well as visualization of the area of study using Bing Map. With this feature, the subbasins, simulated rivers, and outlet, rainfall, and temperature stations can be visualized on the Bing map. In this study, the Sequential Uncertainty fitting (SUFI-2 algorithm) was utilized, which is the most widely used option in the literature and is briefly explained below. Past studies found SUFI-2 to be quite efficient for time-consuming and large-scale models (Abbaspour *et al.,* 2004; Abbaspour *et al.,* 2007; Yang *et al.,* 2008).

Description of SUFI-2

In SUFI-2, uncertainty is defined as the discrepancy between measured and simulated variables. This algorithm maps all uncertainties (parameter, conceptual model, input, etc.) on the parameters (expressed as uniform distributions or ranges) and tries to capture most of the measured data within the 95% prediction uncertainty (95PPU) of the model in an iterative process. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. Two measures were used to assess the goodness of calibration and uncertainty analysis, referred to as *p-factor* and *r-factor*. The p-*factor* represents the proportion of observed data covered by the 95% prediction uncertainty (95PPU), and it varies from 0 to 1, where 1 indicates 100% of the measured data are covered within model prediction uncertainty. On the other hand, the ratio of the average thickness of the 95PPU band to the standard deviation of the corresponding measured variable is called r-*factor*. These two measures are used to determine the accuracy of the calibration and validation. A larger p-*factor* can be achieved at the expense of a larger r-*factor*. Hence, often a balance must be reached between the two. Theoretically, the values for p-*factor* range from 0 to 1, and r-*factor* ranges between 0 and infinity. The value of p-*factor* equal to one and that of r-*factor* close to zero indicate that the simulated results are exactly matching with the observed values (Abbaspour *et al.,* 2007; Abbaspour, 2011). Often multiple iterations are required to have good result. In the final iteration, where acceptable values of r-*factor* and p-*factor* are reached, the parameter ranges are taken as the calibrated parameters. SUFI-2 allows usage of ten different objective functions such as coefficient of determination (R^2), Percent Bias (*PBIAS*), Nash-Sutcliff Efficiency (*NSE*), and Modified Nash-Sutcliffe Efficiency (*MNSE*). In this study, *NSE* and *MNSE* were used as objective functions for simulating streamflow. A full description of SWAT-CUP can be found in the SWAT-CUP manual (Abbaspour, 2015).

2.5.2 Assessment of Model Performance

Results of the calibration and validation phases were evaluated based on the visual comparison and statistical criteria. R^2, *PBIAS NSE*, and *MNSE*, are the model performance metrics used in this study.

Coefficient of Determination (R^2)

The coefficient of determination (R^2) provides a measure of how well observed outcomes are linearly correlated to the model predictions. R^2 can have values ranging from 0 to 1. A value of zero indicates a poor relationship and no correlation between observed and simulated data, whereas a value of one would indicate a perfect correlation between the model and data, but not necessarily a good model performance. R^2 is defined as

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{m,i} - \bar{Q}_m)(Q_{s,i} - \bar{Q}_s)\right]^2}{\sum_{i=1}^{n}(Q_{m,i} - \bar{Q}_m)^2 \sum_{i=1}^{n}(Q_{s,i} - \bar{Q}_s)^2}$$

where, *Q* is the variable of interest (e.g., discharge), *m* and *s* stand for measured and simulated values, *n* is the number of data points, and $\bar{Q}_m$, $\bar{Q}_s$ are average measured and simulated flows, respectively.

Percent Bias (PBIAS)

Percentage bias (*PBIAS*) measures the average tendency of the simulated flow data to be larger or smaller than the observed data (Gupta *et al.,* 1999), with the ideal range for flow data to be ±25%, with positive values indicating a model underestimation bias, and negative values indicating an overestimation bias.

$$PBIAS = 100 * \frac{\sum_{i=1}^{n}(Q_{m,i} - Q_{s,i})}{\sum_{i=1}^{n} Q_{m,i}}$$

Nash-Sutcliffe Coefficient (NSE)

The Nash-Sutcliffe Model Efficiency Coefficient (*NSE*) determines the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970). It indicates how well the observed versus predicted data fit the 1:1 line. Results for NSE range from -∞ to 1, where 1 is perfect model prediction. Results over 0 are generally viewed as acceptable; whereas values below 0 show that the mean of observed values is a better forecaster than the predicted values, indicating an unacceptable performance (Moriasi *et al.,* 2007).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{m,i} - Q_{s,i})^2}{\sum_{i=1}^{n}(Q_{m,i} - \bar{Q}_m)^2}$$

Modified Nash-Sutcliffe Coefficient (MNSE)

The logarithmic form of *NSE* is widely used to overcome the oversensitivity to extreme values, induced by the mean square error in the *NSE* and the index of agreement, and to increase the sensitivity for lower values.

$$MNSE = 1 - \frac{\sum_i |Q_m - Q_s|_i^p}{\sum_i \left|Q_{m,i} - \bar{Q}_m\right|_i^p}$$

where, *p* represents an arbitrary power (i.e., positive integer). In particular, for *p*=1, the overestimation of the flood peaks is reduced significantly resulting in a better overall evaluation. The modified forms are more sensitive to significant over or under prediction than the squared forms (Krause *et al.,* 2005).

2.5.3 Calibration, Validation, Parameterization, and Uncertainty Analysis

The following steps are performed either by the user or by SWAT-CUP under the SUFI-2 algorithm for sensitivity analysis, calibration and uncertainty analysis.

1) Run ArcSWAT once with the default model parameters to generate all the input files as well as output files. The whole "*txtinout*" directory is needed by SWAT-CUP as input.
2) Select an objective function out of ten different options in SUFI-2. In this study, *NSE* and *MNSE* were selected as objective functions.
3) Define the minimum and maximum ranges for the model parameters by paying attention to their allowable, meaningful ranges.
4) Sensitivity analysis is carried out by keeping all the parameters constant at their realistic values, while varying each parameter within their range assigned in step one. Performing sensitivity analyses is helpful to identify the most influential parameters governing model results (Van Griensven *et al.,* 2002; Van Griensven *et al.,* 2006). Furthermore, the results of the sensitivity

analyses allow determining the effects of varying the values of these parameters to get an insight on the uncertainty of the results.

5) Initial uncertainty ranges for the parameters are selected for the first hypercube sampling. In general, these ranges are smaller than the initial ranges. The sensitivity analysis can provide a valuable guide in selecting appropriate ranges.
6) The next step is to perform Latin Hypercube sampling which leads to the combinations of *n* parameters, where *n* represent the number of desired simulations. This number should be relatively large and typically should not exceed 500 simulations for SUFI-2 according to the SWAT-CUP manual.
7) Running SWAT with each Latin Hypercube sample generates an output time series. Using the selected objective functions, likelihood measures are calculated for each.
8) The two indices p-*factor* and r-*factor* were calculated for assessing the uncertainties (95PPU).
9) If the parameter uncertainties are found large (small r-*factor*) after the first round, further rounds of sampling are required with updated ranges of parameters.

The steps mentioned above were followed for the two study watersheds. In this study, thirteen parameters were selected for SWAT-CUP runs. After global sensitivity analysis, the most sensitive parameters (which changed when objective function changed) were identified and used for further analysis for each watershed. The *p-value* and *t-stat* generated by SWAT-CUP are the two measures used in deciding the most sensitive parameters. The *p-value* determines the significance of the sensitivity magnitudes and values close to zero are good. Moreover, *t-stat* also provides a measure of sensitivity. Larger *t-stat* values indicate higher sensitivity. For a successful calibration, SWAT-CUP was run 1500 times (3 iterations with 500 simulations in each) with the eight sensitive parameters, until satisfactory *NSE* and *MNSE* values were obtained. Changes in parameter ranges were made after consulting with various studies that have used SWAT model (Santhi *et al.,* 2001; Abbaspour *et al.,* 2007; Vaghefi *et al.,* 2014; Arnold *et al.,* 2012). The final calibrated ranges of parameters were used during the validation stage as well.

After calibration and validation, the next step was testing the model in the urbanized period using SSURGO and updated soil properties (K_{sat} and ρ_b). To do this, a new ArcSWAT project was created for each watershed with the 2011 NLCD and the whole "txtinout" folders were provided as input to SWAT-CUP. Some parameter ranges from the calibration stage were used to perform model runs. Table 2.6 shows the parameters that were adjusted from the model default values during calibration. These parameters were obtained from a thorough sensitivity analysis for the entire watershed, using SWAT-CUP's global sensitivity approach to determine how sensitive the parameters are and understand their sensitivity ranking.

Table 2.1: PTF functions used in calculating various soil parameters

Hydraulic Soil Characteristic	Equations	Parameters	Source
Saturated hydraulic conductivity (K_{sat}) (mm/hr)	$K_{sat} = \ln[19.52348\phi - 8.96847 - 0.028212C + 0.00018107S^2 - 0.0094125C^2 - 8.395215\phi^2 + 0.077718S\phi - 0.00298S^2\phi^2 - 20.019492C^2\phi^2 + 0.0000173S^2C + 0.02733C^2\phi + 30.001434S^2\phi - 0.0000035C^2S]*10$	ϕ: Porosity C: Clay % S: Sand %	Rawls and Brakensiek, (1985)
Field Capacity (FC)	FC=WP+AWC	WP: Wilting point AWC: Available water content	
Wilting Point (WP)	WP= $0.40*C*\rho_b^d$	C: Percent clay of the layer (%) ρ_b^d: Dry bulk density (g/cm^3)	Neitsch *et al.,* 2009
Dry bulk density (ρ_b^d)	$\rho_b^d = (1-\phi)*\rho_d$ $\rho_b^d = (\rho_b^w$-AWC)/(0.4*C+1)	ρ_b^w: Wet bulk density ρ_d: Particle density (2.65 g/cm^3) AWC: Available water content C: Clay %	
Wet bulk density (ρ_b^w)	ρ_b^w= WP+AWC+(1-ϕ)*2.65	WP: Wilting point AWC: Available water content ϕ: Porosity	
Porosity (ϕ)	$\phi=1-\rho_b^d/\rho_d$	ρ_b^d: Dry bulk density (g/cm^3) ρ_d: Particle density (2.65 g/cm^3)	White, (2013)

Table 2.2: Bulk density (g/cm^3) values observed in ecological studies of forest soils

Source	**Study Area**	**Forest Soil Bulk Density (g/cm^3)**	**Depth (cm)**
Pouyat *et al.,* 2006	-	1.10	10
Nagy R., 2009	-	1.17	30
McGrath *et al.,* 2001	-	1.05	20
Moges *et al.,* 2013	-	1.03	20
Desjardins *et al.,* 1994	-	1.33	20
Price *et al.,* 2010	-	0.80	15
Dhakal *et al.,* 2010	-	1.11	26
Matano *et al.,* 2015	-	0.87	20
Neill *et al.,* 1997	-	0.59 to 1.37	20
Trumbore *et al.,*1995	-	1.02	10
Garcia-Oliva *et al.,* 2006	-	0.90	5
Basaran *et al.,* 2008	-	1.15	20
Campbell *et al.,* 2014	-	1.26	20
Gebremariam and Kebede, 2010	-	1.29	15
Yu *et al.,* 2014	-	1.32	20
Birdsey and Weaver, 1982	-	0.95	23
Helfrich *et al.,* 2006	-	0.91	7
Gol and Deniz, 2008	-	1.01	22
Bewket *et al.,* 2003	-	0.90	15
Franzluebbers *et al.,* 2000	-	1.32	20
O'Neill *et al.,* 2005*	-	0.1-0.7, 0.7, 0.7-1.2	NA
Lauber *et al.,* 2008	-	1.20	7.5
Fox *et al.,* 1986	Piedmont	1.09	15
Schenk *et al*. 2013	Piedmont	0.94	NA
Turner , 2013	Piedmont	0.93	15
Franzluebbers, A.J., 1999	Piedmont	0.95	8
Pouyat *et al.,* 2002	Piedmont	1.18	15
Gent *et al.,* 1984	Piedmont	1.12	8
Gent *et al.,* 1984	Piedmont	1.16	8
Carter and Shaw, 2002	Piedmont	1.23	20
Jackson *et al.,* 2005	Piedmont	1.13	NA
Burke *et al.,* 1999	Piedmont	1.03	NA
Maloney *et al.,* 2008	Piedmont	1.09	10
Meding *et al.,* 2001	Piedmont	1.06	5

(* see chapter II - forest bulk densities section for explanation)

Table 2.3: Bulk density (g/cm^3) values observed in ecological studies of urban soils.

Land Use Types / Sources	G	LD	MD	HD	T	I	I_1	C	PP	G_1	R
Pouyat et al., 2002	-	1.22	1.18	1.22	1.17	1.0	1.41	1.26	-	-	-
Lorenz and Kandeler, 2005	-	1.23	1.2	-	-	-	-	-	2.23	-	-
Pouyat et al., 2007	-	-	-	-	1.3	1.3	1.2	1.3	1.2	-	1.2
Millward et al., 2011	-	-	-	-	-	-	-	-	1.4	1.1	-
Scharenbroch et al., 2005	-	-	-	-	-	-	-	-	1.39	-	1.7
Short et al., 1986	1.61	-	-	-	-	-	-	-	-	-	-
Patterson et al., 1976	2.02	-	-	-	-	-	-	-	-	-	-
Craul et al., 1985	1.73	-	-	-	-	-	-	-	-	-	-
Hiller, 2000	1.67	-	-	-	-	-	-	-	-	-	-
Gbadegesin and Olabode, 2000	1.62	-	-	-	-	-	-	-	-	-	-

(G refers to general average bulk densities with no detailed information on level of urbanization, LD: Low Density, MD: Medium Density, HD: High Density, T: Transportation, I: Institutional, I1: Industrial, C: Commercial, PP: Public Park, G: Garden, and R: Residential)

Table 2.4: Characteristics of gauged streams and drainage basins used in this study.

Stream Flow Gauging Station Name	**USGS Station Number**	**Drainage Area (km^2)**	**Period Of Record**
Big Creek near Alpharetta	2335700	190.0	1985-2013
Suwanee Creek	2334885	121.4	1985-2013

Table 2.5: LULC change from 1992 to 2011 at the study watersheds

LULC	Big Creek Watershed		% of watershed area converted from forest to urban between 1992-2011	Suwanee Creek Watershed		% of watershed area converted from forest to urban between 1992-2011
	1992 NLCD	2011 NLCD		1992 NLCD	2011 NLCD	
Forest (km^2)	131.9	55.4	36.9	94.6	35.4	45.3
Urban (km^2)	11.7	104.8		10.1	73.9	
Agriculture (km^2)	42.4	17.3		14.5	5.3	

Table 2.6: List of parameters and their definitions used in model calibration

Parameter name	Definition
r__CN2.mgt	SCS runoff curve number
v__ALPHA_BF.gw	Baseflow alpha factor (days)
v_GW_DELAY	Groundwater delay time (days)
v__GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow to occur (mm)
v__ESCO.hru	Soil evaporation compensation factor
v__EPCO.hru	Plant uptake compensation factor
r__SOL_AWC.sol	Available water capacity of soil layer (mm H_2O/mm soil)
v__SURLAG	Surface runoff lag coefficient (days)
v__GW_REVAP	Groundwater 'revap' coefficient
r_SOL_K.sol	Saturated hydraulic conductivity (mm/hr)
r__SOL_BD.sol	Soil bulk density (g cm^{-3})
v__CANMX.hru	Maximum canopy storage (mm)
v_REVAPMN.gw	Threshold water depth in shallow aquifer (mm)

The qualifier (*v_*) refers that the default parameter is replaced by a given value, while (*r_*) refers to a relative change in the parameter where the current value is multiplied by 1 plus a factor in the given range.

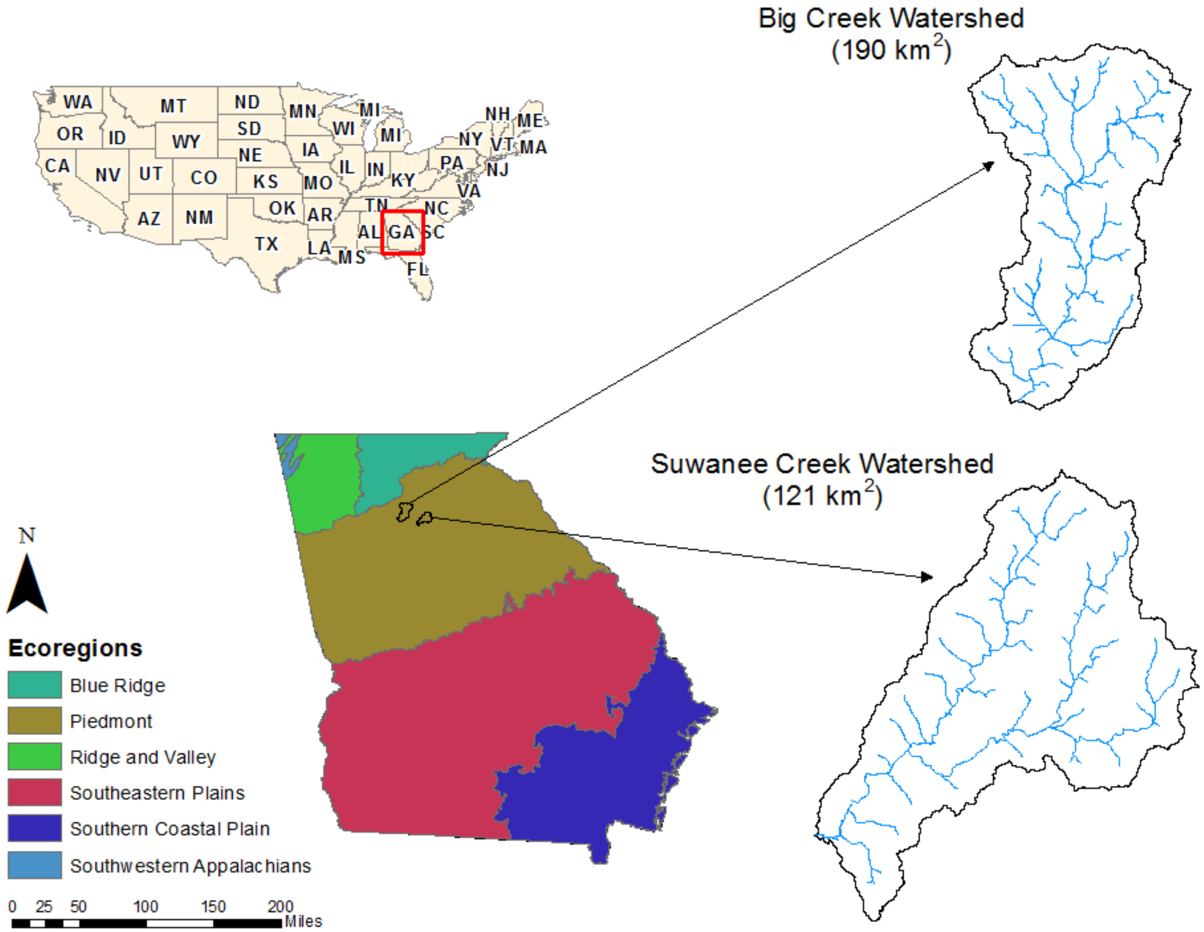

Figure 2.1: Location of study watersheds

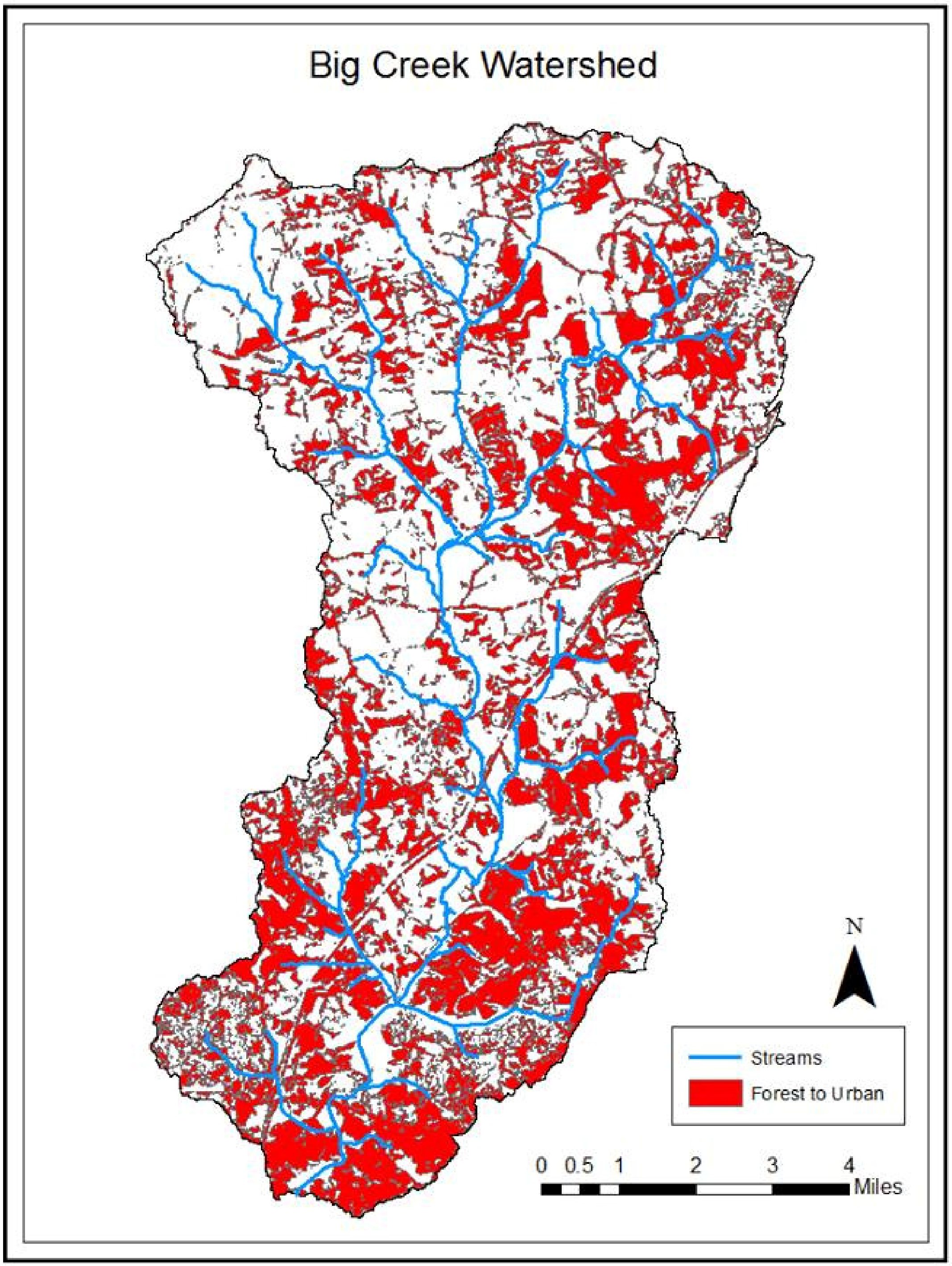

Figure 2.2: Forest to Urban transition from 1992 to 2011 in the Big Creek Watershed

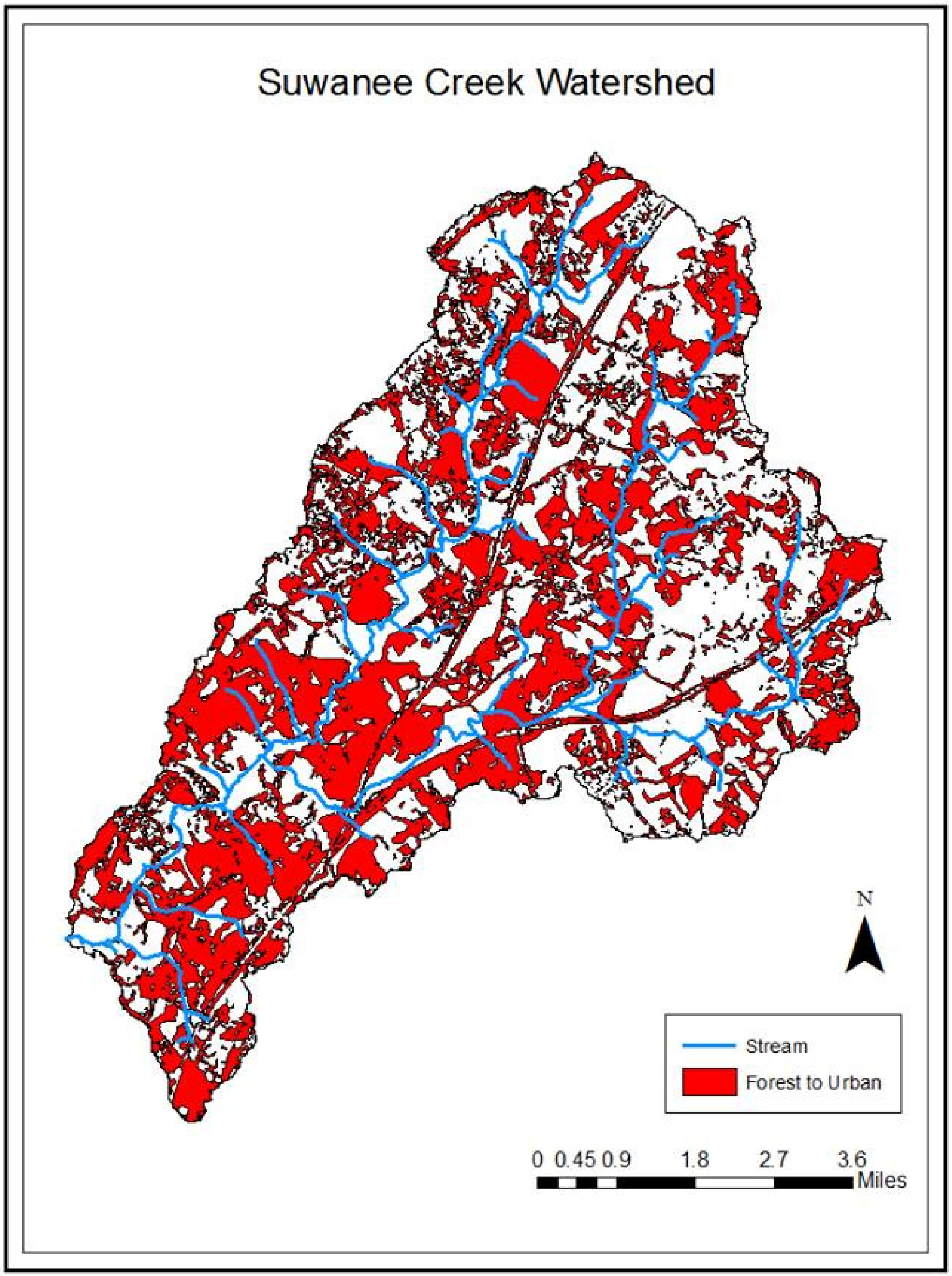

Figure 2.3: Forest to Urban transition from 1992 to 2011 in the Suwanee Creek Watershed

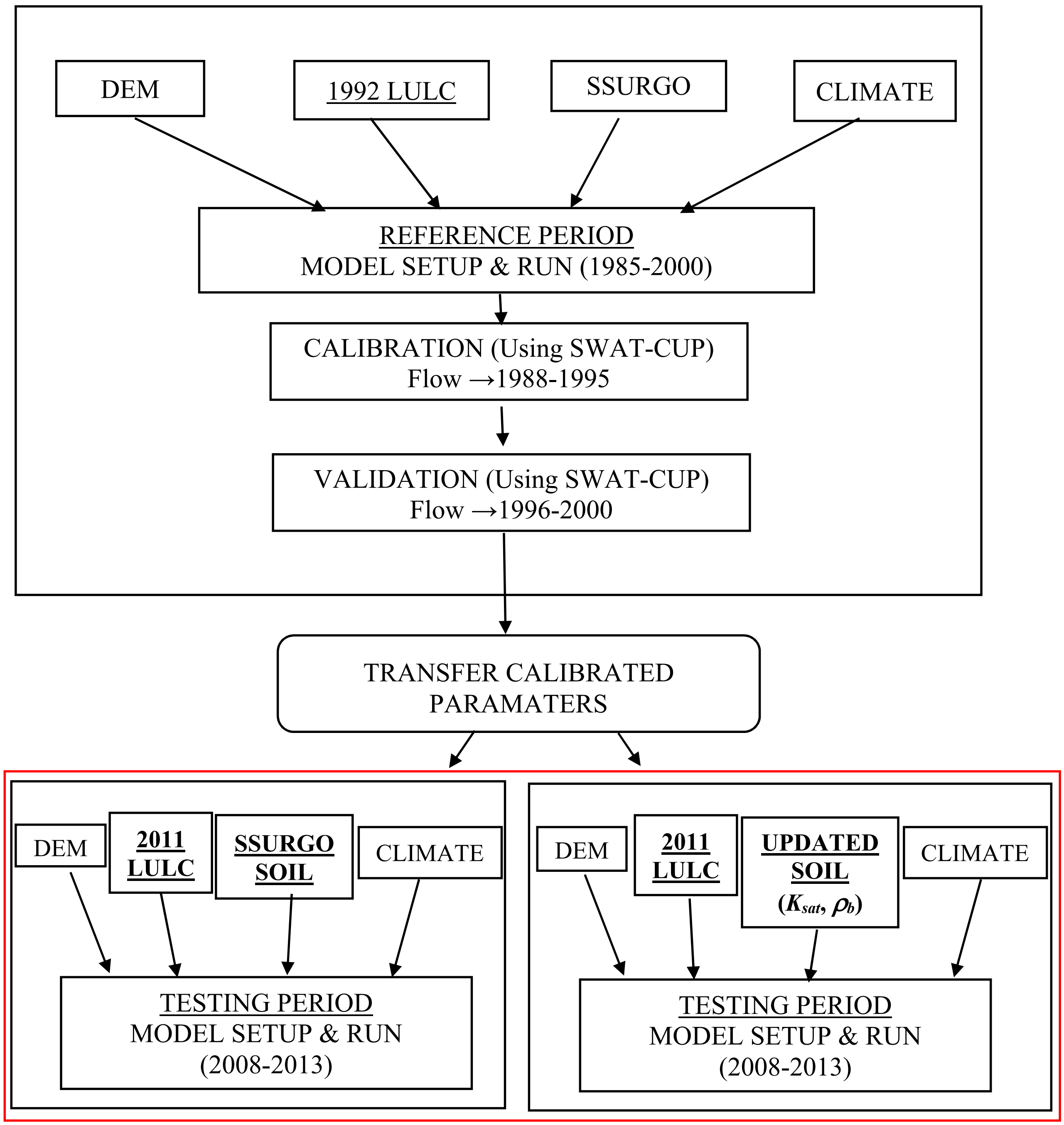

Figure 2.4: The methodology used in the study for model set up, calibration, validation and testing.

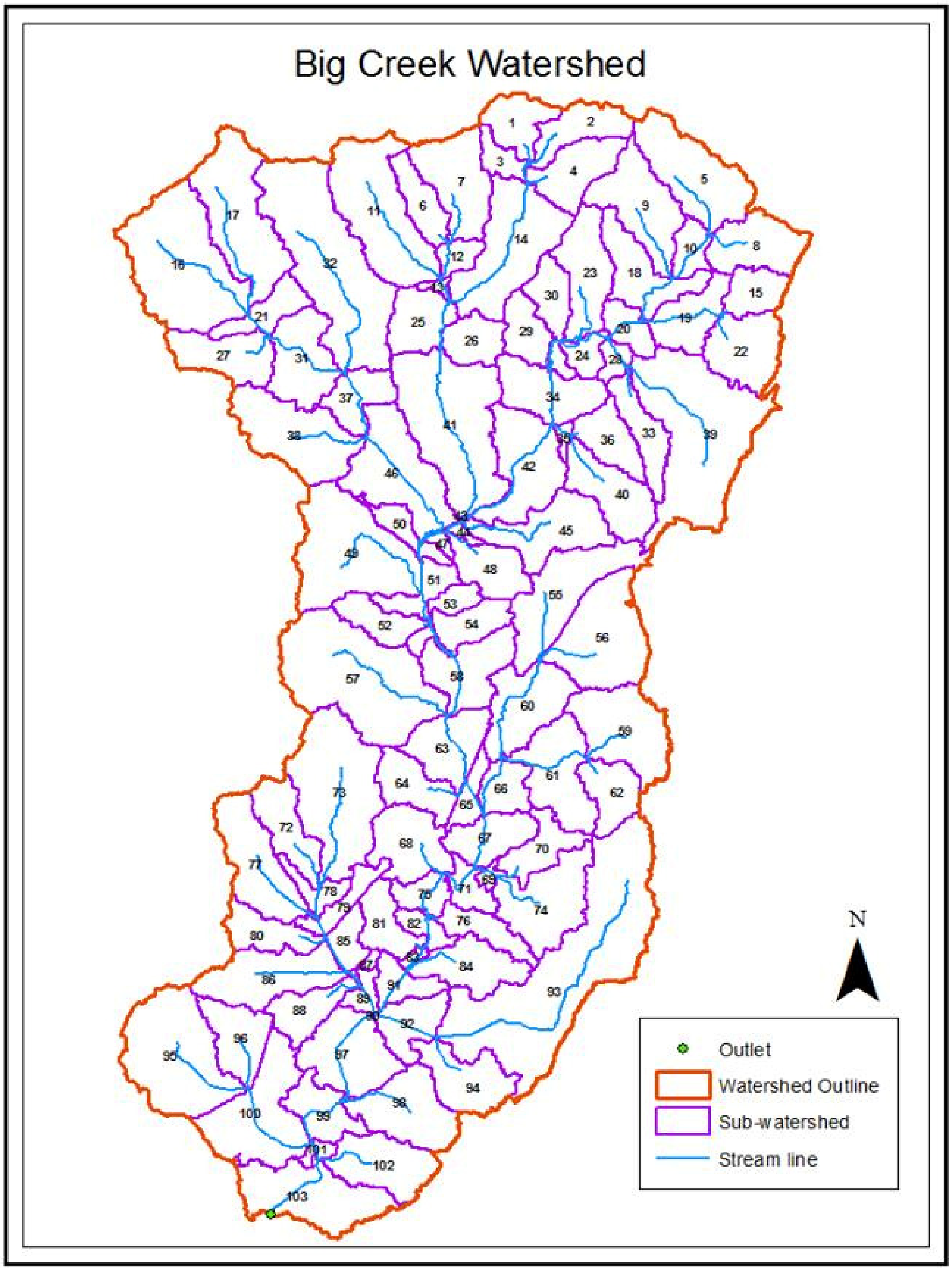

Figure 2. 5: Sub-watersheds of Big Creek Watershed

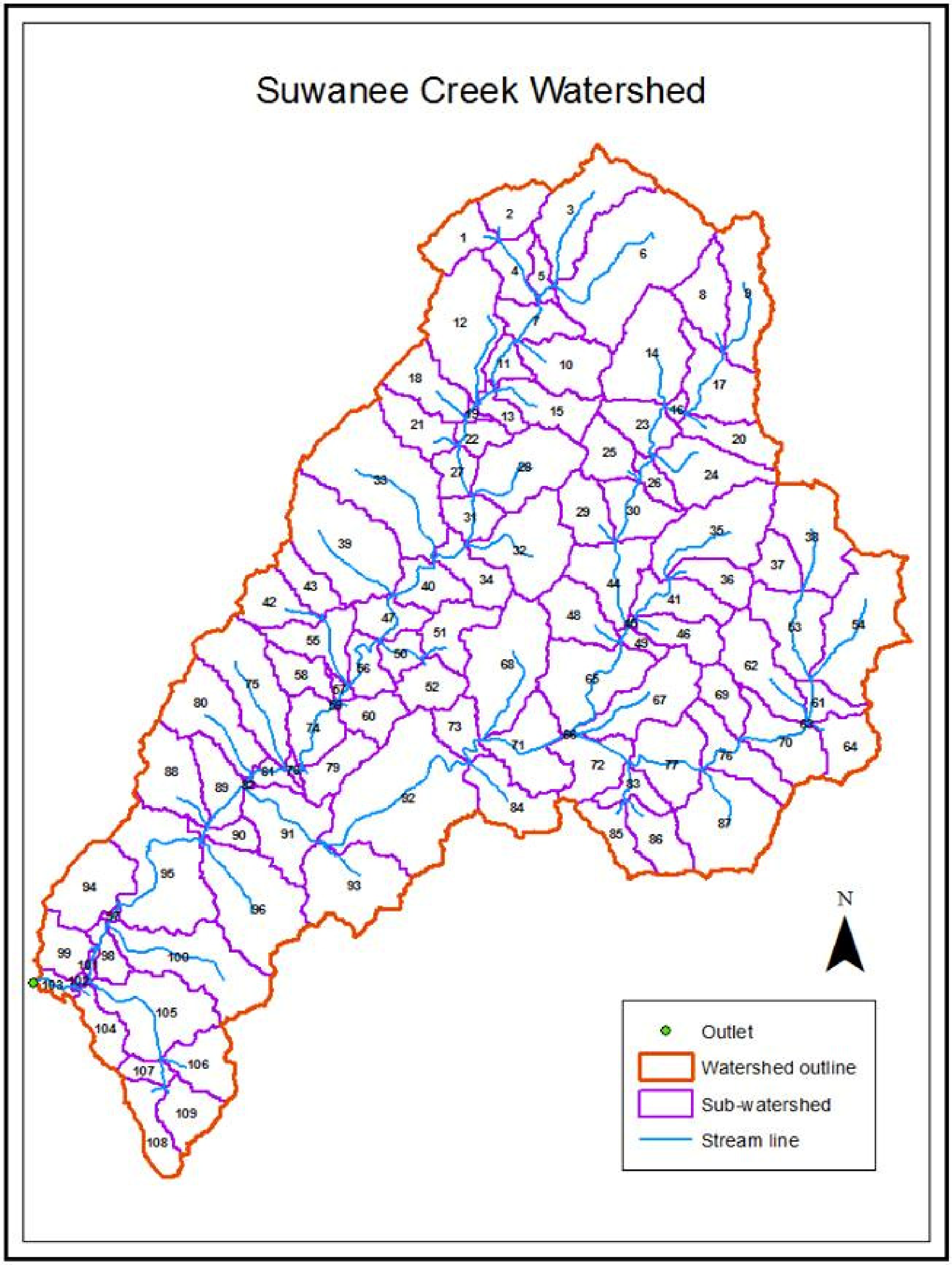

Figure 2. 6: Sub-watersheds of Suwanee Creek Watershed

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CHAPTER III: RESULTS & DISCUSSIONS

In this chapter, results from the application of the methodology to the two study watersheds in metropolitan Atlanta area as outlined in Chapter 2 is presented. Results are presented for the reference period (1988-2000) and testing period (2008-2013). To assess the influences of the changes in soil hydraulic properties and LULC on streamflow prediction, daily streamflow of Big and Suwannee Creek watersheds were simulated through the SWAT model using SSURGO map and 1992 LULC data and then calibrated and validated using the SWAT-CUP program during the reference period using the methodology outlined in previous chapter. Next, 2011 LULC data was utilized in the model and the calibrated model was run for the testing period after updating relevant model parameters.

The most sensitive model parameters were first identified before model calibration. To that end, a thorough literature review was first conducted to narrow down the list of parameters before performing the formal sensitivity analysis. Thirteen model parameters were selected from the literature to which streamflow is generally accepted to be sensitive (Abbaspour *et al.,* 2007; Schuol *et al.,* 2008; Muleta 2012; Singh *et al.,* 2015). SWAT-CUP was then used to perform sensitivity analysis and finalize the list of parameters to be calibrated. It is a known fact that the list and order of sensitive parameters highly depend on the selected objective function (Price *et al.,* 2012). For instance, the use of *NSE* and *MNSE* can yield different sensitive parameters and ranges and, once calibrated, different simulated streamflow characteristics. This section also discusses the implications of using different calibration targets (*NSE* and *MNSE*) in calibrated parameters, their ranges, and simulated streamflow characteristics. The calibrated and validated models were tested for future periods with and without updating soil parameters.

Model calibration, validation and testing were all done at daily time step. Many studies found that when watershed model calibrations are completed on a daily basis, there is a significantly improvement in the prediction of the high and low flows (Bosh *et al.,* 2004; Sudheer *et al.,* 2007; Chu *et al.,* 2004). Also, in this study, two different objective functions, *NSE* which emphasizes on high flows in evaluating simulation fit, and *MNSE* with p=0.25 which emphasizes both high and low flows, were used for calibration and validation of the SWAT model for daily streamflow simulations in both watersheds. Streamflow simulations are generally considered satisfactory if *NSE* > 0.5 and *PBIAS* is within ±25% at monthly time step (Moriasi *et al.,* 2007). Since daily time scale was used in this study, *NSE*> 0.5, *PBIAS*< ±25%, and R^2 > 0.5 can be acceptable for our study (Meaurio *et al.,* 2015, Santhi *et al.,* 2001; Van Liew *et al.,* 2003). Typically, model simulations are poorer for shorter time scales than for longer time steps (e.g., daily versus monthly or yearly) (Engel *et al.,* 2007).

3.1 REFERENCE PERIOD (1988-2000, 1992 NLCD)

3.1.1 Calibration and Validation Result of Big Creek Watershed

Objective Function: NSE

SWAT model was first calibrated and validated at daily time step with 1992 NLCD and SSURGO map for the period 1985-1995. Calibration was carried out in two steps: parameter identification and parameter estimation. Parameter identification included defining and selecting the most sensitive parameters of the model, and parameter estimation included finding the optimal ranges of the parameters chosen that produces high model performance. A restricted set of 13 parameters (deciding processes explained earlier) was used for the sensitivity analysis. From the global sensitivity analysis, eight parameters out of 13 parameters were selected as the most sensitive, including *CN2, SOL_BD, SOL_K, ESCO, SOL_AWC, GWQMN, EPCO*, and *CANMX* (Table 3.1). Although $p<0.05$ is usually recommended, the most sensitive eight parameters were used in this study to increase the number of parameters to a reasonable number. Calibration was then carried out during the period 1988–1995 with the eight most sensitive parameters. The final parameter ranges are shown in Table 3.1. *CN2* is typically the most important parameter in calibration of SWAT (Muleta, 2012; Zang *et al.,* 2012; Singh *et al.,* 2013) and contributes directly to surface runoff generation and indirectly affects baseflow. In order to better match the low flows, values of the *CN2* and *ESCO* were decreased in Big Creek Watershed. Decreasing *CN2* implies a decrease of surface runoff and increase in baseflow while decreasing *ESCO* causes higher soil evapotranspiration. Increasing *SOL_K* increases subsurface storm flow and also it effects travel time in the soil. Therefore, *SOL_K* increases streamflow. *SOL_AWC* and *SOL_BD* of the surface soil layer in Big Creek Watershed were increased during calibration and therefore, the increase in water holding increased the potential for more evapotranspiration by vegetation. In Big Creek Watershed, calibration of groundwater flow was controlled by *GWQMN*. *GWQMN* (deep percolation) was reduced in order to match low flows. Decreasing *GWQMN* increases baseflows. The *EPCO* factor in the SWAT model explains how available soil water could be used to meet plant water uptake either from upper layers or deeper profiles. Calibrated *EPCO* value was 0.89 in Big Creek watershed, indicating soil water from deeper soil profiles could be used, thus increasing ET. In the Big Creek Watershed, evapotranspiration was reduced by increasing *CANMX*, therefore the overall water yield increased.

Validation was then carried out during the period 1996–2000. For this, the same parameter adjustment factors shown in Table 3.1 were used during the validation period with no further adjustment in parameter ranges. The daily streamflow values obtained during the validation period by the SWAT model were compared with observed streamflow. The goodness of fit statistics for the daily flow simulations of Big Creek Watershed are presented for both calibration and validation periods in Table 3.3 for best performances. According to the criteria explained earlier, the model performances are reasonably good during both calibration and validation periods. It was noted that efficiency of the model, which indicates how well the plot of observed versus simulated values fits the 1:1 line, was good during both calibration and validation periods ($NSE_{\text{calibration}}$= 0.66 and $NSE_{\text{validation}}$= 0.66). High values of R^2 during calibration and validation periods (greater than 0.66) indicate a good agreement between the simulated and measured values of daily flows. This watershed was very well simulated with a rather large *p-factor* and small *r-factor* during both calibration and validation periods (Table 3.3). The observed daily streamflows were closely matched with simulated streamflows during calibration and validation periods as shown in time series as well (Figure 3.1). Figure 3.1 also illustrates scatter graphs between the simulated and observed daily streamflows. FDC can illustrate how well the model reproduced the frequency of measured daily flows through the calibration and validation periods. Figure 3.1 also compares flow duration curves (FDCs) of observed and simulated daily streamflows for the calibration and validation periods. In general, the FDCs of observed and simulated flows compare well, especially during the calibration period.

Objective Function: MNSE

Similar procedures were followed to calibrate and validate the model when objective function has changed from *NSE* to *MNSE*. The same 13 parameters listed in Table 3.2 were used for sensitivity analysis. Eight parameters (*CN2, ESCO, SOL_BD, GW_DELAY, SOL_K, SOL_AWC, GWQMN,* and *GW_REVAP*) were identified as the most sensitive parameters based on *MNSE* as the objective function. Compared to the sensitive parameters based on *NSE* objective function, with the *MNSE* objective function, two parameters were different. *GW_DELAY* and *GW_REVAP* were not in the first eight sensitive parameters when *NSE* was used as objective function. *EPCO* and *CANMX* were more sensitive than those two when *MNSE* was used as objective function. Table 3.2 lists the results of the global sensitivity analysis with *MNSE* as the objective function. These eight parameters were then calibrated until satisfactory model results were obtained (Table 3.3). According to the sensitivity analysis, *CN2*, soil parameters, and groundwater parameters had significant effects on streamflow generation. In order to better match observed and simulated streamflows, the *CN2* was increased, which implies an increase in surface runoff and decrease in baseflow. This is interesting because the use of *NSE* as objective function had an opposite effect. *NSE* gives significantly more weight to high flows. On the other hand, *MNSE* with p=0.25 gives weight to both high and low flows, may be more to latter, since *CN2* affects both high and low flows. Changes in *CN2* can affect both. A close look at the FDCs (Figure 3.2) reveals that SWAT underestimates low flows, especially during the validation period. It is very hard to pinpoint source of improvement in low flows because there is so much interaction between parameters. In Figure 3.2 low flows are better represented. Decreasing *ESCO* allowed lower soil layers to compensate for a water deficit in upper layers and induced higher soil evapotranspiration. In Big Creek watershed, calibration of groundwater flow was controlled by *GW_DELAY, GWQMN*, and *GW_REVAP* when *MNSE* was used as the objective function. *GWQMN* and *GW_REVAP* were decreased in order to better match low flows. Increasing the value of the *GW_DELAY* affects both timing and the quantity of water available for baseflow. *SOL_AWC* increased in order to reduce surface runoff. Increasing the *SOL_AWC* also led more water available for streamflow in the baseflow period. Model performance statistics are shown in Table 3.3. The modified efficiency of daily streamflow predictions (*MNSE*) increased from 0.24 in the calibration period to 0.27 during validation. The R^2 and *PBIAS* for calibration period were 0.51 and 3.8%, respectively. The R^2 and *PBIAS* for streamflow in the validation period were 0.48 and 8.7%, respectively. The percentage of data being bracketed by 95PPU (*p-factor*) was high both in calibration and validation periods (0.81 and 0.78). The use of *MNSE* visually resulted in better correspondence between the observed and simulated flows for calibration and validation periods. The results showed that using *MNSE* as the objective function produced respectively good results, not only for the low flows but also during high flow conditions, compared to using *NSE*. This is because *MNSE* is evenly sensitive to low flows and high flows. In summary, results indicate that SWAT is capable predicting streamflow very well at the Big Creek Watershed.

3.1.2 Calibration and Validation Result of Suwanee Creek Watershed

Objective Function: NSE

Suwanee Creek Watershed was the other case study watershed. In this watershed, the most sensitive parameters for predicting flow were *CN2, SOL_BD, SOL_K, SURLAG, ESCO, GW_REVAP, ALPHA_BF,* and *EPCO* when *NSE* was used as the objective function (Table 3.4). These parameters were modified during the model calibration until satisfactory model results were obtained. There was no clear trend in *CN2*. Baseflow portion of streamflow was controlled by *GW_REVAP* and *ALPHA_BF*. *GW_REVAP* was decreased because the simulated baseflow was likely too low before calibration. The temporal distribution of the flow and the shape of the hydrograph improved through calibration of the *SURLAG* and *ALPHA_BF* parameters. The baseflow recession coefficient (*ALFHA_BF*) is a direct index of ground water flow response to changes in recharge. *ALPHA_BF* increased in Suwanee Creek Watershed, thus surface water and ground water travel time was decreased. Increasing *SOL_K* resulted in increased subsurface stormflow. *ESCO* was adjusted between 0.3 and 0.85 in an attempt to reduce total flow. The *EPCO* factor in the SWAT model explains how available soil water could be used to meet plant water uptake, either from upper layers or deeper profiles. Ranges of *EPCO* was close to 0, meaning soil water from top layers was most likely used. The goodness of fit statistics for the daily flow simulations of Suwanee Creek Watershed is tabulated in Table 3.6. According to the model performance criteria explained before, the model performances is satisfactory during both calibration and validation periods. Although, the percentage of data being bracketed by 95PPU (*p-factor*) was high in calibration, it was somehow low in validation (0.75 and 0.48, respectively). If the baseflow were better simulated, then a larger *p-factor* could have been achieved during the validation period. Model performance statistics for the streamflow predictions indicated a generally satisfactory fit between observed and predicted flows. Figure 3.3 illustrates the observed and simulated daily flows during the calibration and validation periods in time series and scatter plots. The FDCs for daily flows also in Figure 3.3 show that SWAT performed relatively well in simulating flows during the calibration period. The daily simulated high and low streamflow almost perfectly matched with observed streamflow in this period. However, 10%-60% range observed streamflow was not close to simulated streamflow as much as low and high flows. On the other hand, FDCs of validation period showed that even though there was a good correlation in high and medium flows, there was an underestimation in low flows. This is also evident on the scatter plot of validation period.

Objective Function: MNSE

When *MNSE* was used as the objective function, parameters having the highest sensitivity to predicted flow were *SOL_BD*, *ESCO*, *SOL_K*, *CN2*, *SOL_AWC*, *EPCO*, *CANMX*, and *GW_DELAY* (Table 3.5). Compared to the sensitive parameters of *NSE* objective function, three parameters replaced with each other. *SOL_AWC, CANMX,* and *GW_DELAY* were not in the first eight sensitive parameters when *NSE* was used as objective function. Instead of these parameters *SURLAG, GW_REVAP,* and *ALPHA_BF* were more sensitive to streamflow when *NSE* used as objective function. Selected parameters and their minimum and maximum ranges are shown also in Table 3.5. Like the previous runs, parameter ranges also varied during the model calibration until satisfactory model results were obtained. Unlike the previous runs, *CN2* was not the most sensitive parameter during the calibration period with *MNSE*. Calibration of groundwater flow was controlled by only *GW_DELAY*. *GW_DELAY* was increased to improve the timing of low flows. *CN2*, *ESCO*, *SOL_AWC*, and *SOL_K* were the most relevant parameters that influence surface flow in SWAT. In order to better match the simulated flows, *CN2* was increased in Suwanee Creek Watershed. Because simulated peak flow was underestimated, *SOL_AWC* and *ESCO* were decreased. Reducing *SOL_AWC* resulted in increased surface flow, reduced evapotranspiration, and increased baseflow. By altering the *CANMX* parameter, evapotranspiration was reduced. Therefore, the overall water yield increased. Ranges of *EPCO* was near 1 when *MNSE* was used, meaning soil water from deeper soil profiles could be used to compensate for evaporative demands. This adjustment ensured a better simulation at the watershed outlet. The model performance statistics of the daily flow simulations are tabulated in Table 3.6. Overall, there was a reasonably good agreement between observed and simulated streamflow for calibration and validation periods. *MNSE* resulted in usually better correspondence between the observed and simulated flows during the calibration period (Figure 3.4) while NSE produced lower predictions in high to medium flows. Unlike the calibration period, *MNSE* still underestimated low flow during the validation period (Figure 3.4). The results showed that using *MNSE* as the objective function produced relatively good results for high and medium flows during calibration; however, not for low flow.

3.2 TESTING PERIOD (2008-2013, 2011 NLCD)

Previous sections showed that SWAT model did a relatively good job in simulating streamflow in Big and Suwanee Creek Watersheds. The next step is to evaluate the effects of the LULC changes and updated soil hydraulic properties, obtained using PTFs, on the streamflow simulation. To do this, a new SWAT project was created with the values of the SSURGO and updated soils. While the sub-watersheds and the stream network for both watersheds remained the same for both LULC datasets of 1992 and 2011, HRUs differed. Calibrated and validated parameters during the reference period were transferred to the testing period. From 1992 to 2011, a vast portion of the watersheds experienced reduction in forest land and increase in urban land (Figure 2.2 and 2.3). Finally, the simulated daily streamflows obtained using SSURGO and 2011 NLCD were compared with the results of updated soil and 2011 NLCD.

3.2.1 Result of Testing Period of Big Creek Watershed

Objective Function: NSE

The same parameters and their ranges used in the reference period were transferred to the testing stage. Measures of model performance including R^2, *NSE*, and *PBIAS* values are listed in Table 3.7. There is very little to no improvement in model performance when updated soil parameters are used compared to the case where SSURGO is used. The model evaluation indices

R^2, *NSE* and *PBIAS* demonstrated that simulated and measured daily discharge agreed well for both SSURGO and updated soil simulations. The simulated and observed streamflow FDCs at the Big Creek Watershed outlet are shown in Figure 3.5 for SSURGO and PTFs approaches during 2008-2013. Because FDCs illustrated visually similar results, percent error graphs were produced. Percent error graph compares the performance of each model for each percentile flows. In the percent error graph, the SSURGO and PTFs lines show the percent deviation (Ɛ) from observed flow for each percentile of flows $\left[\varepsilon = \frac{(Q_m - Q_s)}{(Q_m)}\right]$, where Q_m and Q_s are measured and simulated streamflow. The black line is the ratio of SSURGO and PTFs lines minus 1 $\left[Ratio = \frac{(\varepsilon_{SSURGO})}{(\varepsilon_{PTF})} - 1\right]$. If the black line is below x-axis that means SSURGO produced better compared to PTFs. If the black line is above x-axis, then PTFs had better model performance. From Figure 3.5, for high flows ($Q > Q_{5\%}$) and medium flows ($Q_{46\%} < Q < Q_{68\%}$) PTFs had better results. Appendix C also shows daily time series line graphs and scatter plots of the simulations and the observations for SSURGO and PTFs approach. Even though statistical model performances of simulations with updated soil and SSURGO were very similar, the use of the PTF to recalculate soil properties depicted flow simulations more precisely in high flows than SSURGO as hypothesized. When *NSE* was used as the objective function, the default SSURGO was not good at matching high flows. In most cases, the simulations with updated soil parameters resulted in better simulations of high flows than default SSURGO soil parameters.

<u>Objective Function: MNSE</u>

The best model performance statistics of the daily flow simulations are tabulated in Table 3.7. Overall comparison of daily flow simulation values (2008-2013) resulted in acceptable values. The time series and scatter plots of the observed and simulated flow during testing period are shown on Appendix D. Figure 3.6 illustrates FDCs and percent error graphs. Even though SSURGO and updated soil data statistically resulted in the same *MNSE* values, updated soil parameters improved model performance in medium flows ($Q_{26\%} < Q < Q_{40\%}$) and high flows ($Q_{9\%} < Q < Q_{16\%}$), according to the flow duration curves and percent error graph (Figure 3.6). FDCs showed almost perfect fit between the simulated and observed streamflow when SSURGO and updated soil parameters using PTFs were used.

3.2.2 Result of Testing Period of Suwanee Creek Watershed

<u>Objective Function: NSE</u>

The goodness of fit statistics were computed at daily time step again, and are presented in Table 3.8. The statistical results for SSURGO and updated soil of streamflow were 0.49 and 0.45 for R^2 criteria and 0.48 and 0.43 for *NSE* criteria. The results were very close to the recommended minimum values of R^2 and *NSE* in the literature. The time series plots and scatter plots of the observed and simulated flow during testing period are shown in Appendix F. Figure 3.7 illustrates FDCs and percent error graphs. When *NSE* was used as an objective function, the default SSURGO was good at matching low flows but not at high and medium flows. In contrast, updated soil simulations was close to observed data in high and medium flows. Even though FDC of updated soil shows the best fit on high flows, FDC derived from the updated soil indicated an underestimation of low flows, unlike SSURGO. The percent error graph of Suwanee Creek watershed showed that high and medium flows are generally better predicted than low flows using PTFs, and SSURGO simulated low flows better. *NSE* calibration performed best with high flows when updated soils were used.

Objective Function: MNSE

The best model performance statistics of the daily flow simulations of Suwanee Creek Watershed are tabulated in Table 3.8. The model performance results of *MNSE* were not as good as *NSE* objective function; however, the simulation results were visually good at time series plots. The time series plots and scatter plots of the observed and simulated flow during testing period are shown in Appendix G. To gain more insight, FDCs of observed and simulated flows and percent error graphs were also produced (Figure 3.8). When *MNSE* was used as the objective function, both the default SSURGO and PTFs approach underestimated the low flows in compared to *NSE* objective function. Percent error graphs illustrated that PTFs approach simulated only high flows better ($Q > Q_{2\%}$). SSURGO simulated flows better in comparison to the PTFs when *MNSE* was used as the objective function in the Suwanee Creek Watershed. However, both SSURGO and PTFs underestimated the medium and low flows during the testing period.

Table 3.1: Ranking the sensitivity of flow parameters and their final range of possible values in the Big Creek Watershed using *NSE* as the objective function.

Parameter Name*	t-stat	p-value	Rank	Range of Parameters
r__*CN2*.mgt	-21.932	0.000	1	-0.35 to 0
r__*SOL_BD*.sol	9.787	0.000	2	0.25 to 0.7
r__*SOL_K*.sol	4.847	0.000	3	0.35 to 1.2
v__*ESCO*.hru	-3.600	0.000	4	0.24 to 0.75
r__*SOL_AWC*.sol	3.491	0.001	5	-0.1 to 0.35
v__*GWQMN*.gw	1.702	0.089	6	60 to 150
v__*EPCO*.hru	1.672	0.095	7	0.5 to 0.95
v__*CANMX*.hru	1.065	0.287	8	6 to 12
v__*REVAPMN*.gw	-0.479	0.632	9	-
v__*ALPHA_BF*.gw	0.475	0.635	10	-
v__*SURLAG*.bsn	-0.372	0.710	11	-
v__*GW_REVAP*.gw	-0.295	0.768	12	-
v__*GW_DELAY*.gw	0.067	0.946	13	-

(* Refer to Table 2.6 in Chapter II for parameter definitions)

Table 3.2: Ranking the sensitivity of flow parameters and their final range of possible values in the Big Creek Watershed using the *MNSE* (p=0.25) as the objective function.

Parameter Name*	t-stat	p-value	Rank	Range of Parameters
r__*CN2*.mgt	10.967	0.000	1	0 to 0.3
v__*ESCO*.hru	-10.292	0.000	2	0 to 0.5
r__*SOL_BD*.sol	9.991	0.000	3	0.05 to 0.3
v__*GW_DELAY*.gw	7.839	0.000	4	45 to 120
r__*SOL_K*.sol	7.204	0.000	5	-0.3 to 0.1
r__*SOL_AWC*.sol	4.248	0.000	6	0.05 to 0.6
v__*GWQMN*.gw	-1.507	0.132	7	0 to 70
v__*GW_REVAP*.gw	-1.451	0.148	8	0.09 to 0.14
v__*REVAPMN*.gw	1.286	0.199	9	-
v__*EPCO*.hru	1.002	0.317	10	-
v__*ALPHA_BF*.gw	-0.808	0.419	11	-
v__*SURLAG*.bsn	0.514	0.607	12	-
v__*CANMX*.hru	-0.451	0.652	13	-

(*Refer to Table 2.6 in Chapter II for parameter definitions)

Table 3.3: Best Model Performance for Calibration and Validation Period at the Big Creek Watershed.

Objective Function	***NSE***					***MNSE* (p=0.25)**				
Performance Statistics	*p-factor*	*r-factor*	R^2	*NSE*	*PBIAS*	*p-factor*	*r-factor*	R^2	*MNSE*	*PBIAS*
Calibration Period (1988-1995)	0.64	0.31	0.66	0.66	-3.7%	0.81	0.47	0.51	0.24	3.8 %
Validation Period (1988-1995)	*0.55*	0.25	0.67	0.66	2.3 %	0.78	0.39	0.48	0.27	8.7%

Table 3.4: Ranking the sensitivity of flow parameters and their final range of possible values in the Suwanee Creek Watershed using *NSE* as the objective function.

Parameter Name*	**t-stat**	**p-value**	**Rank**	**Range of Parameters**
r__*CN2*.mgt	-30.588	0.000	1	-0.2 to 0.3
r__*SOL_BD*.sol	7.059	0.000	2	0.25 to 0.55
r__*SOL_K*.sol	3.788	0.000	3	0.45 to 1.1
v__*SURLAG*.bsn	1.834	0.067	4	6 to 14
v__*ESCO*.hru	-1.672	0.095	5	0.3 to 0.85
v__*GW_REVAP*.gw	-0.834	0.405	6	0.11 to 0.18
v__*ALPHA_BF*.gw	-0.454	0.650	7	0.65 to 1
v__*EPCO*.hru	-0.448	0.655	8	0 to 0.5
v__*CANMX*.hru	0.402	0.688	9	
v__*GWQMN*.gw	0.177	0.860	10	
r__*SOL_AWC*.sol	0.156	0.876	11	
v__*REVAPMN*.gw	0.054	0.957	12	
v__*GW_DELAY*.gw	0.044	0.965	13	

(*Refer to Table 2.6 in chapter II for parameter definitions)

Table 3.5: Ranking the sensitivity of flow parameters and their final range of possible values in the Suwanee Creek Watershed using the *MNSE* (p=0.25) as the objective function.

Parameter Name*	t-stat	p-value	Rank	Range of Parameters
r__*SOL_BD*.sol	9.607	0.000	1	0.35 to 0.5
v__*ESCO*.hru	-8.672	0.000	2	0.15 to 0.75
r__*SOL_K*.sol	6.546	0.000	3	-0.35 to 0.4
r__*CN2*.mgt	-2.809	0.005	4	-0.15 to 0.27
r__*SOL_AWC*.sol	1.756	0.080	5	-0.15 to 0.05
v__*EPCO*.hru	-1.722	0.086	6	0.65 to 0.98
v__*CANMX*.hru	1.094	0.275	7	10 to 15
v__*GW_DELAY*.gw	0.992	0.322	8	33 to 98
v__*GW_REVAP*.gw	-0.973	0.331	9	-
v__*REVAPMN*.gw	-0.650	0.516	10	-
v__*ALPHA_BF*.gw	0.646	0.518	11	-
v__*SURLAG*.bsn	-0.254	0.800	12	-
v__*GWQMN*.gw	-0.040	0.968	13	-

(*Refer to Table 2.6 in chapter II for parameter definitions)

Table 3.6: Best Model Performance during Calibration and Validation Period at the Suwanee Creek Watershed.

Objective Function	***NSE***					***MNSE* (p=0.25)**				
Performance Statistics	*p-factor*	*r-factor*	R^2	*NSE*	*PBIAS*	*p-factor*	*r-factor*	R^2	*MNSE*	*PBIAS*
Calibration Period (1988-1995)	0.75	0.54	0.50	0.50	-9.8%	0.78	0.47	0.32	0.24	3.5%
Validation Period (1988-1995)	0.48	0.37	0.54	0.54	8.8%	0.57	0.37	0.41	0.22	6.9%

Table 3.7: Best Model Performance during Testing Period (2008-2013) using the *NSE* and *MNSE* (p=0.25) as objective functions at the Big Creek Watershed.

Objective Function	***NSE***					***MNSE* (p=0.25)**				
Performance Statistics	*p-factor*	*r-factor*	R^2	*NSE*	*PBIAS*	*p-factor*	*r-factor*	R^2	*MNSE*	*PBIAS*
SSURGO	0.51	0.23	0.74	0.73	4.1%	0.69	0.34	0.62	0.29	11.4%
UPDATED	0.48	0.20	0.72	0.72	0.3%	0.62	0.30	0.64	0.29	15.1%

Table 3.8: Best Model Performance during Testing Period (2008-2013) using the *NSE* and *MNSE* (p=0.25) as objective functions at the Suwanee Creek Watershed.

Objective Function	***NSE***					***MNSE* (p=0.25)**				
Performance Statistics	*p-factor*	*r-factor*	R^2	*NSE*	*PBIAS*	*p-factor*	*r-factor*	R^2	*MNSE*	*PBIAS*
SSURGO	0.40	0.23	0.49	0.48	-10.6%	0.37	0.22	0.41	0.23	22.2%
UPDATED	0.21	0.20	0.45	0.43	17.2%	0.35	0.21	0.37	0.21	29.4%

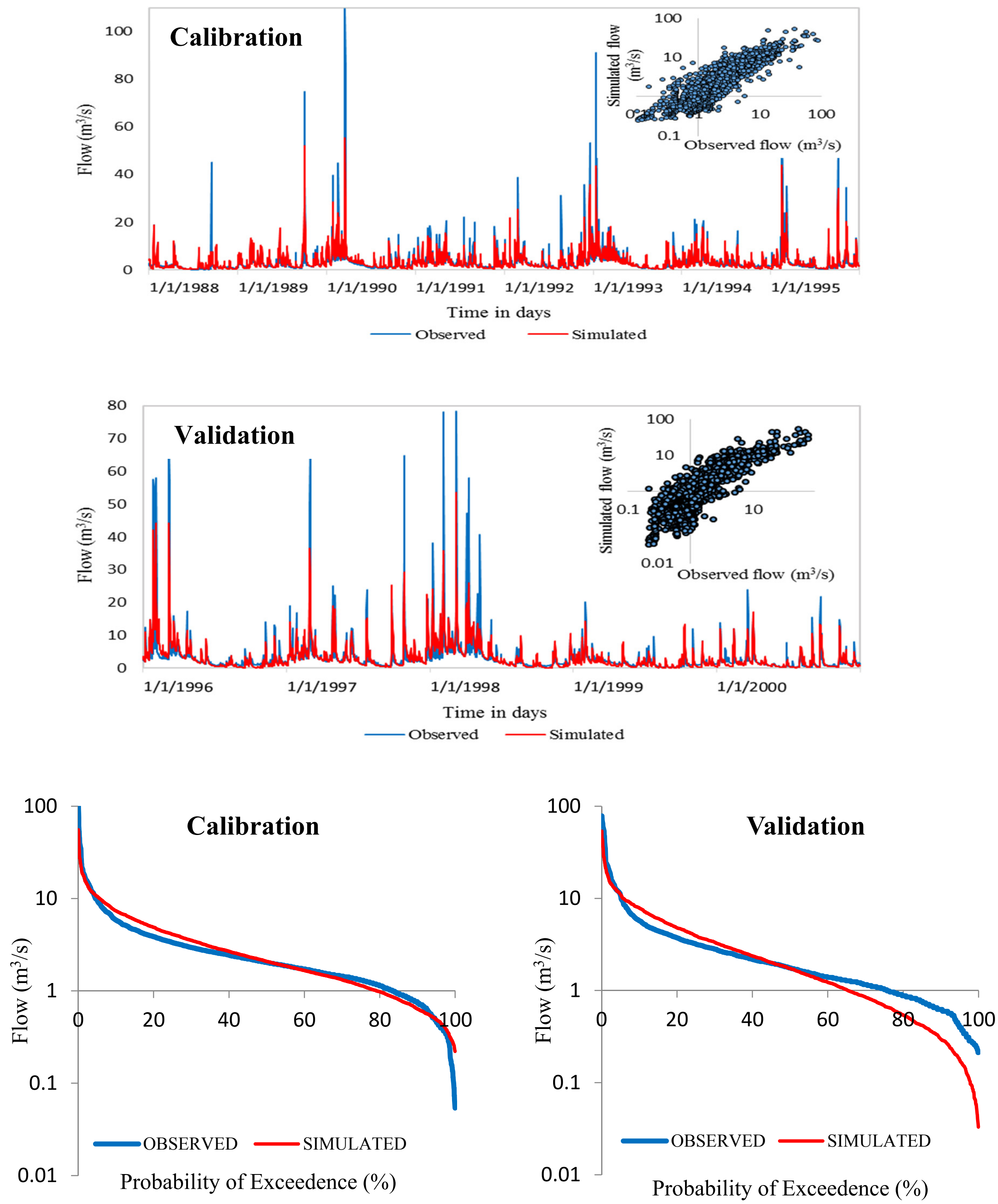


Figure 3.1: Observed and simulated daily streamflow during the calibration and validation periods for the best performance and scatter plots of simulated and observed streamflow in Big Creek Watershed with *NSE* as objective function. Flow duration curves (FDCs) for the calibration (1988-1995) and validation (1996-2000) periods.

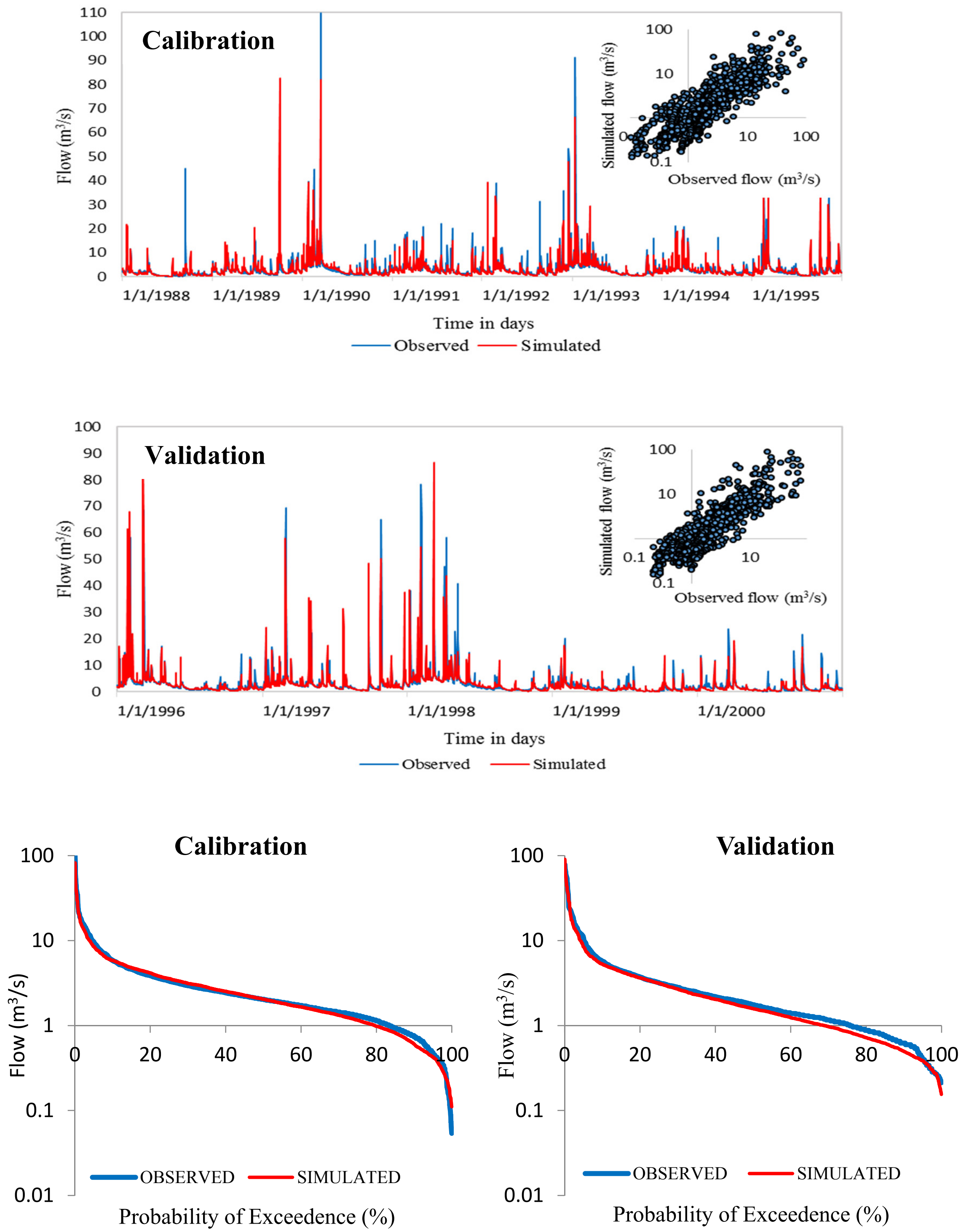


Figure 3.2: Observed and simulated daily streamflow during calibration and validation periods for the best performance scatter plots of simulated and observed streamflow in Big Creek Watershed with *MNSE* objective function (p=0.25). Flow duration curves (FDCs) for the calibration (1988-1995) and validation (1996-2000) periods.

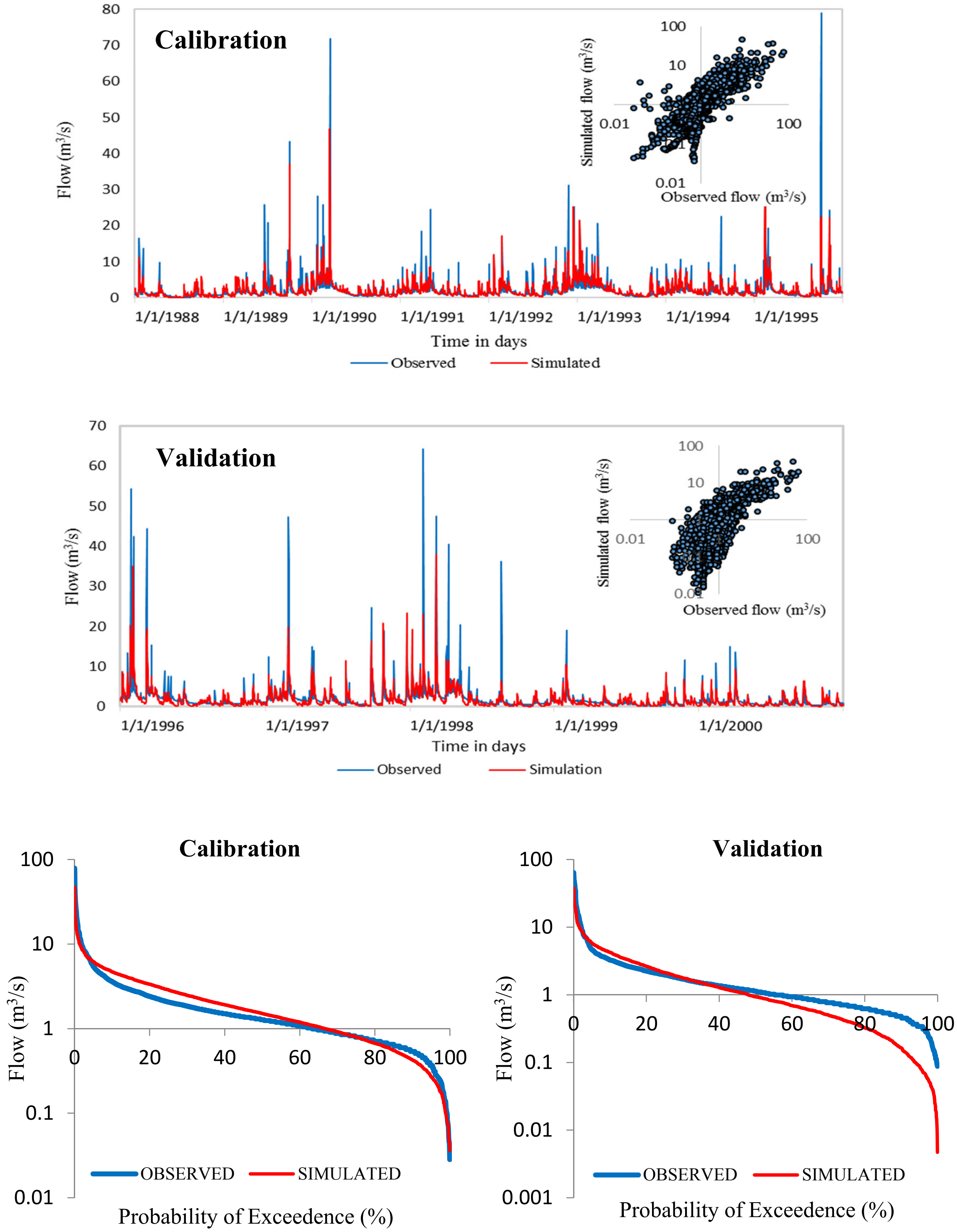


Figure 3.3: Observed and simulated daily streamflow during calibration and validation periods for the best performance scatter plots of simulated and observed streamflow in Suwanee Creek Watershed with *NSE* objective function. Flow duration curves (FDCs) for the calibration (1988-1995) and validation (1996-2000) periods.

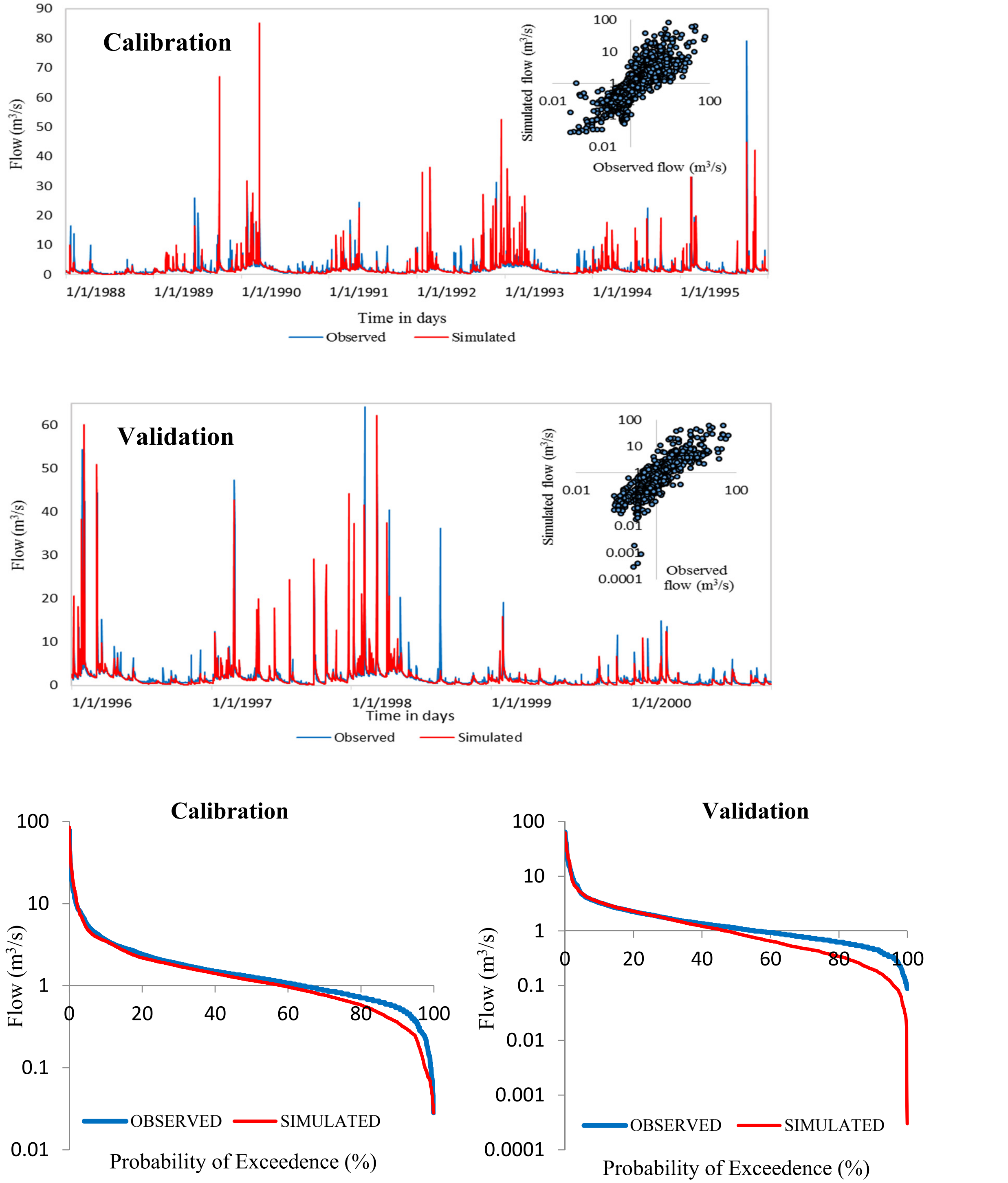


Figure 3.4: Observed and simulated daily streamflow during calibration and validation periods for the best performance scatter plots of simulated and observed streamflow in Suwanee Creek Watershed with *MNSE* objective function (p=0.25). Flow duration curves (FDCs) for the calibration (1988-1995) and validation (1996-2000) periods.

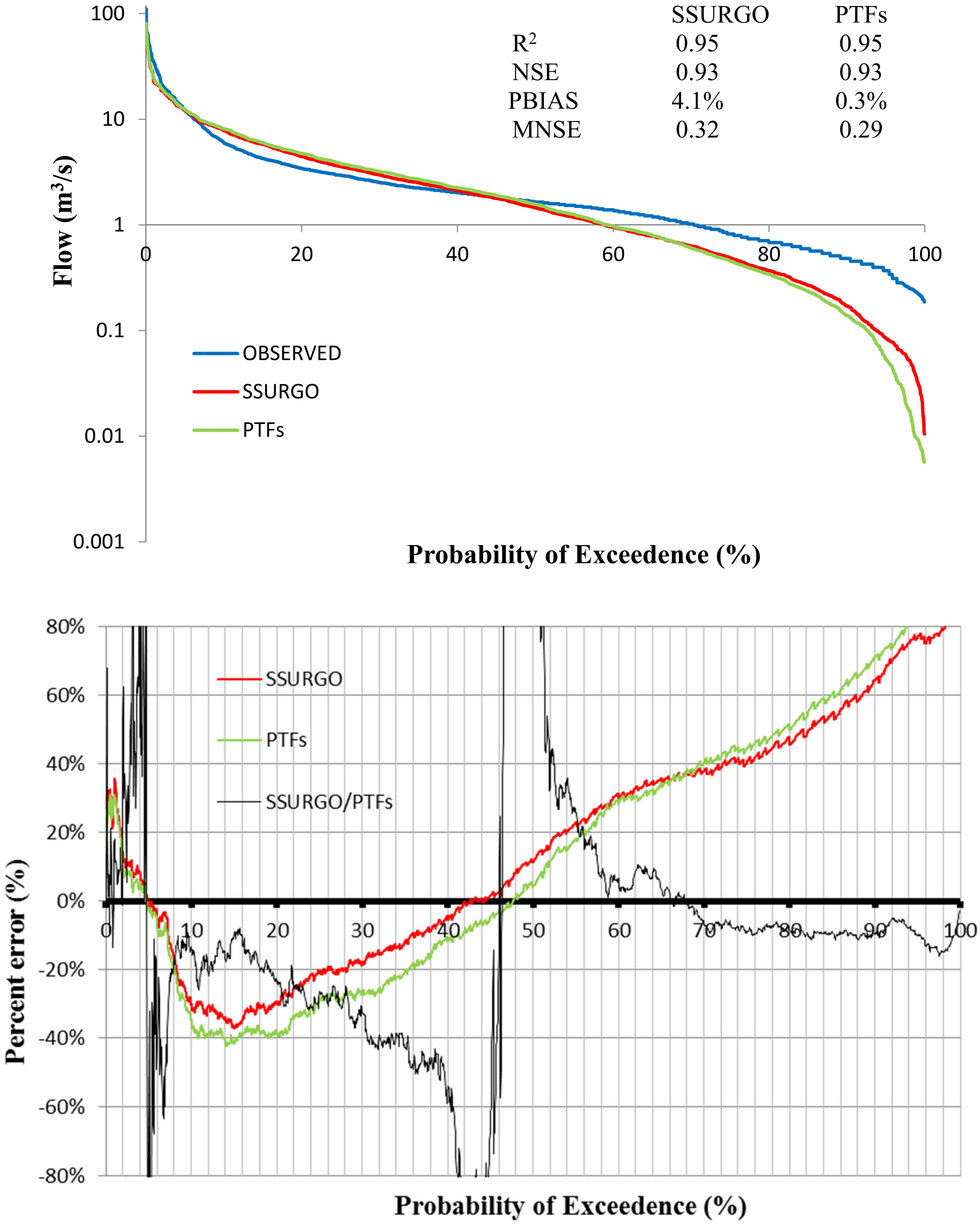
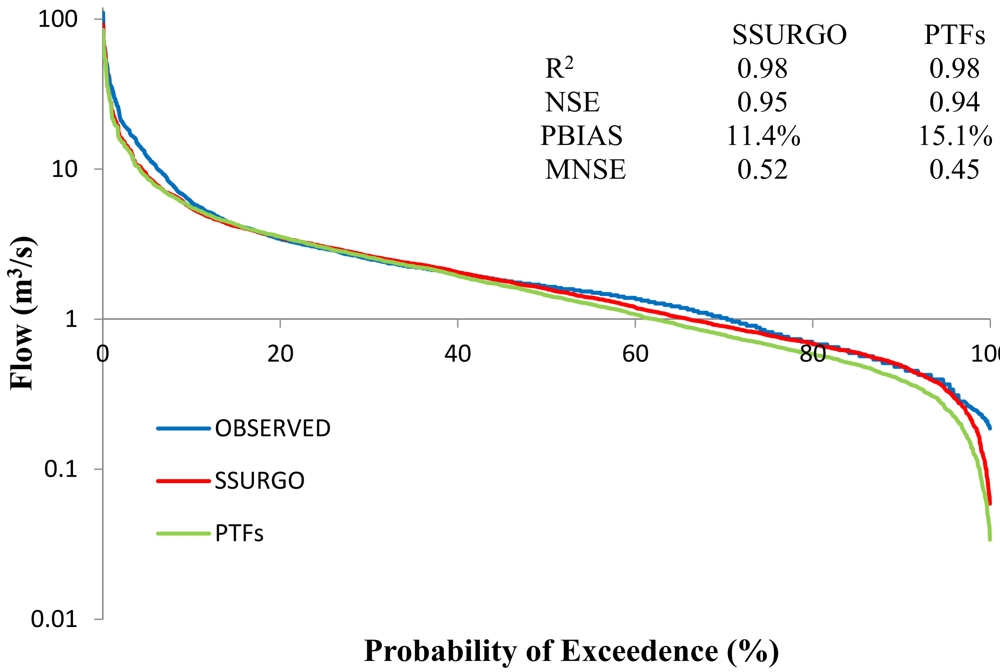


Figure 3.5: Flow duration curves (FDCs) (above) and percent error graph (below) in Big Creek Watershed with *NSE* objective function for the SSURGO and UPDATED soil. The black line in the error graph was calculated as $\left[Ratio = \frac{(\mathcal{E}_{SSURGO})}{(\mathcal{E}_{PTF})} - 1\right]$, where $\mathcal{E}_{SSURGO}$ and $\mathcal{E}_{PTF}$ are percent errors of PTF and SSURGO based simulations.



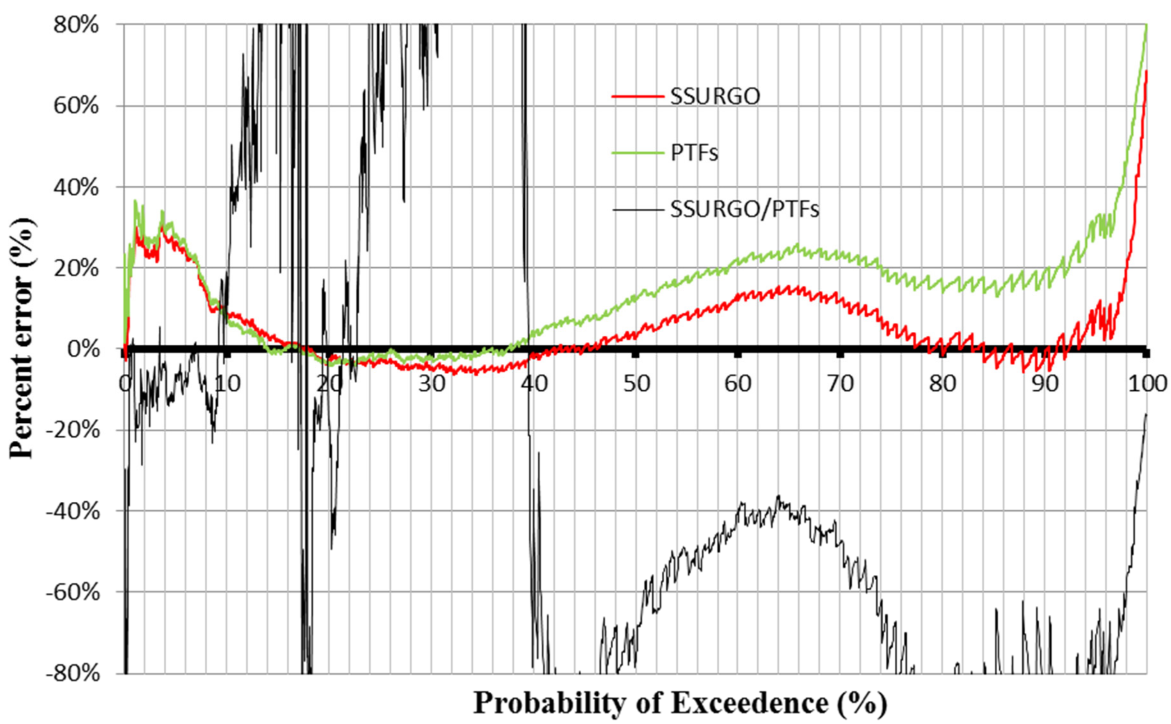
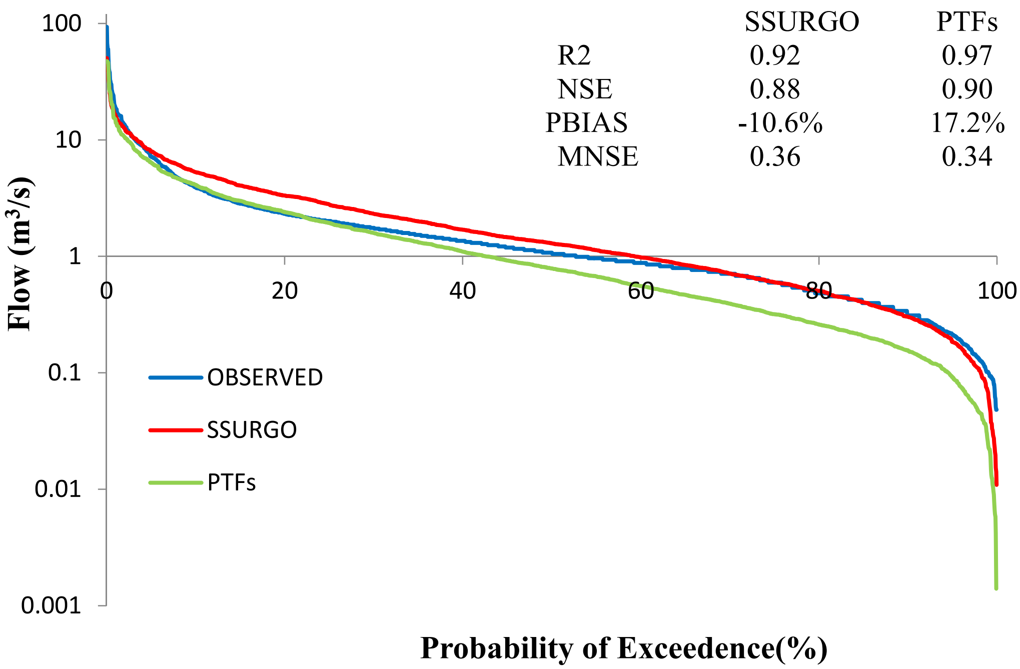


Figure 3.6: Flow duration curves (FDCs) (above) and percent error graph (below) in Big Creek Watershed with *MNSE* objective function (p=0.25) for the SSURGO and UPDATED soil. The black line in the error graph was calculated as $\left[Ratio = \frac{(\varepsilon_{SSURGO})}{(\varepsilon_{PTF})} - 1\right]$, where ε_{SSURGO} and ε_{PTF} are percent errors of PTF and SSURGO based simulations.



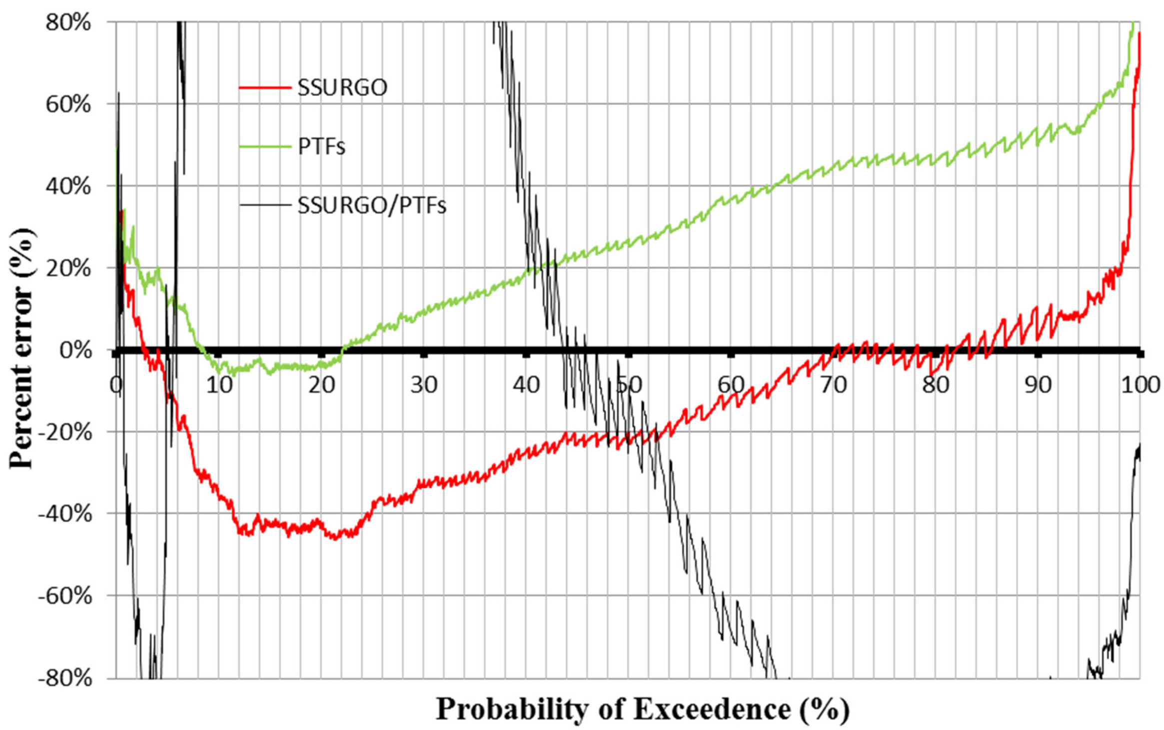


Figure 3.7: Flow duration curves (FDCs) (above) and percent error graph (below) in Suwanee Creek Watershed with *NSE* objective function for the SSURGO and UPDATED soil. The black line in the error graph was calculated as $\left[Ratio = \frac{(\mathcal{E}_{SSURGO})}{(\mathcal{E}_{PTF})} - 1\right]$, where $\mathcal{E}_{\mathrm{SSURGO}}$ and $\mathcal{E}_{\mathrm{PTF}}$ are percent errors of PTF and SSURGO based simulations.

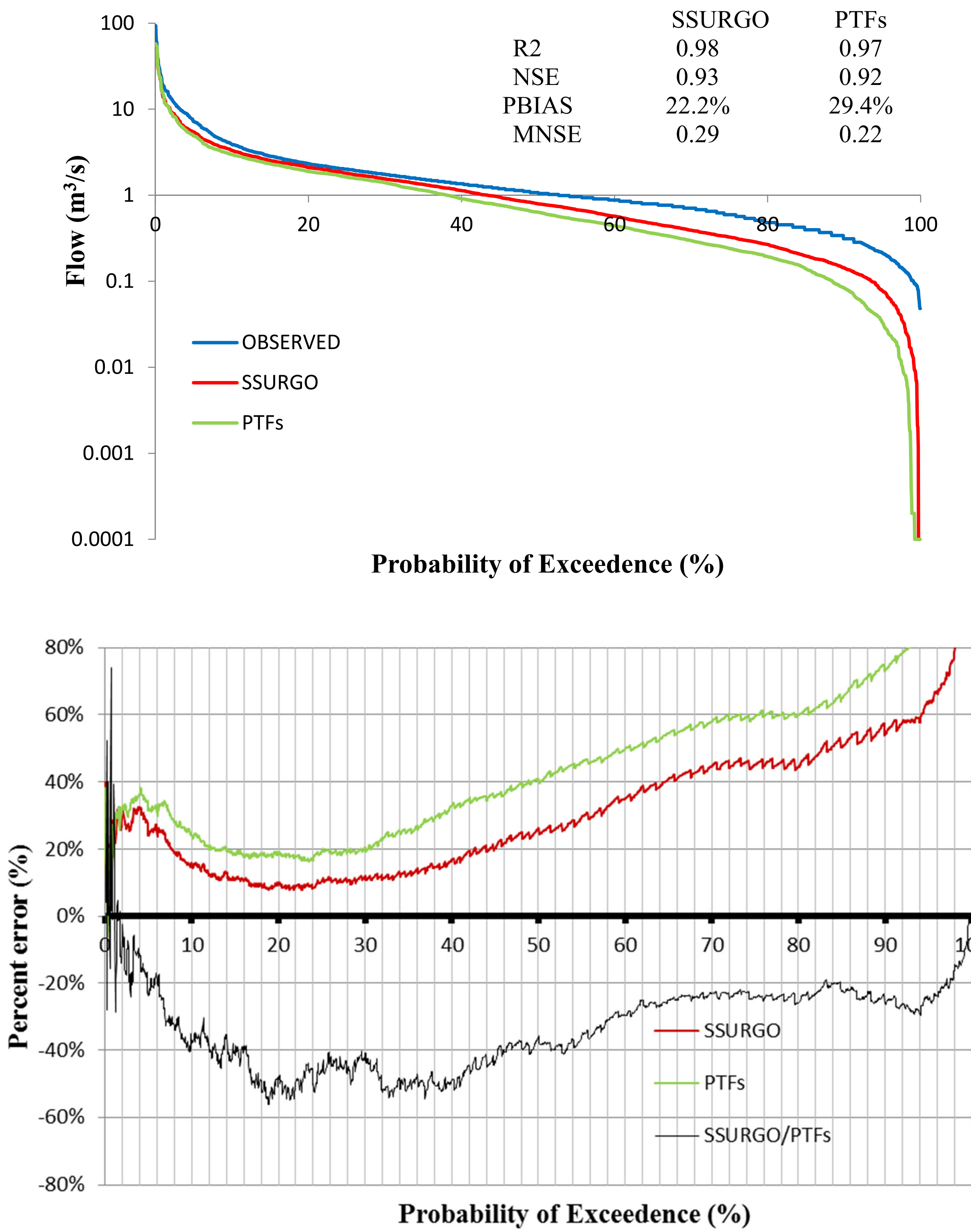


Figure 3.8: Flow duration curves (FDCs) (above) and percent error graph (below) in Suwanee Creek Watershed with *MNSE* objective function (p=0.25) for the SSURGO and UPDATED soil. The black line in the error graph was calculated as $\left[Ratio = \frac{(\varepsilon_{SSURGO})}{(\varepsilon_{PTF})} - 1\right]$, where ε_{SSURGO} and ε_{PTF} are percent errors of PTF and SSURGO based simulations.

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CHAPTER IV: SUMMARY & CONCLUSIONS

The goal of this study was to come up with a blueprint to update certain soil hydraulic parameters using PTFs under changing LULC for improved hydrologic predictions. Because of the dynamic nature of watersheds, there is a need for a systematic approach in updating soil hydraulic properties under changing LULC, which are mostly derived from readily available soil databases in the US, in order to improve streamflow predictions by watershed models. Soil hydraulic properties are often taken from soil survey databases. A combination of soil properties such as texture, bulk density and porosity can be used to determine the K_{sat} of a soil using pedotransfer functions (PTFs). In this study, a PTF based method was proposed for updating key soil hydraulic parameters. The proposed approach was tested with the SWAT model in two urban watersheds that underwent forest to urban transition, within the metropolitan Atlanta area in Georgia, USA. SWAT model was calibrated and validated for the periods when both watersheds were heavily forested (reference period, 1988-2000). The calibrated models were then tested during the urbanized periods (testing period, 2008-2013) with and without updated K_{sat} and bulk density values.

Reported changes in bulk density in the literature were used to assess soil properties, and the PTF developed by Rawls and Brakensiek (1985) was used to translate the reported changes in bulk density into changes in hydraulic model parameterization. The SWAT model reacted sensitively to the assumed changes in soil properties in two different watersheds and showed different results when changes in soil properties due to LULC was considered.

We used a suite of model objective functions to better understand how streamflow simulations are parameterized and interpreted under different calibration frameworks. We calibrated daily streamflow from two different watersheds in the Piedmont Region of Georgia, using two individual objective functions: Nash-Sutcliffe efficiency *(NSE)* and modified Nash-Sutcliffe efficiency *(MNSE).* Ranges of calibrated parameters also varied according to the calibration target (*NSE* and *MNSE*). The objective function for calibration is a critical point in SWAT model, driving the flow simulations and, therefore, its impact on modeling performance. The statistical analyses indicated a good model calibration and validation for the discharge of both watersheds. These results showed reliable values for flow calibration and validation periods during the reference period (1988-2000 with 1992 NLCD). The calibrated and validated model were used for prediction of daily streamflow under changing LULC and soil hydraulic properties. The most frequently used objective function, *NSE,* was very sensitive to high flows as expected. Moreover, *MNSE* with p=0.25 was more sensitive to both high and low flows. Overall, it can be stated that *NSE* seems more robust in describing the model performance and simulating flows especially for high flows ($Q_{0\%} < Q < Q_{10\%}$). Flow duration curves (FDCs) revealed that using *MNSE* resulted in a better agreement between the observed and simulated flow. The simulated flows at the outlet of Big Creek watershed were strongly influenced by the use of updated soil properties compared to Suwanee Creek Watershed. Also, the model underestimated the low flows during testing period for both study watersheds. The modeling performance analysis suggested that derived soil properties can be calculated directly from the available basic soil data to simulate streamflow under changing LULC. On the other hand, when model simulations generated with the default model parameters are compared to observed flows PTFs always seem to generate better results. This is evident from the error graphs shown in appendix (Appendix E-H). This indicates that the calibration of the SWAT model with the SSURGO parameters gives an edge to SSURGO simulations. If the model was initially calibrated with PTF based parameters it could be argued that updated soil parameters could have resulted in better model performance than SSURGO.

The results support conclusions of other researches, who found that streamflow predictions are influenced by different objective functions (Price *et al.,* 2012), and changes in soil properties due to LULC changes (Huisman *et al.,* 2004; Borman *et al.,* 2007). Our results concluded that discharge was affected by the updated soil hydraulic properties (K_{sat} and ρ_b). This study also indicated that SWAT model is very sensitive to the soil and land use/cover data. Consequently, the input data of soil should be updated prior to the hydrological modeling itself by using PTFs. Calibration of the model with updated soil can produce a better performance at the daily time step. We suggest that watershed model calibrations should be completed with updated soil properties in order to preserve the hydrological behavior of the watershed accurately. Hence, we identify a need for developing methods for simple and effective calibration procedures at a daily time step for watershed models.

Limitations

LULC changes may influence both soil properties and streamflow predictions. In our study, only forest to urban transition was considered to simulate flow predictions through the both watersheds; however, there was very small percent of agriculture to urban and forest to agriculture transitions. If we were able to calculate changes in soils in these areas, the simulation results may have been improved. In order to determine how changes in soil characteristics may impact streamflow modeling, changes in soil hydraulic properties under agriculture to urban or agriculture to forest should be studied as well. Also, during the HRUs definition processes, dominant land use, soil and slope definition option was used. Therefore, only dominant soil values were updated through the watersheds. If we could use threshold based option, more soil types could be updated and it might improve the streamflow prediction as well.

As mentioned earlier available water content (*AWC*) may have an influence on K_{sat}. Because of limited data, *AWC* values could not be updated. The alteration in AWC due to LULC changes could cause increase or decrease on K_{sat}. Therefore, it may be important to recalculate AWC values for improved simulations.

Future Recommendations

When field measured soil data is not available, PTFs are one of the best alternatives for watershed modeling. Even though many researches evidenced that calculating K_{sat} using PTFs is acceptable, there are still limitations. In our study, PTF of Rawls and Brakensiek (1985) was utilized, which only used clay, sand, and porosity, to update K_{sat}; however, other soil properties, which have influence on K_{sat} were ignored such as AWC. Therefore, using available water content data could provide some advantages to calculate K_{sat} more precisely. Also recommended other future work is that the same work could be done with different LULC maps and pedotransfer functions in different watersheds. This can help contribute to simulating streamflows and to update the hydraulic conductivity data stored in the soil databases.

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Appendix A: Calculation of K_{sat} for Big Creek Watershed

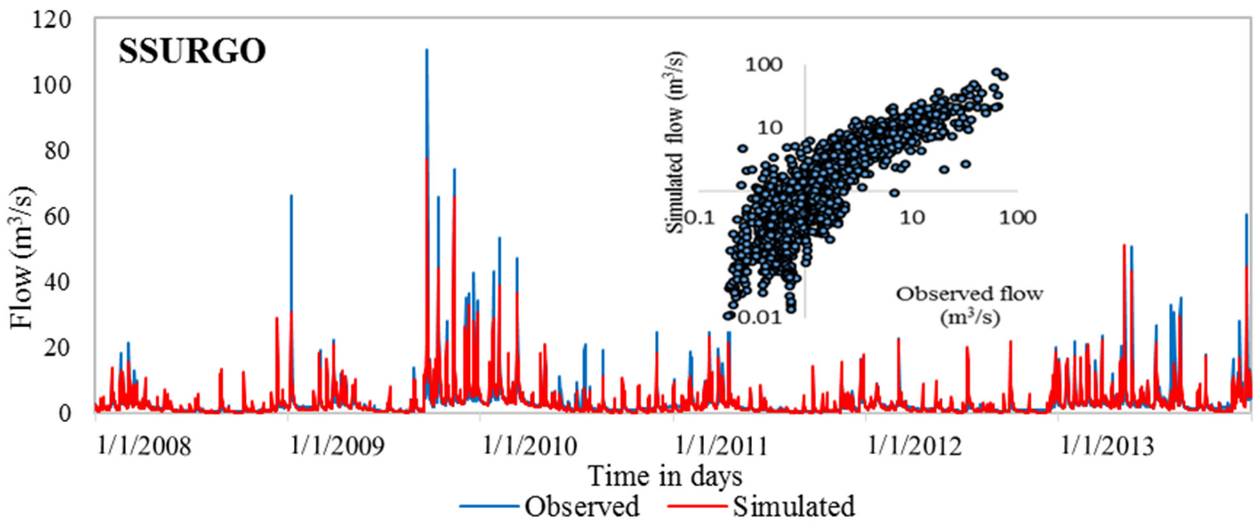
ArcSWAT	SSURGO						Calculated Values				
HRU number	**Soil**	**Clay**	**Sand**	**K_{sat} (mm/hr)**	**AWC**	**Wet bulk density**	**Dry bulk density**	**Increased wet bulk density**	**Increased dry bulk density**	**Porosity**	**K_{sat} (mm/hr)**
8	124369	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
10	124337	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
18	124337	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
19	124337	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
22	124337	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
24	124312	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
36	124323	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
40	124368	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
42	124328	0.26	0.197	100.8	0.14	1.35	1.10	1.71	1.42	0.46	27.46
45	124325	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
46	124325	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
56	124337	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
58	124381	0.23	0.246	32.4	0.2	1.43	1.13	1.80	1.46	0.45	7.29
59	124371	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
61	124319	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
62	124312	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
69	124320	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
70	124310	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
71	124312	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
72	124326	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
73	124325	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
74	124311	0.3	0.335	32.4	0.14	1.35	1.08	1.71	1.40	0.47	7.39
76	1654037	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
77	1654037	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
78	124320	0.125	0.673	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.89
79	124325	0.125	0.679	100.8	0.13	1.55	1.35	1.98	1.76	0.34	1.82
80	1654011	0.15	0.65	100.8	0.12	1.53	1.33	1.95	1.73	0.35	2.42
84	1672421	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
85	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
86	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
88	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
89	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
91	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
93	1672424	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
98	1672424	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
99	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
100	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
101	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
102	1672423	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38
103	1674092	0.31	0.354	32.4	0.18	1.38	1.07	1.74	1.39	0.48	7.38

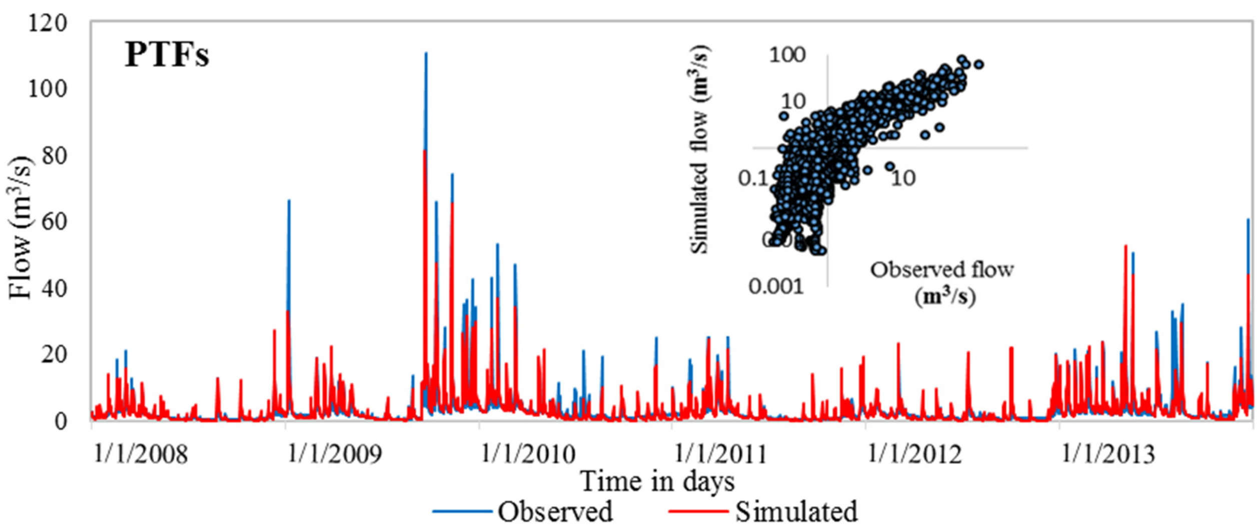
Appendix B: Calculation of K_{sat} for Suwanee Creek Watershed

ArcSWAT	SSURGO						Calculated Values				
HRU number	Soil	Clay	Sand	K_{sat} (mm/hr)	AWC	Wet bulk density	Dry bulk density	increased dry bulk density	increased wet bulk density	porosity	K_{sat} (mm/hr)
5	639968	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
7	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
8	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
9	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
11	639950	0.3	0.335	32.4	0.14	1.45	1.17	1.52	1.84	0.43	5.89
12	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
13	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
14	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
17	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
20	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
22	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
23	640009	0.11	0.657	100.8	0.12	1.43	1.25	1.63	1.82	0.38	3.04
26	640009	0.11	0.657	100.8	0.12	1.43	1.25	1.63	1.82	0.38	3.04
27	725706	0.085	0.646	100.8	0.11	1.48	1.32	1.72	1.89	0.35	2.43
29	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
30	640009	0.11	0.657	100.8	0.12	1.43	1.25	1.63	1.82	0.38	3.04
31	725706	0.085	0.646	100.8	0.11	1.48	1.32	1.72	1.89	0.35	2.43
32	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
33	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
34	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
35	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
38	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
43	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
44	639987	0.125	0.679	100.8	0.14	1.43	1.23	1.60	1.82	0.40	3.00
48	639987	0.125	0.679	100.8	0.14	1.43	1.23	1.60	1.82	0.40	3.00
49	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
51	639950	0.3	0.335	32.4	0.14	1.45	1.17	1.52	1.84	0.43	5.89
54	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
60	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
61	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
64	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
65	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
71	639987	0.125	0.679	100.8	0.14	1.43	1.23	1.60	1.82	0.40	3.00
74	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
75	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
76	639929	0.125	0.679	100.8	0.13	1.53	1.33	1.73	1.95	0.35	1.97
78	725706	0.085	0.646	100.8	0.11	1.48	1.32	1.72	1.89	0.35	2.43
79	640004	0.125	0.679	100.8	0.1	1.4	1.24	1.61	1.79	0.39	2.89
80	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59

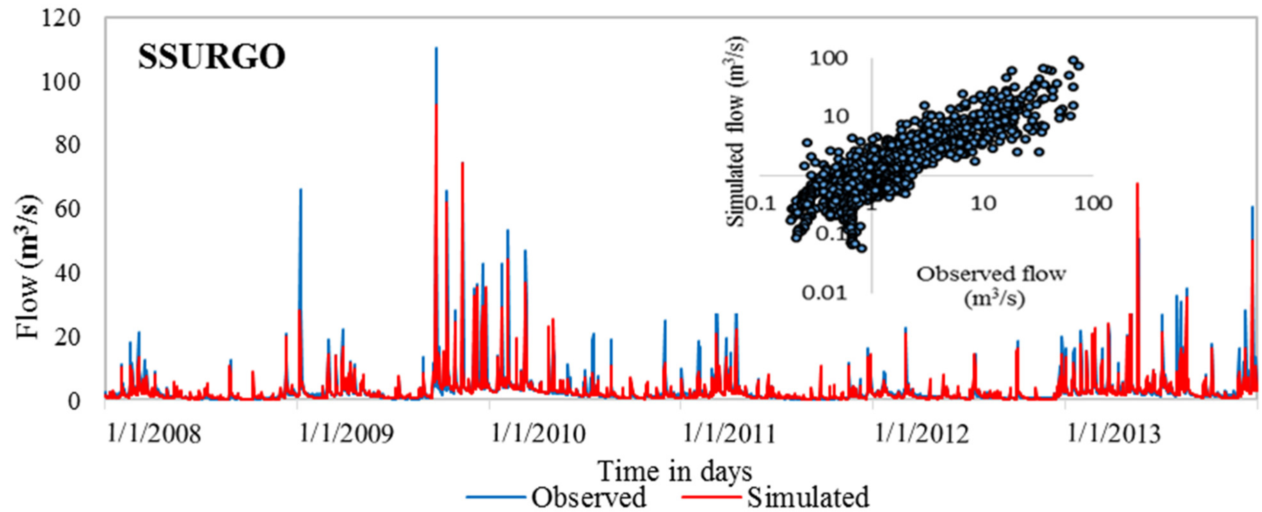
81	725706	0.085	0.646	100.8	0.11	1.48	1.32	1.72	1.89	0.35	2.43
83	639987	0.125	0.679	100.8	0.14	1.43	1.23	1.60	1.82	0.40	3.00
84	639987	0.125	0.679	100.8	0.14	1.43	1.23	1.60	1.82	0.40	3.00
88	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
90	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
92	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
94	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
95	639969	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
96	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
99	639968	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
100	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
105	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
106	639970	0.3	0.555	32.4	0.14	1.35	1.08	1.40	1.71	0.47	3.59
107	639941	0.125	0.679	100.8	0.13	1.4	1.21	1.57	1.78	0.41	3.23
108	639940	0.125	0.679	100.8	0.13	1.4	1.21	1.57	1.78	0.41	3.23
109	639976	0.275	0.551	32.4	0.12	1.4	1.15	1.50	1.78	0.43	2.79

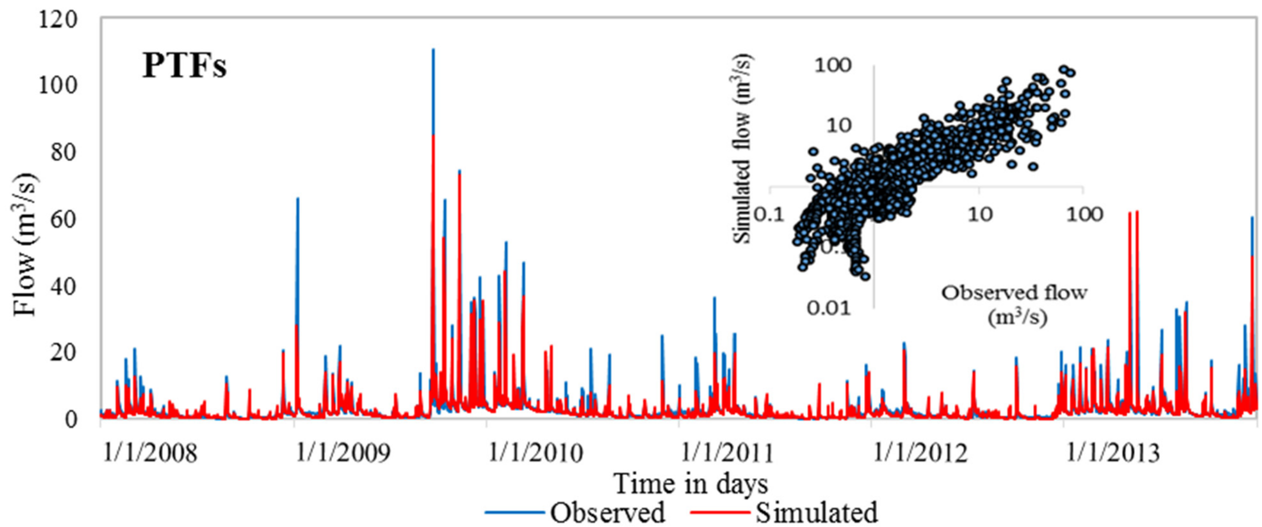
Appendix C: Observed and simulated daily discharge with using SSURGO soil (above) and UPDATED soil (below) data for the best performance scatter plots of simulated and observed streamflow in Big Creek Watershed with *NSE* objective function.



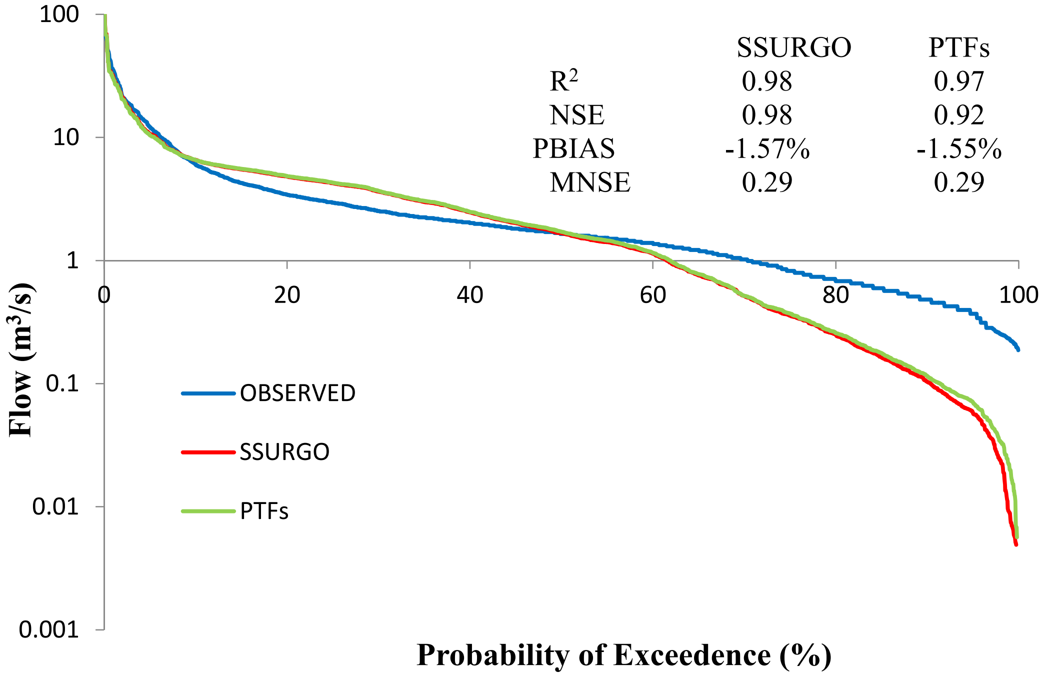


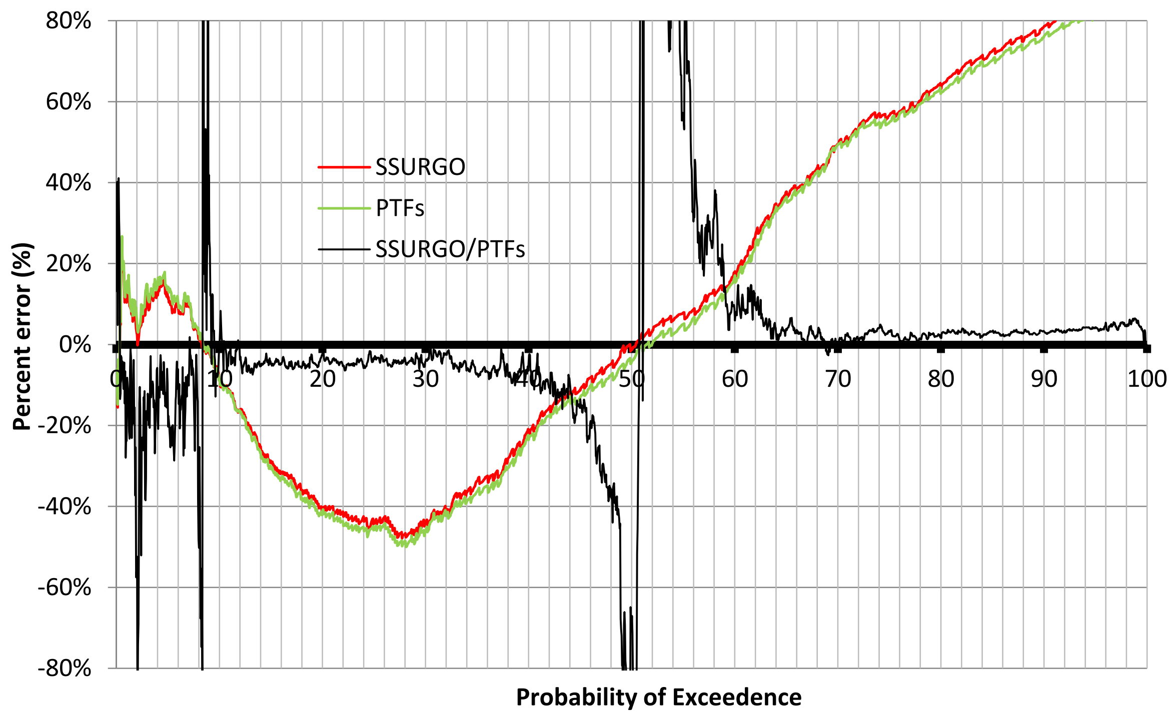
Appendix D: Observed and simulated daily discharge with using SSURGO soil (above) and UPDATED soil (below) data for the best performance scatter plots of simulated and observed streamflow in Big Creek Watershed with *MNSE* objective function (p=0.25).



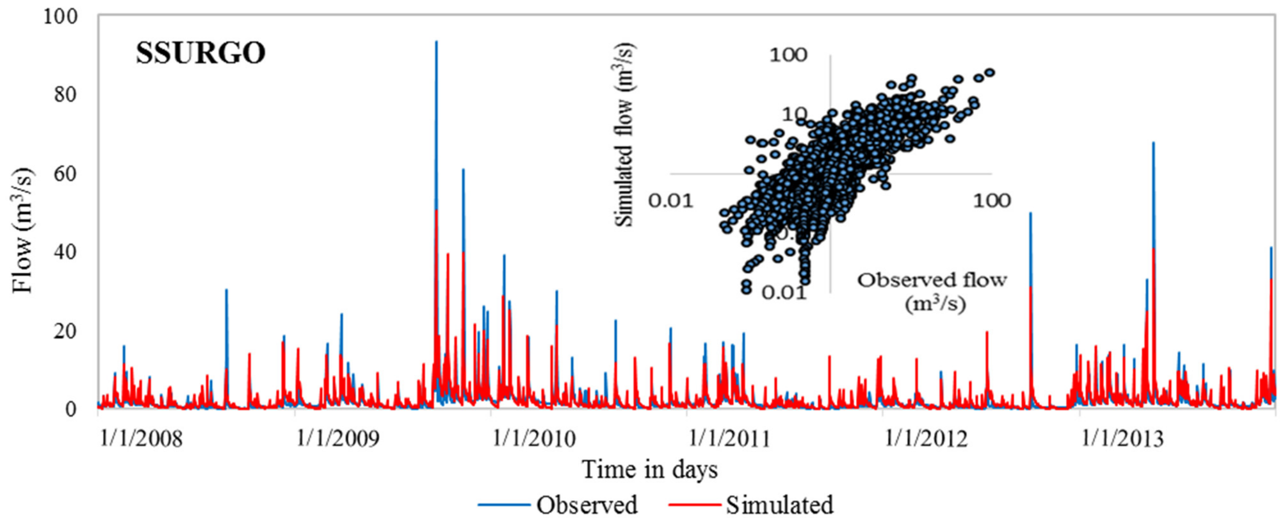


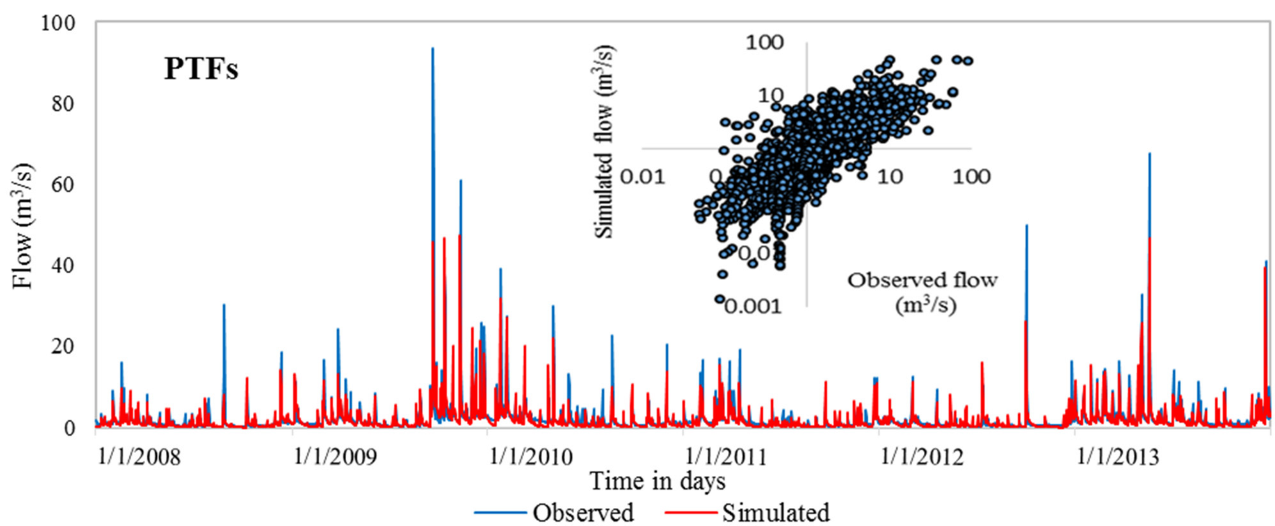
Appendix E: Flow duration curves (FDCs) (above) and percent error graph (below) in Big Creek Watershed for the SSURGO and UPDATED soil without calibration. FDCs and percent error graph illustrate the flows simulations without calibration for each output.



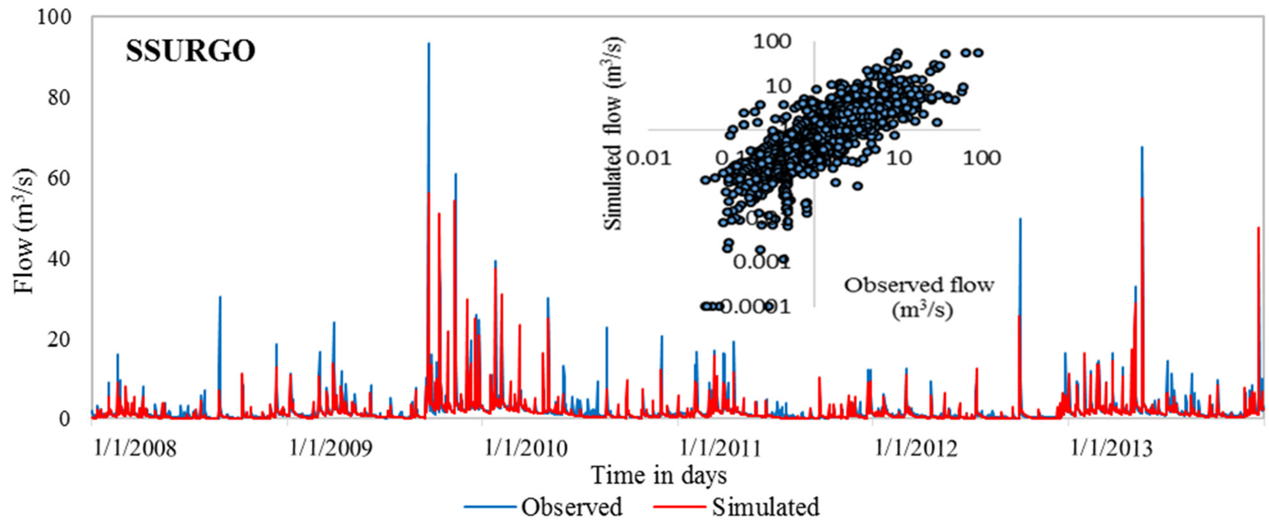


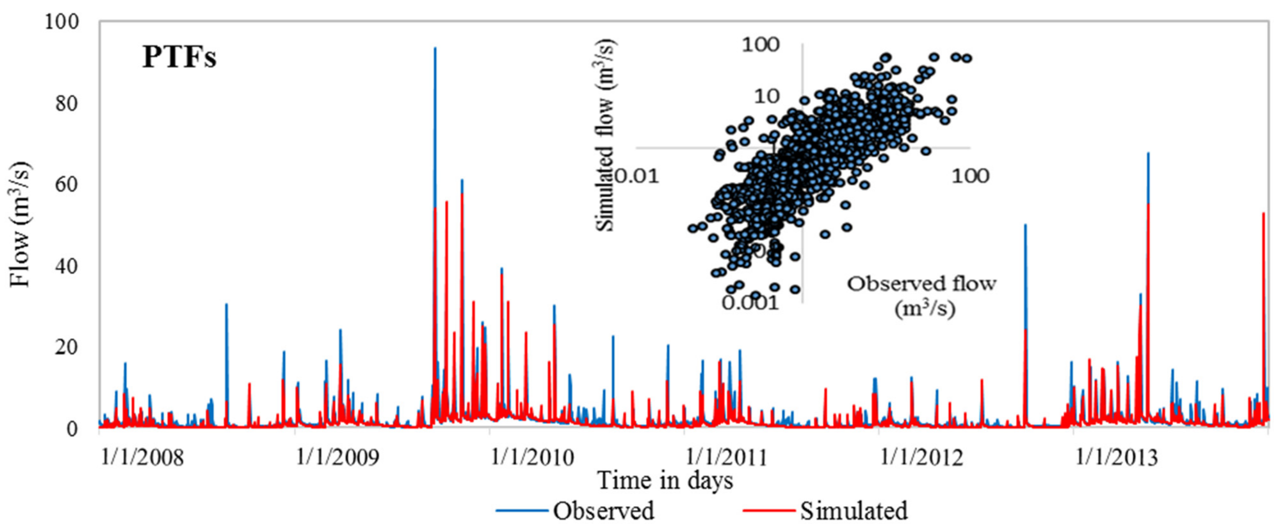
Appendix F: Observed and simulated daily discharge with using SSURGO soil (above) and UPDATED soil (below) data for the best performance scatter plots of simulated and observed streamflow in Suwanee Creek Watershed with *NSE* objective function. FDCs illustrates the flows without calibration for each output.





Appendix G: Observed and simulated daily discharge with using SSURGO soil (above) and UPDATED soil (below) data for the best performance scatter plots of simulated and observed streamflow in Suwanee Creek Watershed with *MNSE* objective function (p=0.25). FDCs illustrates the flows without calibration for each output.





Appendix H: Flow duration curves (FDCs) (above) and percent error graph (below) in Suwanee Creek Watershed for the SSURGO and UPDATED soil without calibration. FDCs and percent error graph illustrate the flows simulations without calibration for each output.