Assessment of the Impacts of Land-use Change on Streamflow of the Chipola River

by

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DEDICATION

This thesis is dedicated to my Mother, Zahida Nasreen, who always stood by my side and supported me through the thick and thins of my life.

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ABSTRACT

Analysis of the impacts of land-use change on streamflow is crucial for the sustainable development of water resources and land-use management practices. Specifically, the understanding of the urbanization impacts on streamflow will significantly help water resources and land-use managers and planners in decision-making processes. Therefore, this study was designed to analyze the potential impacts of future land-use change, specifically of urbanization on the streamflow of the Chipola River using the Soil and Water Assessment Tool (SWAT) in ArcGIS for four years (2015-2018).

Implementing the SWAT model required 1) a digital elevation model (DEM); 2) land use maps from 2016 and future years; 3) a soil map; and, 4) meteorological data as inputs. Meteorological data included hourly rainfall, temperature (min., max.), wind, solar radiation, and relative humidity data. Scenario-based land-use change analysis was performed using two land use maps. A land-use map for the year 2016 was considered as the “baseline scenario” and was used to develop future land use maps, which represented the “future scenario” in this study. In developing a future land-use map, a five-mile buffer was developed along primary and secondary roads of the basin. It was assumed that low-density urban areas would be converted to high-density, and agricultural areas would be converted to low-density urban areas within the five-mile buffer. After inputting all the required data into SWAT, the model was run for four years (2015-2018) using the baseline scenario and the future scenario.

The SWAT streamflow outputs were calibrated and validated against real-world, observed streamflow data of the United States Geological Survey (USGS) stream gauge. The Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT Calibration and Uncertainty Procedures (SWAT-CUP) were used for calibration and validation. The recommended split data approach was used; one-half of the data (from 2015-2016) was used in calibration, and the other half of the data (from 2017-2018) was used in the validation process.

Model goodness of fit was evaluated using the following statistical coefficients: 1) Nash Sutcliffe efficiency (NSE); 2) coefficient of determination (R^2); and, 3) percent bias (PBIAS). These statistical analyses gave values of 0.81, 0.84, and 9.5 for calibration, and values of 0.76, 0.80, and -11.4 for validation, respectively. Defined evaluation criteria of these statistics suggest that values of NSE and $R^2 > 0.75$, while the value of PBIAS < 10 is considered "very good." Compared with the defined evaluation criteria, the calibrated and validated values represented successful calibration and validation of the streamflow of the Chipola River.

After the successful calibration and validation of the SWAT outputs, calibrated parameters were written back to the original models of the baseline scenario and the future scenario. Results of calibrated streamflow between the two scenarios showed that there was an average increase of 2% streamflow between the selected years of study. The statistical difference of 2% in calibrated streamflow between the two land-use scenarios may suggest a positive link between urbanization and streamflow. This link between increased urbanization and streamflow of the Chipola River may provide useful information to land-use managers and planners designing policy for the Chipola Basin.

CHAPTER 1: INTRODUCTION

Streamflow is a critical component of the global hydrologic cycle because of its tendency to affect the distribution of water resources (Tao et al., 2014). It is also a primary control of surface water bodies due to impacting various biogeochemical factors such as water temperature, chemical/nutrient loading, stream geomorphology, suspended sediment regime, and aquatic habitat and biodiversity (Kellner & Hubbart, 2019).

Various factors can have long-term effects on the streamflow of a river. These factors include climate change, construction of large artificial lakes, diversion of water for irrigation purposes, and land-use change in the upstream river basin (Costa, Botta, & Cardille, 2003). Of these variables, land-use change is especially critical (Du et al., 2013).

Land-use change, specifically urbanization, has the potential to alter the global hydrologic cycle by affecting soil infiltration, evapotranspiration, and streamflow (Kim, Choi, Choi, & Park, 2013). For example, covering large-area watersheds with impervious cover often results in reduced local surface erosion rates, and increased surface runoff, (Lin, Hong, Wu, Wu, & Verburg, 2007) flooding events, and peak discharges. Impervious cover is also linked to altered streamflow (Kim, Kwon, Park, & Lee, 2005).

Besides its impacts on existing water resources, land-use change is also recognized as a significant variable for its effects on future water resources (Takamatsu, Kawasaki, Rogers, & Malakie, 2014). Therefore, for the maintenance and sustainability of future water resources, appropriate adaptation measures, and land-use management policies are necessary (Tong, Sun, Ranatunga, He, & Yang, 2012).

The effects of land-use change on water resources depend on soil-climate-topography-vegetation interactions. These interactions vary among basins and therefore they remain difficult to predict (Dos Santos, Laurent, Abe, & Messner, 2018). Although some global-level studies have highlighted the role of existing land-use change on streamflow, the role of future land-use change remains far from clear (Tao et al., 2014).

A physical understanding of the interactions between land-use change and streamflow is essential for predicting the potential streamflow consequences of land-use change (Du et al., 2013). The methods for detecting the effects of land-use change on streamflow include historical data analysis and hydrologic modeling (Tang, Yang, Hu, & Gao, 2011).

An analysis of the historical effects of land-use on streamflow may be used to predict the impacts of future land-use change (Schilling, Jha, Zhang, Gassman, & Wolter, 2008). Hydrologic modeling is also a valuable tool for quantifying the complex interactions of land-use change and the streamflow (Dos Santos et al., 2018; Ghaffari, Ghodousi, Ahmadi, & Keesstra, 2010).

Although the effects of existing land-use change on the streamflow of the basins are well documented, studies that quantify the impacts of future land-use change on streamflow are limited (Chu, Knouft, Ghulam, Guzman, & Pan, 2013; Kim et al., 2013).

Therefore, this study was designed to quantify the potential impacts of future land-use change on the streamflow of the Chipola River using historical data analysis and a hydrologic model, Soil and Water Assessment Tool (SWAT).

1.1 Objectives

The specific objectives of this study were:

- to quantify the potential impacts of future land-use change on the streamflow of the Chipola River by using an integrated hydrologic simulation model – Soil and Water Assessment Tool (SWAT) in ArcGIS;
- to calibrate and validate the streamflow of the SWAT model by using the Sequential Uncertainty Fitting (SUFI-2) in SWAT Calibration and Uncertainty Procedures (SWAT-CUP); and,
- to give recommendations, based on the results, for better land-use and water management practices in the future.

1.2 Hypotheses

The null hypothesis stated that there would be no change in the streamflow of the Chipola River due to land-use change, while the alternate hypothesis stated that there would be an increase in the streamflow of the Chipola River.

CHAPTER 2: LITERATURE REVIEW

2.1 Streamflow and Land-use Change

Streamflow (Q) is composed of baseflow (BF) and stormflow (SW). Stormflow is surface runoff and comprises the significant portion of the streamflow during a rainy season. Baseflow (BF) is groundwater discharge to a stream and is considered a primary source of seasonal streamflow. The relative proportion of the stormflow and the baseflow vary with time and are affected by numerous factors including: watershed characteristics, climate change, and anthropogenic activities such as land-use change (Zhang & Schilling, 2006).

Land-use change is a process of transforming the natural landscape by anthropogenic activities. There are generally two types of land-use change: 1) conversion, and 2) modification. The conversion deals with the process of converting one land-use type to another. The modification involves maintenance of the land-use type in regard to changes in its attributes (Paul & Rashid, 2016).

Urbanization is an essential component of land-use change and is defined as the conversion of a traditional agricultural area to a metropolitan city area. The significance of urbanization continues to increase with the increasing migration of the world's population into cities. Urbanization falls into four categories, such as 1) leapfrog expansion, 2) concentric expansion, 3) linear expansion, and 4) multi-nuclei expansion (Liu, Zhan, & Deng, 2005).

A type of urbanization that shows scattered development on isolated tracks, that are separated from other and vacant areas, is called leapfrog expansion. The growth of a city in all directions that causes substantial changes in urban land use is called concentric expansion. An expansion that occurs along a transportation axis, such as a highway, expressway, and along rivers, is called linear expansion. Finally, multinuclei expansion is a type of urbanization in which a city has more than one center apart from the central business district (Liu et al., 2005).

Land-use change, such as urbanization, can affect critical atmospheric components in the global hydrologic cycle (Sun & Caldwell 2015; Takamatsu et al., 2014). These components include precipitation, evapotranspiration, and land surface temperatures (Takamatsu et al., 2014). In addition to affecting atmospheric components, land-use change can also result in the alteration of infiltration and groundwater recharge. These alterations, in turn, affect the runoff-base flow ratio, as well as the streamflow quantity (Niraula, Meixner, & Norman, 2015).

The effect of land-use change on streamflow is scale-dependent as it varies over time and space (Buck, Niyogi, & Townsend, 2004). Streamflow change is the most common estimate for studying the effects of climate change and land-use change on water resources. It can also inform the decision-making processes of water resources management (Niraula et al., 2015). Assessment of land-use change impacts on streamflow usually involves an approximation of spatial patterns of hydrologic consequences to various factors. These factors include land-use change maps, an examination of temporal responses in channel discharge concerning land-use change, and a comparison of simulated streamflow to land-use change (Nie et al., 2011).

2.2 Role of Hydrologic Models in Quantifying Relationship Between Land-use Change and Streamflow

Hydrologic models are playing an essential role in planning for the sustainable use of water resources (Abbaspour et al., 2015). Several hydrologic models have been developed to analyze and predict the complicated relationship between land-use change and streamflow. Types of such models include: 1) conceptual lumped models, 2) fully distributed models, and 3) semi-distributed models (Isik, Kalin, Schoonover, Srivastava, & Lockaby, 2013).

Conceptual lumped models typically use empirical or conceptual formulations for hydrologic components (Paudel, Nelson, Downer, & Hotchkiss, 2010). These models use spatially-averaged parameters for the whole watershed (Pullar & Springer, 2000), and represent the hydrological components, as well as watershed as a single homogeneous unit (Paudel et al., 2010). However, due to heterogeneity in the watershed's characteristics, the model predictions become less accurate and informative (Pullar & Springer, 2000). Examples of conceptual lumped models include Nedbor-Afstromnings Model (NAM), and Identification of unit Hydrographs And Component flows from Rainfall, Evaporation, and Streamflow data (IHACRES) (Isik et al., 2013).

Fully distributed models tend to simulate both the physical processes as well as the spatial heterogeneity of a watershed. These models divide the watershed into smaller grid cells. Water flowing through the basin is routed from one grid cell to another and allows simulation of the basin heterogeneity at each grid cell. The grid resolution chosen is generally small enough to characterize the spatial variation of hydrological components (Paudel et al., 2010).

Distributed models tend to account for local heterogeneity conditions and provide a better understanding of land processes within a watershed (Pullar & Springer, 2000). However, requiring a large amount of input data, these models become complex and, therefore, ineffective for daily operational hydrology. There is also sometimes inadequate information about the physical processes of the basin. However, these models require complete information on the basin processes to evaluate the model's parameters. Some studies have reported that simple models were equally successful as complex models (Gosain et al., 2011). Examples include: Water balance-Simulation Model (WASIM), European Hydrological System Model (MIKE-SHE), The Distributed Hydrology Soil Vegetation Model (DHSVM), Systeme Hydrologique Europeen Transport (SHETRAN), Regional Hydro-Ecological Simulation System (RHESSys), Tracer Aided Catchment model – Distributed (TAC-D), and TOPMODEL-Based Land surface-atmosphere Transfer Scheme (TOPLATS) (Isik et al., 2013).

Semi-distributed models were developed to address the difficulties associated with conceptual lumped and fully-distributed models. These models represent a compromise between the conceptual lumped and fully-distributed models (Gosain et al., 2011).

The semi-distributed models divide the basin into homogeneous sub-basins based on the drainage area or the topography. Hydrological components are considered homogeneous within each sub-basin (Paudel et al., 2010). These models operate on simple, but physically-based, algorithms. These models represent spatial heterogeneity by using observable physical characteristics of the basin, such as topography, land use, and soil. Studies also report that semi-distributed models were better than the conceptual lumped models. The significant advantage of these models lies in their relating of parameter values to land-use characteristics, providing an approach for land-use change analysis (Gosain et al., 2011). Examples of these models include: Simple Lumped Reservoir Parametric (SLURP), Hydrological Land-use Change (HYLUC), Precipitation Runoff Modelling System (PRMS), Soil and Water Integrated Model (SWIM) and the Soil and Water Assessment Tool (SWAT) (Isik et al., 2013).

Among the aforementioned physically-based, semi-distributed models, the SWAT model is well-recognized for its ability to analyze the impacts of land-use management practices on water resources of large complex watersheds (Khatun, Sahana, Jain, & Jain, 2018; Setegn, Srinivasan, & Dargahi, 2008).

2.3 Application of SWAT model in Urbanization and Streamflow Studies

The primary use of the SWAT model is to address the impacts of land-use change practices on the streamflow of rivers (Spellman, Webster & Watkins, 2018). The SWAT model is being applied globally, and its application suggests that urbanization and streamflow have a linear relationship (Nguyen, Recknagel, & Meyer, 2019).

For example, Wu et al. (2015) studied the relationship between future urbanization and streamflow of the three rural catchment basins in Oregon's Willamette Valley. Land-use change scenarios were developed assuming increasing urbanization and decreasing agricultural trends between 1990 and 2050. The findings of their study suggest that urbanization resulted in increased streamflow quantity.

Similar results were also reported by Nguyen et al. (2019) in their study on the impacts of projected climate change and urbanization on the streamflow of the Torren River, Australia. Climate change and land-use change scenarios of hypothetical urbanization were developed for the period 2021 to 2050. Climate change scenarios represented a decrease in the monthly streamflow of the Torren River, while land-use change scenarios depicted an increase. Therefore, urbanization was a more significant concern than climate change for this basin.

Kim et al. (2013) also studied the impacts of future land-use change and climate change on the streamflow of the Hoeya River Basin, Korea, and reported similar trends as reported in other studies. They developed two climate change, and two land-use change storylines for the period 2020 to 2050. First, the land-use change storyline called for more rapid urbanization than the second storyline. The results of this study suggest that although the effects of climate change were greater on the streamflow, land-use change resulted in significant seasonal impact, with the first storyline having a greater impact than the second one.

While the studies mentioned above reported increased streamflow linked to increased urbanization, Quyen et al. (2014) reported no change in the streamflow of the Srepok River, Vietnam. They studied the historical effects of land-use change on the streamflow of Srepok River Basin, Vietnam, using maps of the years 2000 and 2010. Urbanization increased, while agricultural land decreased, between the selected years of study.

Besides its global application, the SWAT model was used by Hovenga (2015) to study the Apalachicola River Basin, Florida. In this study area, the Chipola River, which is a tributary of the Apalachicola River, was also included. They studied the impacts of land-use change and climate change on streamflow and sediment loading of the river. The findings of their study suggest that climate change was linked to increased streamflow and sediment loading. The future land-use change also resulted in increased sediment loading due to reduced forest cover, but resulted in minimal streamflow increase. The minimal streamflow increase could be stated in terms of a low urbanization trend considered in the study.

Analysis of these studies also suggests that long-term urbanization trends are linked to an increased streamflow of the rivers. However, short-term urbanization trends may have little to no impact on the streamflow, as reported by Quyen et al. (2014) and Hovenga, 2015. Analysis of these studies also suggests that the SWAT model is a successful one for quantifying the relationship between urbanization and streamflow. Following the success of the Apalachicola-Chipola River study by Hovenga, 2015, it is concluded that SWAT model can be used in quantifying the relationship between urbanization and streamflow of the Chipola River.

2.3 The SWAT Modelling

The Soil and Water Assessment Tool (SWAT) is a time-continuous, and process-based river basin model. It was developed to measure the effects of non-point sources of pollution in large river basins and to assess the alternate management decisions for water resources (Arnold et al., 2012).

The SWAT model requires a digital elevation model (DEM), land use-map, soil map, and meteorological data (Nie et al., 2011). The SWAT model divides a watershed into sub-watersheds or sub-basins. Sub-basins are further divided into a series of uniform hydrological response units (HRUs) based on soil type and land-use (Kibena, Nhapi, & Gumindoga, 2014).). HRUs have unique occurrences of land cover, soil type, and slope class. Any piece of land within one sub-basin comprising the same combination of land-use, soil, and the slope will be considered as one HRU. The SWAT models all hydrological processes for each HRU independently of the position of that HRU in the watershed (White et al., 2011).

The sub-basin or sub-watershed components of the watershed can be divided into eight major categories in SWAT: such as hydrology, nutrients, weather, pesticides, soil temperature, sedimentation, agricultural management, and crop growth (Arnold et al., 1998a).

Water balance is the major force behind all SWAT processes as it can affect the movement of nutrients, sediments, pathogens, pesticides, and plant growth. The SWAT uses the following equation for the calculation of water balance (Pervez & Henebry, 2015).

$$SWt = SW_{\text{o}} + \sum_{i=1}^{t} 0\,(\mathrm{R} - \mathrm{Qsurf} - \mathrm{ETi} - \mathrm{Pi} - \mathrm{Qgw})$$

where,

Swt = final soil water content (mm)

SWo = initial soil water content on a day_i(mm)

R = amount of precipitation

Qsurf = amount of surface runoff

ETi = amount of evapotranspiration

Pi = amount of percolation

Qgw = amount of return flow

Hydrological components simulated by the SWAT model include evapotranspiration, percolation, lateral flow, groundwater flow (return flow), surface runoff, transmission losses, and ponds. Evaporation and transpiration are simulated independently of one another. Evaporation is simulated using exponential functions of water content and soil depth, whereas transpiration is calculated using a linear function of leaf area index and potential evapotranspiration (Nie et al., 2011).

The SWAT model can use one of three methods to calculate potential evapotranspiration, including Priestley and Taylor, Hargreaves, and Penman-Monteith methods (Nie et al., 2011). The Penman-Monteith method requires air temperature, wind speed, relative humidity and net radiation as inputs. The Priestley-Taylor method requires net radiation, and the Hargreaves method requires air temperature as input (Saleh et al., 2018).

Percolation is calculated using the crack-flow model and storage routing technique. Lateral flow is simulated simultaneously with percolation using a kinematic storage model. In contrast, groundwater flow (baseflow) into each channel is calculated based on water table height, hydraulic conductivity of shallow aquifer, and distance from sub-basin to the main channel (Nie et al., 2011).

In SWAT modeling, runoff is predicted separately for each sub-basin and routed to obtain the total flow for the basins. This process increases the accuracy of the model and provides a better physical description of the water balance (Arnold et al., 1998a).

The SWAT model uses two methods to model surface runoff: 1) the Green-Ampt method and 2) the curve number (CN) method (White et al., 2011).

The Green-Ampt method is a physically-based, infiltration excess, rainfall-runoff method. It is used to calculate runoff of the regions having hydrologic soil groups A or B. In these regions, the rainfall rate often exceeds the saturated conductivity of the soil (White et al., 2011). These regions have a high percentage of sandy soil and low runoff potential when thoroughly wet. The water transmission is not restricted (de Boer, 2016).

The Green-Ampt method is also applied to regions having dual soil hydrologic group B/D. This dual group suggests these regions have low runoff potential, water transmission is not restricted, and the water table exists within 60cm of the surface (de Boer, 2016). The SWAT model requires sub-daily precipitation data to simulate surface runoff by the Green-Amp method (King, Arnold, & Bingner, 1999).

The curve number (CN) is an empirically-based, infiltration loss, rainfall-runoff method (Kannan, Santhi, Williams, & Arnold, 2008). It is used to calculate runoff of the regions with hydrologic soil groups C or D. These regions have a high percentage of clay and high runoff potential when thoroughly wet. The water movement is somewhat restricted in soils of hydrologic group C, while highly restricted in group D (de Boer, 2016). The SWAT model requires daily precipitation data to simulate surface runoff by the curve number method (Ndomba, Mtalo, & Killingtveit, 2008).

In the SWAT model, flow from all hydrologic response units (HRUs) are summed at the sub-basin level and are routed through the stream using either the variable storage method or the Muskingum method. Both of these methods are variations of the kinematic wave approach (Gassman et al., 2007).

Due to its comprehensive nature, the SWAT model is recognized by the United States Environmental Protection Agency (USEPA) and has been integrated into the USEPA’s Better Assessment Science Integrating Point and Non-Point Sources (BASINS) (Abbaspour et al., 2015).

2.3.1 Advantages and Disadvantages of the SWAT Model

Following several decades of development, the Soil and Water Assessment Tool (SWAT) model has become a highly-used water quality and river basin-scale model. It is highly supported by online documentation, multiple geographic information systems (GIS) interface tools, and online resources. It also has the capability to address a wide range of water resources issues due to its comprehensive nature, strong model support, and open access to the users (Gassman et al., 2014).

The SWAT model is versatile as it can incorporate multiple environmental processes. It also supports effective watershed management practices (Gassman et al., 2007) by effectively simulating surface water quality and quantity (Glavan & Pintar, 2012).

The SWAT model also is known as a deterministic model – each successive model run that uses the same inputs will produce the same outputs. This characteristic of the SWAT model makes it a valuable tool for isolating hydrologic response to a single variable, such as land-use change (Baker & Miller, 2013).

The fundamental strength of the SWAT model lies in its flexibility to combine upland and channel processes and land management (Gassman et al., 2007; Arnold et al., 2012). However, this strength sometimes becomes a weakness due to the lack of sufficient monitoring data required for the characterization of input parameters (Gassman et al., 2007).

The strength of the SWAT model that enables its widespread use also has associated weaknesses that require further improvement, such as the oversimplification of hydrologic response units (HRUs). There are also some weaknesses associated with depicting the physical processes accurately due to a lack of sufficient monitoring data, inadequate data needed to characterize input parameters, or insufficient scientific understanding (Gassman 2007).

Although the SWAT model has associated advantages and disadvantages, the SWAT model was chosen for this study to quantify the impacts of land-use change on streamflow of the Chipola River for the three reasons: free access for the users, the availability of online resources, and its successful application in previous urbanization and streamflow studies.

2.4 Calibration of Hydrologic Models

When a combination model is used to simulate the processes of a physical system, it produces outputs affected by the input data. Therefore, to test the accuracy of the developed model, simulated results need to be compared with the observed data. The observed data is also sometimes subject to uncertainties. Accuracy of the desired model can be achieved by the process of calibration (Refsgaard & Storm, 1990), which is crucial for proper hydrological modeling (Shivhare, Dikshit, & Dwivedi, 2018).

Calibration is the process of modifying the parameters that can influence model outputs, assisted by observed data and evaluated estimations of evapotranspiration, runoff, and other model outputs (Shivhare et al., 2018).

In principle, three calibration techniques can be applied: 1) manual calibration, 2) automatic calibration and, 3) a combination of manual calibration and automatic calibration (Refsgaard & Storm, 1990).

2.4.1 Manual Calibration

Manual calibration, also known as trial and error calibration (Refsgaard & Storm, 1990), is a process whereby model parameters are adjusted by the user to predict the model results corresponding to the observed data. It is an essential step for analysis of a simulated model (Sultana, Dhungana, & Bhatta, 2019).

Manual calibration is performed to reduce prediction uncertainty by adjusting the model parameters to the desired level (Sultana et al., 2019). Expert judgment and extensive knowledge about the catchment are required for adequate determination of the parameter adjustments (Gassman et al., 2007; Sultana et al., 2019). Following the adjustment of parameters, model outputs are compared with the observed data for analysis of the yielded results (Sultana et al., 2019; Gassman et al., 2007).

However, manual calibration is a daunting and tedious task because it can take a longer time in the calibration of a single basin depending on the size of the basin, spatial resolution, and the simulation period (Sultana et al., 2019; Bekele & Nicklow, 2007). Manual calibration also becomes less feasible in visualizing the conceptual relationship between the model parameters and the basin characteristics due to the involvement of numerous parameters in hydrologic models**.** The involvement of numerous parameters can also result in unpredictable results during the adjustment of multiple parameters (Bekele & Nicklow, 2007). Furthermore, due to heterogeneity of the calibrated parameters, and the subjectivity involved, confidence in the model simulations and consistency among users cannot be fully achieved (Kim, Benham, Brannan, Zeckoski & Doherty, 2007).

Due to the issues involved and the daunting nature of the manual calibration, automatic calibration procedures are developed, which are more efficient and effective (Kim et al., 2007).

2.4.2 Automatic Calibration

The automatic calibration uses a numerical algorithm, which finds the minimum and maximum values of the given objective function. The purpose of automatic calibration is to find parameter values through as many combinations and permutations as possible and to achieve the “best” parameters. The best parameter values are used to ensure accuracy (Refsgaard & Storm, 1990).

Automatic calibration can find the “best” parameters quickly and is less subjective than manual calibration (Bekele & Nicklow, 2007). It is also faster than manual calibration, and therefore, confidence in the model simulations can be stated explicitly. An added benefit is the easy use of optimization packages. These packages may also result in a good agreement between the model outputs and the observed data (Kim et al., 2007)

However, algorithms used in optimization packages try to compensate for data errors by adjusting parameter values, which may result in inadequate and physically unrealistic simulation outputs when applied to a dataset not included in the calibration process. Automatic calibration also avoids use of prior knowledge inherent to the structure of the model and results in uncertainty of the statistical analysis (Refsgaard & Storm, 1990).

Due to the stated issues with automatic calibration, many surface water hydrologists do not consider it helpful. Therefore, automatic calibration has not been incorporated into surface water hydrologic models (Kim et al., 2007).

2.4.3 Combination of Manual and Automatic Calibration

A combination of manual and automatic calibration provides for an initial adjustment of the parameter values made manually, followed by automatic calibration within the defined range of physically-realistic values. Reversing the order is also feasible; testing the sensitivity of parameters using automatic calibration first, followed by manual calibration. Combining the calibration processes is valuable in the calibration for hydrologic models (Refsgaard & Storm, 1990).

2.5 Calibration and Validation of the SWAT model

The manual calibration of hydrological models, such as SWAT, is not feasible for large-scale basins. Whereas, automatic calibration provides a reliable, labor-saving tool by significantly reducing the subjectivity and frustrations involved in manual calibrations (Arnold et al., 2012).

The SWAT-CUP (calibration and uncertainty procedures) is a free auto-calibration program and was developed for the calibration of the SWAT outputs (Abbaspour et al., 2015; Sultana et al., 2019). It can also be used for validation, and sensitivity and uncertainty analysis of the SWAT outputs (Sultana et al., 2019). In SWAT-CUP, all model parameters such as streamflow, water quality, and weather generator parameters, can be included in the process of calibration (Arnold et al., 2012).

The SWAT-CUP comprises five different calibration methods and functionalities for validation and sensitivity analysis (Abbaspour et al., 2015). These methods and functionalities include: Particle Swarm Optimization (PSO), Markov chain Monte Carlo (MCMC), Parameter Solution (ParaSol), Generalized Likelihood Uncertainty Estimation (GLUE), and Sequential Uncertainty Fitting (SUFI-2) (Rouholahnejad et al., 2012).

Of these methods and functionalities, the Sequential Uncertainty Fitting (SUFI-2) is the algorithm in the SWAT-CUP (Abbaspour, Vaghefi, & Srinivasan, 2018) that uses a combination of manual and automatic calibration approaches (Pagliero, Bouraoui, Diels, Willems, & McIntyre, 2019).

2.5.1 Calibration and Validation using SUFI-2 in SWAT-CUP

The SUFI-2 program provides the flexibility to manually adjust the parameters and their ranges between the automatic calibration runs. It also provides the flexibility to perform sensitivity and uncertainty analyses on outputs as the user moves between manual and automatic calibration. Sensitivity analysis helps smooth the process of calibration, while uncertainty analysis provides statistics for the goodness of fit (Arnold et al., 2012).

The SUFI-2 involves the following steps in the process of calibration:

1. Development of default or initial parameters as created by the SWAT model and preparation of input files for the SUFI-2 program in SWAT-CUP.
2. Running the model with default parameters and plot the observed and simulated results at each gauge station for the entire duration.
3. Splitting the entire data equally for calibration and validation periods.
4. Determining the most sensitive parameters for the observed values of interest.
5. Assigning an initial uncertain range to each parameter globally.
6. Running the SWAT-CUP-SUFI2 model with 300-500 simulations and analyzing the results for each gauge station.
7. Performing the sensitivity analysis and analyzing the results.
8. After analyzing the model performance in step 6, regionalizing the respective parameters (Arnold et al., 2012).

Correct parameterization is the most crucial step in the process of calibration. The selection of correct parameters is based on the knowledge of hydrologic processes and the variability in the land-use, soil, slope type, and location of the sub-basin (Arnold et al., 2012). Parameterization is therefore defined as "the process of imparting the analyst's knowledge of the physical processes of the watershed to the model" (Arnold et al., 2012, p. 1500).

After correct parameterization, sensitivity analysis can be performed, which is the process of analyzing the rate of change in model outputs concerning changes in model inputs. It is, therefore, necessary to identify critical parameters and to ensure their precision for calibration (Arnold et al., 2012). Sensitivity analysis provides information on the most critical parameters in the study area. It also helps to decrease the number of parameters by eliminating non-sensitive parameters during the calibration process (Abbaspour et al., 2018)

Two types of sensitivity analysis can be performed: local sensitivity analysis or one-at-a-time (OAT), and global sensitivity analysis or all-at-a-time (AAT). In OAT, all parameters are kept constant except one. The remaining parameter is variable while its effect on objective function or model output is analyzed. While in AAT, all parameters are kept variable, and a large number of simulations (500-1000 or more) are required to see their impacts on the objective function or the output model (Abbaspour et al., 2018).

Both types of sensitivity analyses have associated advantages and disadvantages. The local sensitivity analysis is simple and quick; however, the sensitivity of one parameter is often dependent on the sensitivity of other parameters, which are fixed to values of unknown accuracy (Arnold et al., 2012; Abbaspour et al., 2018). The global sensitivity analysis produces more reliable results than the local sensitivity analysis. However, it requires a substantial number of simulations (Arnold et al., 2012), which affects parameter values and the relative sensitivity of the parameters (Abbaspour et al., 2018).

After performing sensitivity analysis, a student t-test identifies the significance of each parameter. In the student t-test, parameters having the larger absolute t-stat, and smaller p-values are considered the most sensitive (Abbaspour et al., 2018).

The SUFI-2 program is also used to map all the uncertainties on the parameters. It also tries to capture maximum observed data within 95% prediction uncertainty (95PPU) of the model in an iterative process. The 95PPU is calculated at the 97.5% and 2.5% levels of the cumulative distribution of an output variable that is obtained through Latin hypercube sampling (Abbaspour et al., 2018) – a statistical method that produces controlled random samples (Emam, Kappas, Fassnacht, & Linh, 2018).

For the goodness of fit, two bands are compared (the 95PPU for model simulation, and the band representing the measured data including its error), known as p-factor and r-factor by the first author (Abbaspour et al., 2015). The p-factor is known as the fraction of measured data and its error bracketed by 95PPU, while the r-factor is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. The p- and r-factors are used to measure the strength of the calibration. The p-factor varies from 0 to 1, while r value <1.5 is desirable. When acceptable p and r values are reached, the parameter ranges are known as calibrated (Abbaspour et al., 2015; Abbaspour et al., 2018). Subsequently, 1- p-factor is the model error, and it represents the observed data not captured by the model during the process of calibration (Abbaspour et al., 2018).

After the successful calibration of parameters, validation is used to build confidence in the calibrated parameters (Abbaspour et al., 2018). Validation is the process of comparing the model outputs with the observed data without further modifying the parameters used in the process of calibration (Shivhare et al., 2018). Similar to calibration, validation is also quantified by p-factor, r-factor (Abbaspour et al., 2018).

The SUFI-2 allows the user to select the objective function from a range of ten different objective functions (Abbaspour et al., 2015). The selection of an objective function must correspond to the goal of the project as there is no defined unique creation for the selection of objective function (Abbaspour, Johnson, & Van Genuchten, 2004). So far, Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), are most commonly used statistics for calibration and validation (Arnold et al., 2012).

The Nash-Sutcliffe efficiency (NSE) represents the fraction of the observed streamflow variance produced by the model (Van Liew, & Mittelstet, 2018). For Nash-Sutcliffe efficiency (NSE), model quality is tested using different levels. If the model has value NSE value of <0.5, it is considered “unsatisfactory,” if it has NSE value from 0.54-0.65, it is considered “satisfactory.” When the model has an NSE value of 0.65-0.75, it is considered “good,” and the model with NSE value of 0.75-1 is considered “very good” (Me, Abell, & Hamilton, 2015).

The coefficient of determination (R^2) represents how well the observed streamflow and simulated regression line approaches a perfect match (Gassman et al., 2007). Similar to NSE, model quality is tested using different levels. If the coefficient of determination (R^2) has a value of <0.5, the model is considered “unsatisfactory.” However, if it has the value of “0.5-0.6”, the model is considered as “satisfactory.” With a value of 0.6-0.7, the model is considered "good," and with a value of 0.7-1, the model is considered "very good" (Me et al., 2015).

Vilaysane et al. (2015) used the two commonly-used statistics; Nash-Sutcliffe efficiency (NSE), and coefficient of determination (R^2) to evaluate the model's goodness of fit. Using the SUFI-2 algorithm, they calibrated (1993-2000) and validated (2001-2008) the streamflow of the Xedone River Basin for daily, as well as monthly, time-step. For daily time-step, calibration gave NSE and R^2 values of 0.819, 0.821, while validation gave 0.707 and 0.732, respectively. For monthly time-step, calibration gave NSE and R^2 values of 0.925 and 0.927, and validation gave values of 0.856, 0.910, respectively. As the values of these statistics were "very good" for daily, as well as monthly, time-step, Vilaysane et al. (2015) suggested that the calibrated streamflow values could be used for the analysis of land-use change, climate change, water quality analysis, sediment yield, and for planning dam and flood disaster risk management.

Mehan et al. (2017) also used NSE and R^2 to determine the model's goodness of fit. Using the SUFI-2 algorithm, they calibrated (1987-1994) and validated (1995-2000) the streamflow of the Skunk Creek watershed for daily, as well as monthly, time-step. For daily time-step, calibration gave NSE, and R^2 values of 0.56 and 0.70, and validation gave values of 0.55 and 0.44, respectively. For monthly time-step, both statistics gave a similar value of 0.84 for calibration and values of 0.76 and 0.77 for validation. The results of this study suggest that model performance was better for monthly time-step rather than for daily time-step. A conclusion of this study, therefore, is that the integration of SUFI-2 in SWAT-CUP sped-up the calibration process.

NSE and R^2 statistics were also used by Jain et al. (2017) to evaluate model goodness. Daily calibration (1992-2000) and validation (1992-2000) was performed for the streamflow of the Beas River, India. Both statistics, NSE and R^2, gave similar values, 0.60 for calibration, and differing values of 0.48 and 0.57 for validation. They suggested that results of calibration and validation were acceptable for daily time-step, and calibration values could be used to simulate future changes in streamflow and water balance of the watershed.

While studies are most commonly using the NSE and R^2 statistics, Van Liew & Mittelstet (2018) recommended the use of another objective function, percent bias (PBIAS), for the evaluation of model's goodness of fit. Percent bias (PBIAS) signifies the measure of average bias of the simulated output as smaller or higher than their observed values (Van Liew, & Mittelstet, 2018). A positive value of PBIAS indicates model underestimation bias, while a negative value indicates model overestimation bias (Molina-Navarro, Trolle, Martinez-Prrez, Sastre-Merlin, & Jeppesen, 2014).

Similar to NSE and R^2, PBIAS results are tested using four different levels. When PBIAS has a value >25, the model results are considered as "unsatisfactory," when PBIAS has a value from 15-25, then model performance is considered "satisfactory," is considered "good" when it has a value from 10-15, and is considered "very good" when it has a value <10 (Nie et al., 2011; Me et al., 2015).

PBIAS is being used in combination with other commonly-used statistics, such as NSE and R^2. For example, Oliveira et al. (2018) used PBIAS, in addition to NSE, to evaluate the model goodness of fit. Using the SUFI-2 algorithm, they performed calibration and validation for the streamflow of the Grande River. Calibration was performed from 1994 to 1998, and validation was performed from 1999 to 2001. Calibration gave an NSE value of 0.72 and a PBIAS value of 2%, while validation gave an NSE value of 0.63 and a PBIAS value of 10%. These statistics were considered “satisfactory” for the daily time-step. Oliveria et al. (2018) suggested that the calibrated values could be used to analyze the impact of land-use change on the streamflow of the Grande Riven Basin.

Although the aforementioned studies have used a combination of two statistics to describe the results of their calibration and validation, the usage of multiple statistics is also in practice. Besides the statistical selection criteria, these studies only calibrated and validated streamflow at one gauge station. However, SUFI-2 is capable of calibrating and validating the streamflow at multiple gauge stations (Abbaspour et al., 2018)

The above-mentioned two approaches were used by Zhou et al. (2014) for the calibration and validation of the streamflow of the Lake Dianchi Basin. They used three statistical criteria; R^2, NSE, and PBIAS to test the model performance, and performed calibration and validation at three gauge stations. However, calibration (2001-2006) and validation (2007-2009) was performed for monthly time-steps only. Calibration for the first gauge station, “Panlongjiang,” gave R^2, NSE, and PBIAS values of 0.64, 0.60, and 3.63, respectively, and validation gave values of 0.56, 0.48, and 27.02, respectively. Calibration for the second gauge station, “Baoxianghe,” gave R^2, NSE, and PBIAS values of 0.81, 0.76, and -11.20 respectively, and validation gave 0.86, 0.78, and 7.98, respectively. Calibration for the third gauge station, “Haikouflow,” gave R^2, NSE, and PBIAS values of 0.68, 0.62, and -13.91 respectively, and validation gave 0.76, 0.72, and -4.19, respectively. Zhou et al. (2014) suggested that the results of calibration could be used to analyze the streamflow of Lake Dianchi. An observation resulting from this study, was that PBIAS values suggest that streamflow was underestimated for the first stream gauge, while it was overestimated for the second and third stream gauge. Thus, it can be concluded that, in addition to explaining the acceptability of the results of calibration and validation, the use of PBIAS is constructive for explaining the "overestimation" or "underestimation" of the calibrated and validated streamflow results.

Following an analysis of all the reviewed papers, I concluded that these studies successfully employed the SUFI-2 algorithm in streamflow calibration and validation. The selection of SUFI-2 made the calibration process quick. I also concluded that selection of multiple statistical criteria helps to better explain the results of calibration and validation and that SUFI-2 gives better results of monthly calibration and validation rather than the daily.

Although researchers successfully employed SUFI-2 in reviewed studies, most of did not apply split data approach recommended by Arnold et al. (2012). Rather, most used their data for calibration and only a small amount of data for validation. The only exception was the study by Vilaysane et al. (2015).

Following the analysis of all the papers reviewed herein, this study aimed to use the recommended split data approach for calibration and validation in the SUIF-2 program. This study also aimed to calibrate and validate the simulated streamflow on a monthly time-step to obtain better average streamflow results. Finally, this study aimed to use three statistical techniques, NSE, R^2, and PBIAS, to evaluate the model's performance.

CHAPTER 3: METHODOLOGY

3.1 Study Site

The study site for this research is the Chipola River Basin, the largest tributary of the Apalachicola River Basin, Florida (Chen et al., 2012). The Chipola River has a surface water drainage basin of approximately 3,333 square kilometers (km^2) (Denson, Rasmussen, & Harris, 2016; Barrios & Chelette, 2004). The study site has an average elevation of 120 meters above the mean sea level and has flat terrain sloping down to the southwest and southeast (Verdi, 2007).

The Choctaw, headwaters of the Chipola River, originates southeast of Dothan in Houston County, Alabama, to the south of the Dead Lakes area in central Gulf County, Florida (Denson et al., 2016; Barrios & Chelette, 2004). The two main tributaries of the Chipola River - Cowarts Creek, and Marshall Creek - unite in northern Jackson County, Florida, approximately 14 kilometers north of Marianna (Barrios, & Chelette, 2004). The tributaries then flow south through Calhoun and Gulf Counties, join the Apalachicola River near the Wewahitchka town and ultimately drain into the Gulf of Mexico (Denson et al., 2016; Verdi, 2007).

The Chipola River Basin was selected as the study site for this research for several compelling reasons. The Chipola Basin is undeveloped, having only a few towns located near the river. There are no large urban city centers, and industrialization is minimal (Elder & Mattraw, 1984). Urbanization within this basin has steadily increased over the last 30 years (Verdi, 2007). Dothan City, Alabama, has a major developed area within the basin. Land-uses in this basin consist of farms, bottomland deciduous forests, and silviculture. During low and medium flows of the Chipola River, groundwater is the greatest contributor, while during high flows, groundwater flow is diluted and replaced by surface runoff (Barrios & Chelette, 2004). Further development in the upstream basin may result in altering the streamflow of the river (Elder & Mattraw, 1984). For example, as a result of clearing for urbanization, the Chipola Basin may no longer be able to control and hold the streamflow and may result in downstream flooding (Clark, 1980).

The Chipola River is being fed by 63 springs, including a first magnitude spring, Jackson Blue. This spring makes the Chipola River Basin a vital source of freshwater for the Apalachicola River and Bay. The Chipola River is distinctive among Florida rivers for its relatively clear water and hard limestone bottom that provides habitats and support for a variety of aquatic organisms (Birdsong et al., 2015). Apart from providing habitat to diverse aquatic organisms, the Chipola River also hosts and protects a threatened fish species, Alabama Shad (Collins, 2016).

Currently, the Chipola River Basin is relatively rural but may be subject to urbanization in the future. An increase in streamflow linked to increased urbanization could present major issues for this basin in the future, such as increased runoff and flood events, which would ultimately affect aquatic organisms. In order to and prevent the impacts of urbanization on this river, it is necessary to first have a comprehensive understanding of the response of streamflow to increased urbanization.

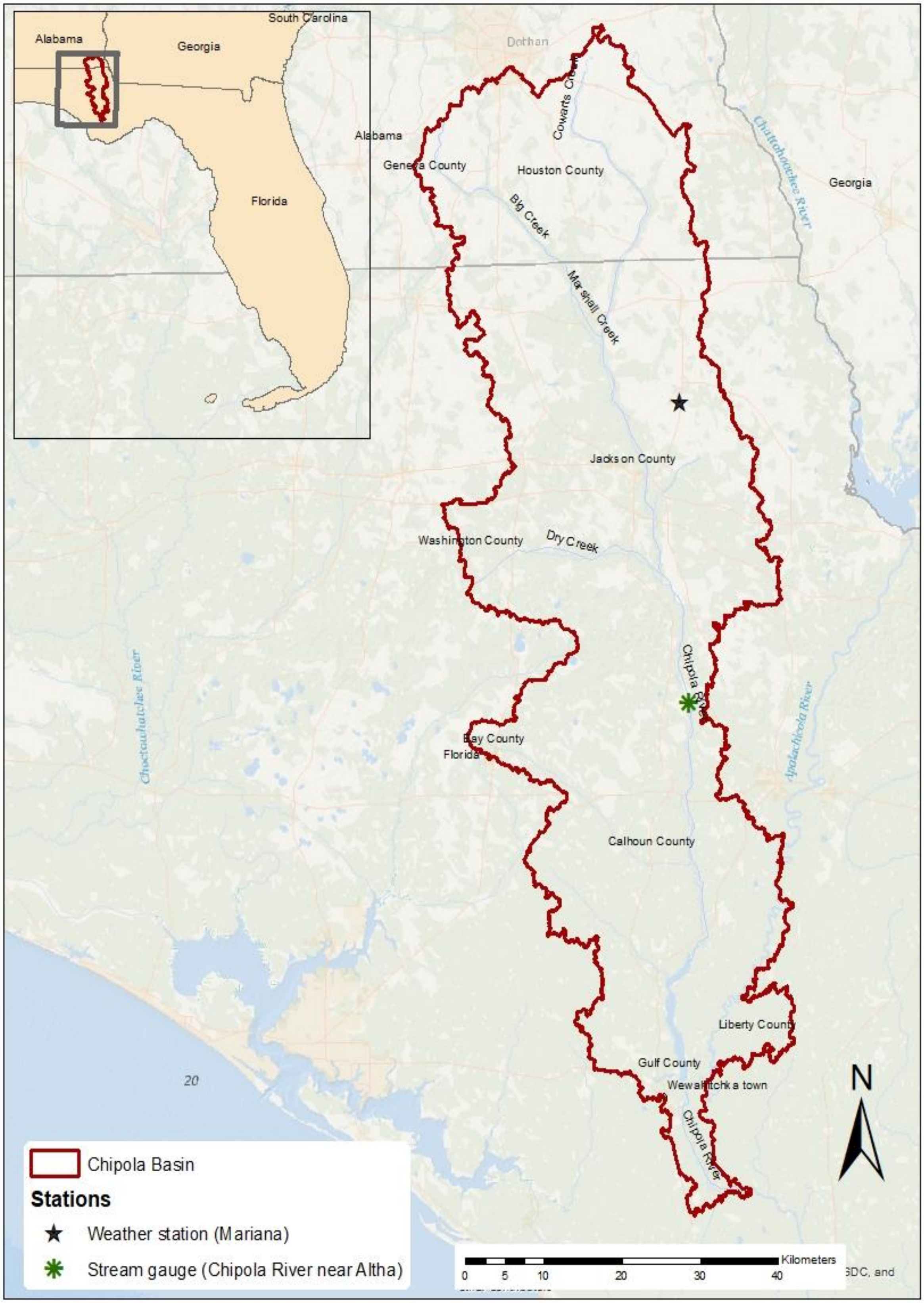


Figure 1: Study Site

3.2 Data Collection

This study required a digital elevation model (DEM), land use maps (current and future), a soil map, and meteorological data as inputs for the SWAT model. Meteorological data included hourly rainfall, temperature (min., max.), wind, solar radiation, and relative humidity; data were obtained from the weather station, “Mariana.”

Real-world observed streamflow data required for the calibration and validation of the simulated streamflow were obtained from the stream gauge, “Chipola River near Altha.” Figure 1 represents the location of the weather station and the stream gauge. A brief summary of all data sources used in this study is provided in Table 1.

Table 1: Data Sources

Data Type	Data Sources
Hydrologic unit code 8 (HUC 8) watershed boundary	United States Geological Survey National Hydrography Dataset (USGS NHD) http://prd-tnm.s3-website-us-west-2.amazonaws.com/?prefix=StagedProducts/Hydrography/NHD/HU8/HighResolution/
United States (US) shapefile	Topologically Integrated Geographic Encoding and Referencing (TIGER) https://catalog.data.gov/dataset/tiger-line-shapefile-2017-nation-u-s-current-state-and-equivalent-national
Primary and secondary roads' shapefiles (2019)	Topologically Integrated Geographic Encoding and Referencing (TIGER). https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html
Digital elevation model (DEM), 10m (2019)	United States Geological Survey National Elevation Dataset (USGS NED) https://viewer.nationalmap.gov/basic/
Land-use land cover (LULC) map, 30m (2016)	National Land Cover Database (NLCD) https://www.mrlc.gov/data?f%5B0%5D=region%3Aconus
STATSGO Soil map (2016)	United States Department of Agriculture (USDA) https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx
Meteorological data (2013-2018)	Florida Automated Weather Network (FAWN) https://fawn.ifas.ufl.edu/data/fawnpub/
Streamflow data (2015-2018)	United States Geological Survey (USGS) https://waterdata.usgs.gov/fl/nwis/rt

Note: This study used a "land-use land cover map" to represent "land-use map."

3.3 Data Pre-processing

The digital elevation model (DEM) grids were merged using the "create mosaic dataset" and "add rasters to mosaic dataset" tools in ArcGIS 10.5.1. After merging, DEM was projected into universal transverse Mercator (UTM).

A rectangular shapefile using, "ArcCatalog" and "Editor Tool," was created in ArcGIS using the study area as a reference. This shapefile served to extract land-use and soil maps' area greater than the area of hydrologic unit code 8 (HUC 8) basin. The extracted land-use and soil maps covered the entire delineated basin defining hydrologic unit response (HRU) analysis in the SWAT. After extraction, land-use and soil maps were projected to UTM projection. Projection (WGS_1984_UTM_Zone_16N) was kept similar for each dataset to avoid inaccuracies.

The units of meteorological data and streamflow data were converted to SWAT-required units. The SWAT model requires “millimeter (mm)” units for precipitation, “Celsius (C˚)” for temperature, “meters per second (m/s)” for wind, “percent” for relative humidity, and the “megajoule per square meter (MJ/m2)” for solar radiation data. After unit conversion, meteorological data were written into text files for the SWAT, and locator files for each dataset were written as well.

3.4 Development of Future Land-use Map

For the development of a future land-use map of the Chipola Basin, “linear expansion urbanization” was considered due to the rural characteristics of the basin. In this expansion, it was assumed that low-density urban areas would be converted to high-density, and agricultural areas would be converted to low-density within a five-mile buffer of primary and secondary roads. The five-mile buffer was used to analyze the urbanization impacts in the maximum area of the basin. All other land-use classes were kept constant.

Primary and secondary road shapefiles for the states of Alabama and Florida were merged and clipped. After clipping, the roads shapefile was projected using UTM projection. A five-mile buffer was produced along the primary and secondary roads.

The land-use (2016) map was converted to a vector shapefile, clipped, and then erased, using the five-mile buffer. The clip feature provided a shapefile of land-use classes within the five-mile buffer. The erase feature removed the land-use classes within the five-mile buffer of the existing land-use map of 2016. Clipped and erased shapefiles were then dissolved using the “gridcode” field. In the clipped shapefile, the low-density urban areas were converted to high-density, and the agricultural areas were converted to low-density by changing the value of the “gridcode” field. After the conversion of land-use classes, clipped and erased shapefiles were merged, one vector shapefile containing the future land-use map remained.

The final step was to convert this vector shapefile into raster format because SWAT requires a raster format of a land-use map for simulation. The vector shapefile was converted to raster, with the same cell size (30m), and same number of columns and rows (3144, 6048) as the 2016 land-use map to keep the area of the two maps similar. The cell size was described, and the “same processing extent” feature was used in the “feature to polygon” tool. Figure 2 illustrates the methodology for the development of the roads’ buffer. Figure 3 illustrates the methodology for the development of the future land-use map.

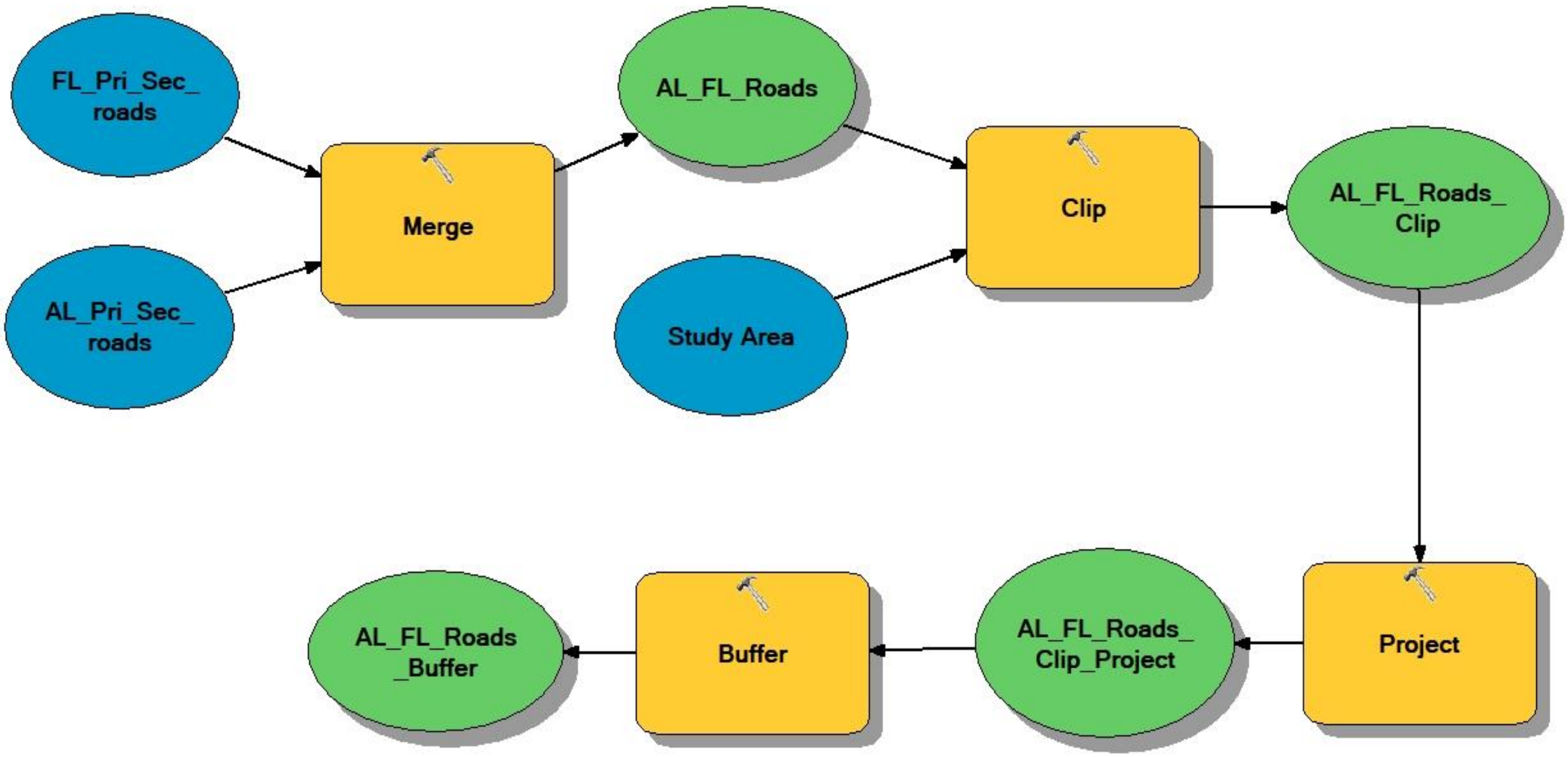


Figure 2: Flowchart for the development of the five-mile roads buffer along Alabama (AL) and Florida (FL) roads

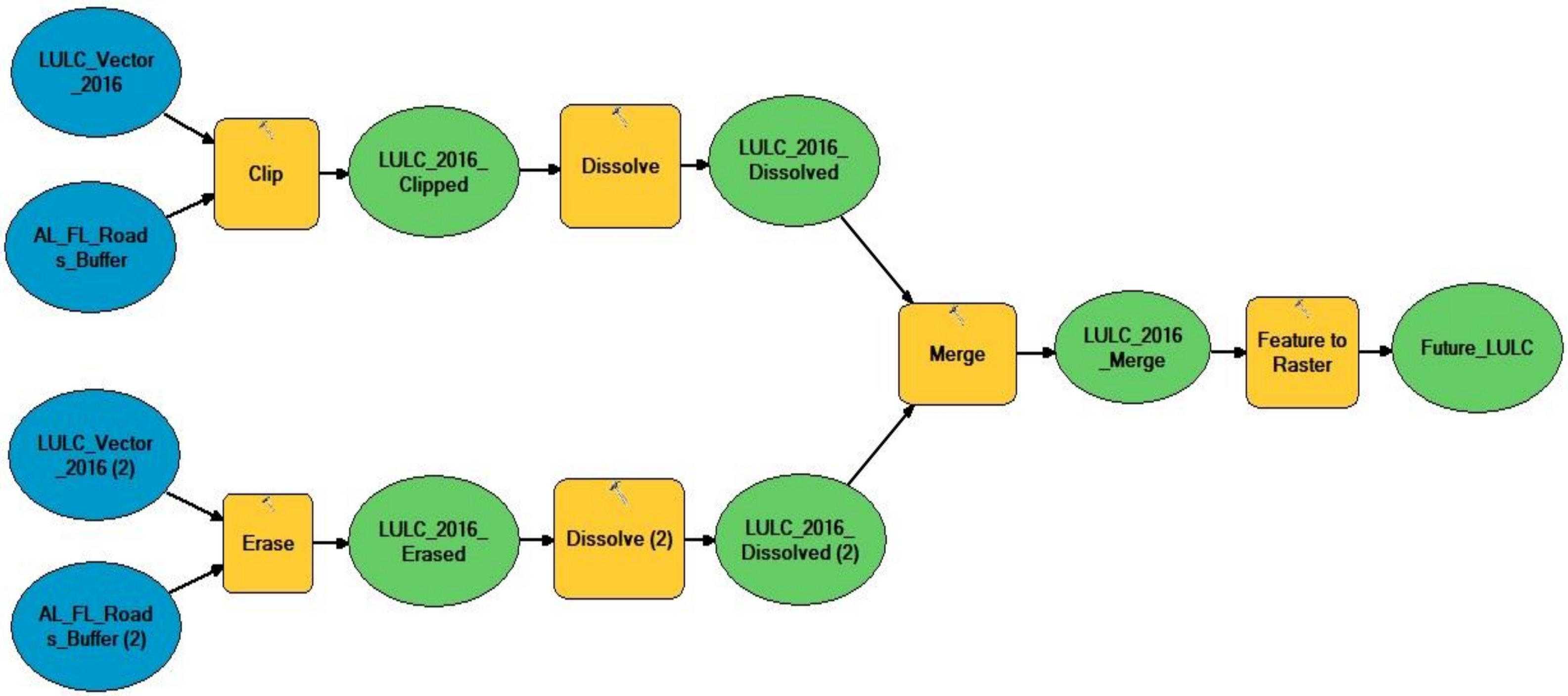


Figure 3: Flowchart for the development of future land-use land cover map using the five-mile buffer (figure 2)

3.5 SWAT Modelling

After pre-processing, data were ready to be input into the SWAT model. For this study, SWAT version 2012 was used as an extension in ArcGIS 10.5.1. The sections that follow discuss the methodology for hydrologic modeling of the Chipola Basin. The conceptual framework for the methodology is provided in Figure 4.

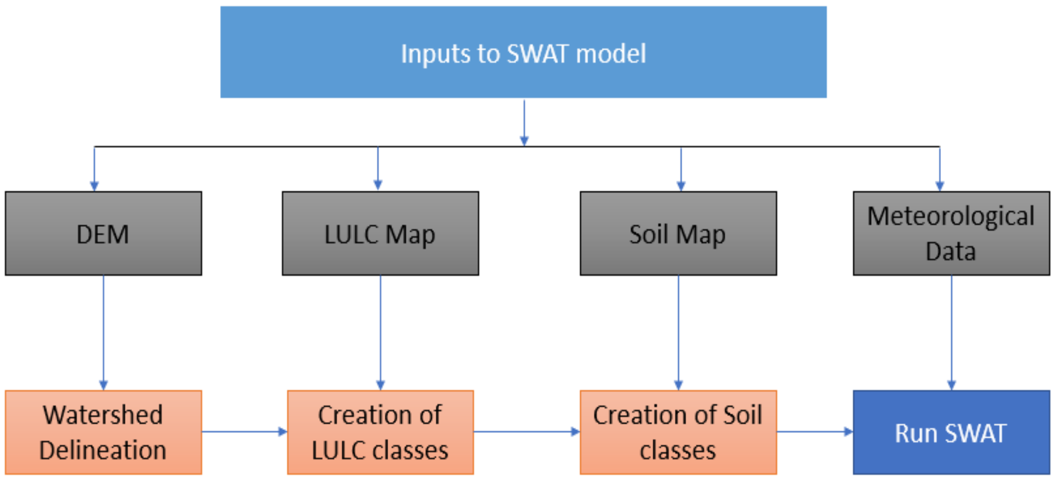


Figure 4: Conceptual framework for the SWAT modelling

3.5.1. Automatic Watershed Delineation

For automatic watershed delineation, a 10m digital elevation model (DEM) was uploaded into the SWAT model and the meter was selected as its z unit. After selecting the z unit, flow direction and accumulation was calculated. A threshold area of 2000 Hectares (Ha) was defined for each hydrologic response unit (HRU) for depiction of the streams' frequency and extent in the watershed. An outlet close to the location of the United States Geological Survey (USGS) stream gauge was added manually to calculate streamflow for that sub-basin. The streamflow for this sub-basin could then be used in the process of calibration and validation. Streams and outlets were created, which resulted in the creation of 100 outlets and 100 sub-basins. The watershed was delineated and the sub-basin parameters were calculated (Figure 5).

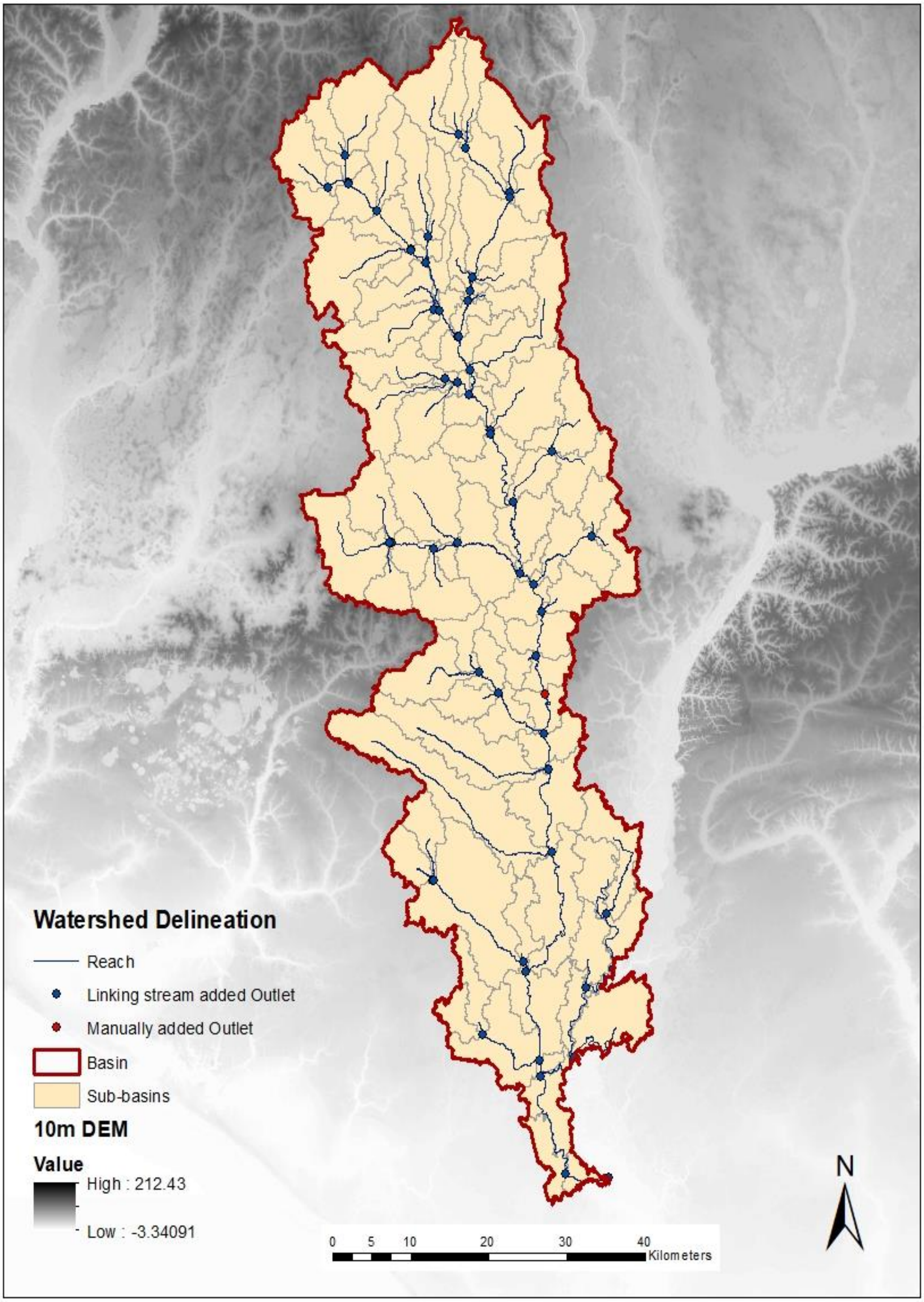


Figure 5: Automatic watershed delineation of the Chipola River

3.5.2 HRU Analysis

A land-use map, soil map, and slope definitions were required for hydrologic response unit (HRU) analysis.

3.5.2.1 Land-use Data

The land-use map for the year 2016 was uploaded and “value” was selected in the grid field. After selecting the grid field, the SWAT model calculated the percentage area for each land-use class. The user table created for land-use classes was uploaded, which resulted in land-use codes for the SWAT model. The same process was repeated in the second simulation, which used future land-use map.

The land-use map of 2016 was considered as the “baseline scenario” and the future land-use map was considered as the “future scenario.” Figure 6 shows land-use maps of the two scenarios. Figure 7 shows the total change in the land-use classes that occurred between the baseline and future scenarios. As figure 7 shows, most of the low-density urbanization occurred in the upstream river basin, while high-density urbanization occurred in the middle stream. Results for the agricultural area were negligible, occupying only 0.01% area of the basin’s area.

Table 2 shows the SWAT land-use codes, along with the percentage area of each land-use class of the two scenarios, and the percentage difference between these scenarios.

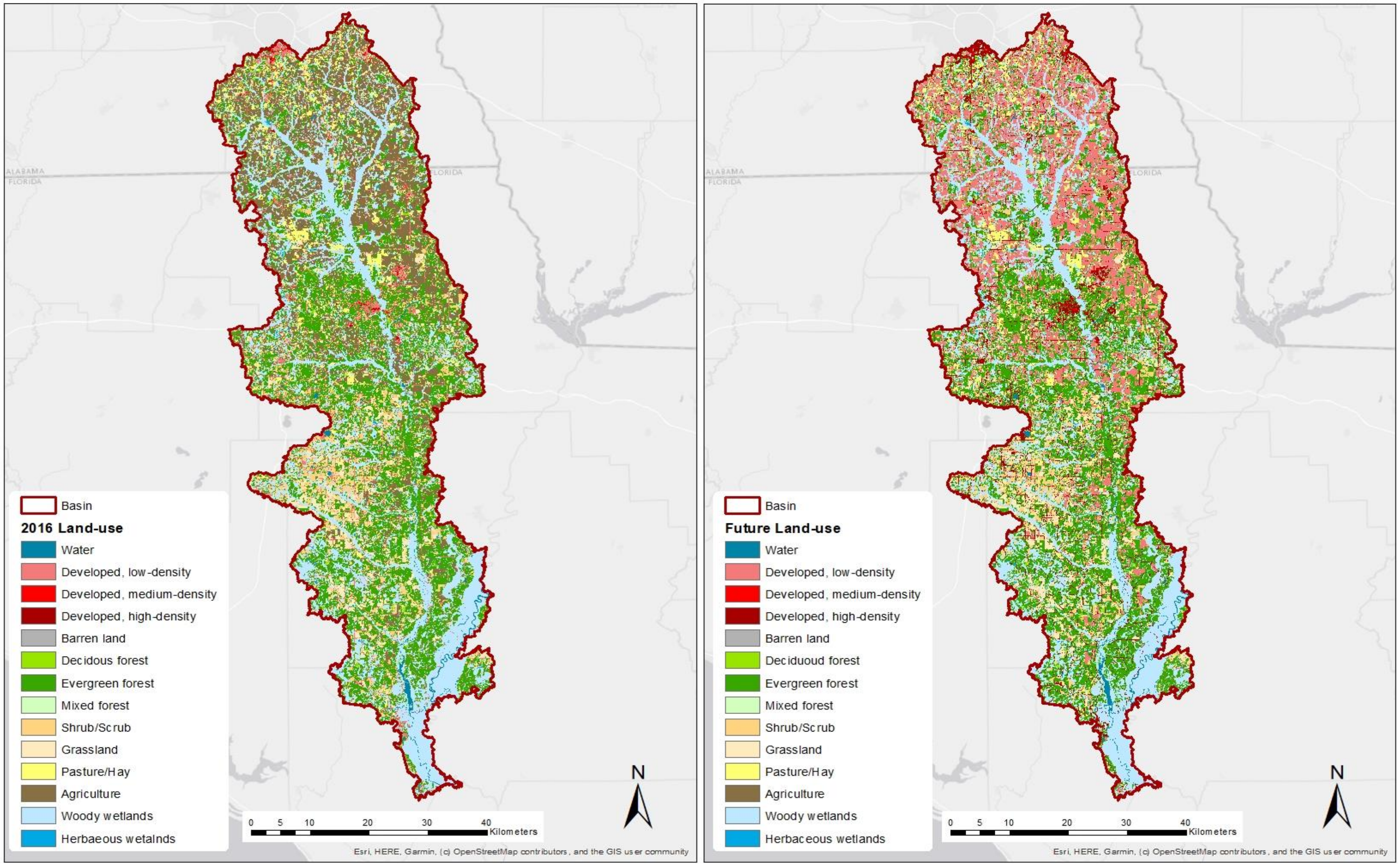


Figure 6: Land-use maps for baseline and future scenarios

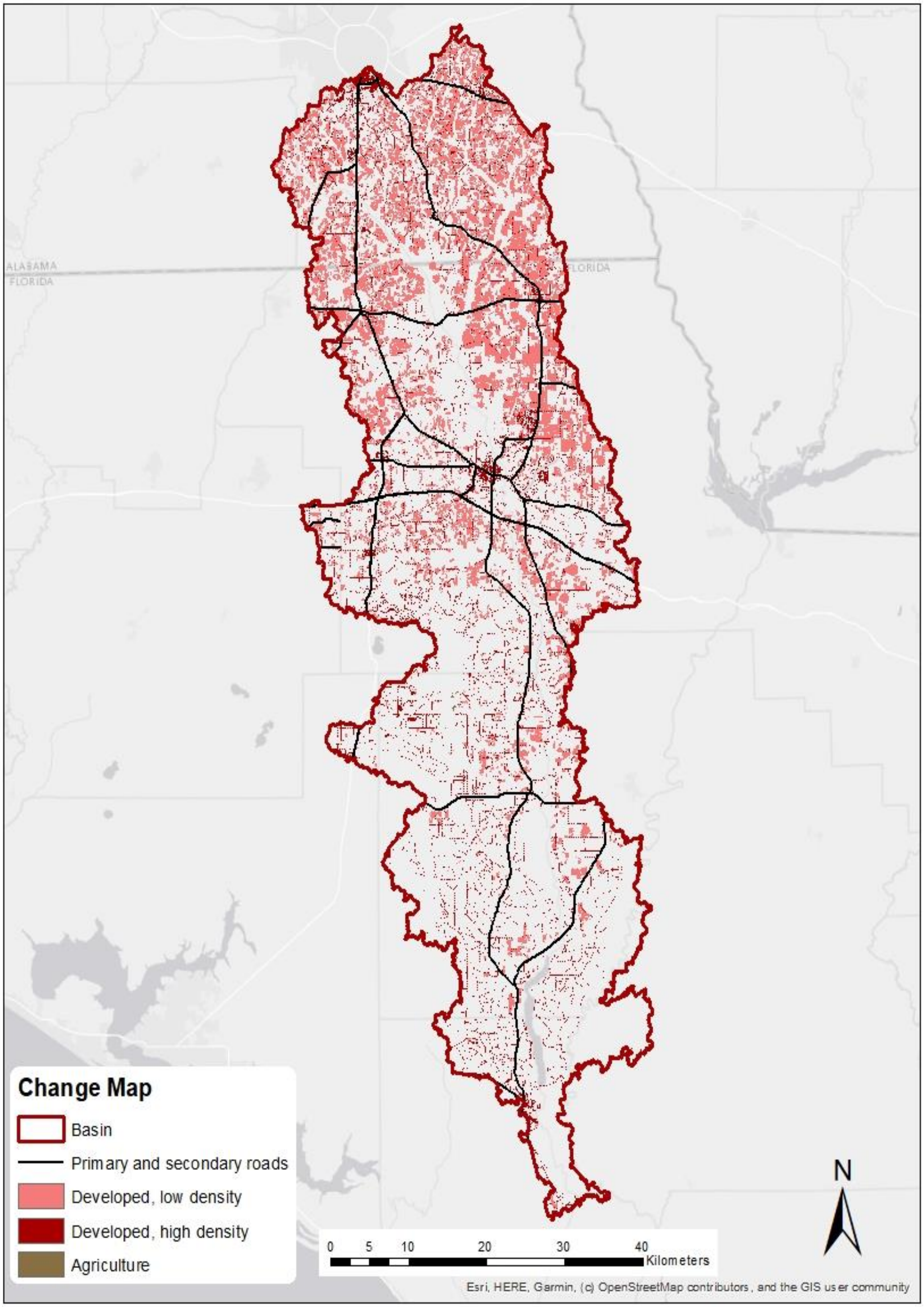


Figure 7: Total change in land-use classes

Table 2: Description of SWAT codes and LULC classes' percentages

Land Use Classes	SWAT Land-use Codes	Area/year 354532.9 Hectares/ 2016 LULC	Area/year 354532.9 Hectares/ Future LULC	%age Difference in Area
Open water	WATR	0.93%	0.93%	0%
Developed, low-density	URLD	6.37%	19.34%	12.97%
Developed, medium-density	URML	0.24%	0.24%	0%
Developed, high-density	URHD	0.07%	6.24%	6.17%
Barren land	SWRN	0.08%	0.08%	0%
Deciduous forest	FRSD	0.72%	0.72%	0%
Evergreen forest	FRSE	29.31%	29.31%	0%
Mixed forest	FRST	0.70%	0.70%	0%
Shrub/Scrub	RNGB	7.87%	7.87%	0%
Herbaceous	RNGE	4.92%	4.92%	0%
Hay/Pasture	PAST	3.51%	3.51%	0%
Agriculture	AGRR	19.15%	0.01%	-19.14%
Woody wetlands	WETF	25.61%	25.61%	0%
Emergent herbaceous wetlands	WETN	0.52%	0.52%	0%

3.5.2.2 Soil Data

The soil map was uploaded using the “Load ArcSWAT US STATSGO from disk” option. “Value” was selected in the grid field, and “ArcSWAT STATSGO” was selected automatically by the SWAT for the soil database options. The SWAT model calculated the percentage area for each soil class, then soil class codes were written by the SWAT using the “Stmuid” field. Reclassification was done using the “reclassify” feature.

Figure 8, shows that hydrologic soil groups A, B and B/D dominate the Chipola Basin while hydrologic soil groups C and D cover only a minor portion. The dominance of hydrologic soil groups A, B and B/D suggests that sandy soil is abundant and that runoff should be calculated using the Green-Ampt method rather than the Curve Number method (White et al., 2011).

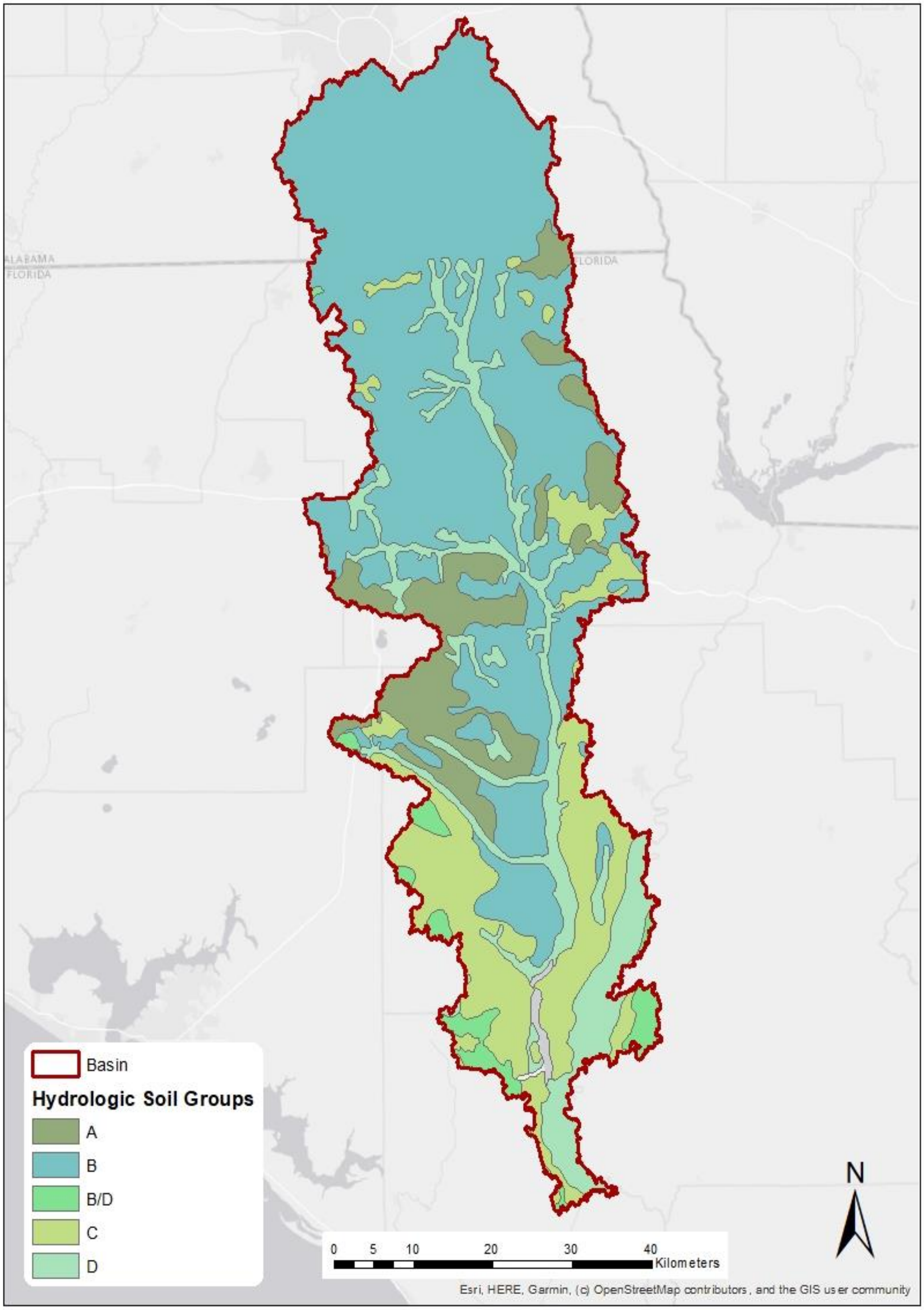


Figure 8: Hydrologic soil groups of the Chipola Basin

3.5.3.3 Slope Definition

The SWAT model automatically calculates slope percentage using a digital elevation model (DEM), which can be reclassified into multiple classes. Five slope classes were created with the first-class showing 0%-2% slope, the second class with 2%-5% slope, the third class with 5%-7% slope, the fourth class with 7%-10% slope, and the fifth class with >10% slope (Figure 9).

Following the reclassification of slope classes, "land-use, soil, and slope definition" was completed using the overlay button.

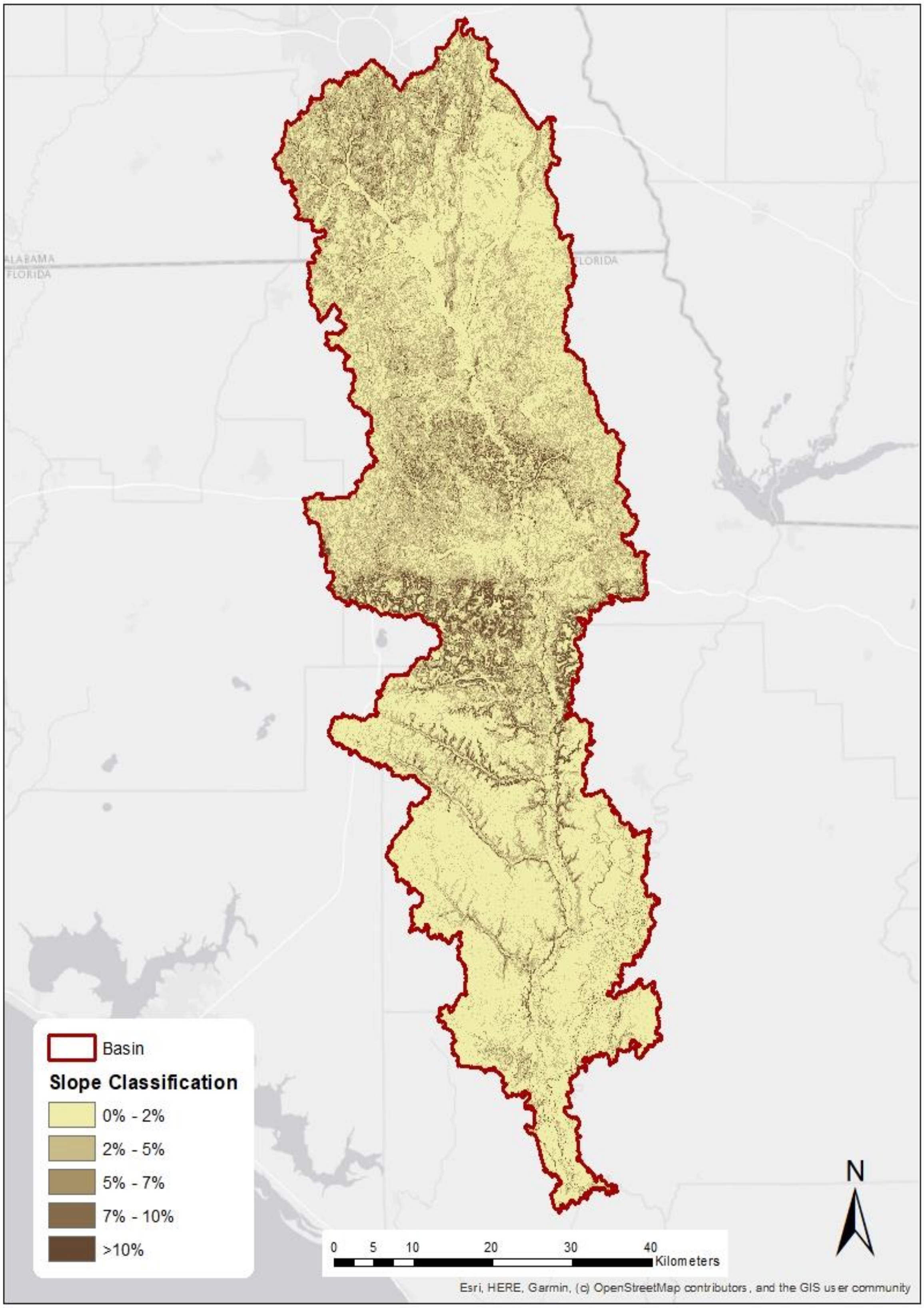


Figure 9: Slope classification of the Chipola Basin

3.5.4 HRU Definition

As a result of this study, multiple hydrologic response units (HRUs) were created and thresholds for land-use, soil, and slope classes were defined. Five percent (5%) threshold for land-use classes, ten percent (10%) threshold for soil classes, and a five percent (5%) threshold for slope classes were defined. Definitions of these thresholds suggest that any sub-basin with an area less than these identified thresholds will be reapportioned to the dominant classes, resulting in the modeling of the whole basin area (Butcher, Johnson, Nover, & Sarkar, 2014). From a total of 100 sub-basins, 2938 hydrologic response units (HRUs) were created for the baseline scenario, while 2942 HRUs were created for the future scenario. The difference in the creation of HRUs can be attributed to different land-use maps.

3.5.5 Writing Input Tables

The SWAT model required meteorological data for writing input tables. Weather data definition was selected under "writing input tables," and "WGEN_US_FirstOrder" was selected for weather generator data.

Hourly-rainfall data were uploaded for the calculation of runoff using the Green-Ampt method. The selection of the Green-Ampt method was essential due to the dominance of soil hydrologic groups A and B in the Chipola Basin. Daily temperature (min., max.), wind, solar radiation, and relative humidity data were uploaded. The respective locator files were also uploaded and "weather data definition" was completed. The availability of all the meteorological data resulted in the calculation of evapotranspiration and potential evapotranspiration using the Penman-Monteith method.

3.5.5 Write SWAT input tables

After the completion of weather data definition, SWAT database tables were selected to be written.

3.5.6 Edit SWAT input

The watershed parameters were edited, and the rainfall-runoff method was selected as "Sub-daily Rain/G&A/Hourly route (1)," and channel routing was selected as "Muskingum." After editing the watershed parameters, the basin file was rewritten.

3.5.7 SWAT Simulation

The SWAT model was simulated for monthly time-step with a warm-up period of 2 years. The warm-up period is required by the SWAT to ensure accurate results. The SWAT model was run for the period, 2015 through 2018, using the baseline scenario (first simulation) and the future scenario (second simulation). During these simulations, the land-use map was replaced, keeping all input data constant. Only land-use maps were replaced as focus of this study was analysis of the impacts of land-use change on the streamflow of the Chipola River.

The SWAT simulations produced streamflow data for both the baseline and future scenarios. After establishing the simulated streamflow, the next step was to perform a sensitivity analysis and to calibrate and validate these outputs.

3.6 Sensitivity Analysis, Calibration, and Validation

The following section discusses the sensitivity analysis, calibration, and validation of the simulated streamflow when compared with the observed streamflow data provided by the USGS gauge station "Chipola River near Altha." The sensitivity analysis, calibration, and validation were performed using the Sequential Uncertainty Fitting (SUFI-2) program in the SWAT-CUP 2019 version 5.2.1 by linking "TxtInOut" files generated by the SWAT. The SUFI-2 algorithm was selected for this study for its semi-automatic nature, common usage, and its free availability. Methodology (attached as appendix B) for SUFI-2 was given in the SWAT-CUP user manual and was followed after making some changes according to the study area. The most commonly-used statistical method, Nash-Sutcliffe efficiency (NSE), was selected as the primary objective function. The recommended split data approach was used; one-half of the data (2015-2016) was used for calibration, and the other half (2017-2018) was used for validation. Global sensitivity analysis was performed prior to performing calibration and validation to analyze the sensitivity of the parameters.

3.6.1 Global Sensitivity Analysis or AAT

Sensitivity analysis was performed using "global sensitivity analysis" in SUFI-2 for its ability to analyze the sensitivity of parameters all at once. The sensitivity analysis was performed by running 500 simulations of four default parameters (CN2, ALPHA_BF, GW_DELAY, and GWQMN) in SUFI-2.

The first parameter, runoff curve number (CN2), computes runoff depth after a rainfall event in a river basin (Liew, Arnold, & Bosch, 2005). It is associated with initial soil water conditions, soil permeability, and land-use (Cao et al., 2018). The second parameter, baseflow alpha-factor (ALPHA_BF), is the index of groundwater flow response to recharge (Malago, Pagliero, Bouraoui, & Franchini, 2015).

The third parameter, groundwater delay (GW_DELAY), is the lag between the time during which the water exits the soil profile and enters the shallow aquifer (Arnold et al., 2013). The fourth parameter, water depth in shallow aquifer required for return flow (GWQMN), is the threshold water depth in the shallow aquifer required for return flow to the stream (GWQMN) (de Andrade et al., 2019; Liew et al., 2005).

Parameters were deemed sensitive if they had a p-value ≤0.05 (Me et al., 2015). Of the four default parameters, two parameters (ALPHA_BF and GW_DELAY) were found sensitive during the student t-test. Therefore, the non-sensitive parameters (CN2, GWQMN) were eliminated.

Global Sensitivity Analysis was performed again by adding four additional parameters (GW_REVAP, ESCO, CH_N2, CH_K2) to the list of sensitive parameters to improve the calibration results. The first parameter, groundwater “revap” coefficient (GW_REVAP), controls the amount of water that leaves the shallow aquifer to the root zone. The second parameter, soil evaporation compensation factor (ESCO), adjusts the depth distribution for evaporation from the soil to measure the impact of capillary action, cracks and crusting (Liew et al., 2005).

The third sensitive parameter, channel hydraulic conductivity (CH_K2) in the main channel alluvium, and the fourth sensitive parameter, main channel Manning’s “n” (CH_N2) for channel flow, are the physical parameters that control the flow of water and sediment transport in the channel network of the basin (Arnold et al., 2013).

The added parameters were selected by “trial and error” calibration. These parameters were selected by making inferences about the hydrological processes of the study area. Five hundred simulations were run again to get the results of global sensitivity analysis. Four parameters, ALPHA_BF, CH_N2, CH_K2, and GW_DELAY, were found sensitive in this process. The non-sensitive parameters (GW_REVAP, ESCO) were eliminated. Table 5 represents the final list of sensitive parameters found in the student-t-test, along with their p-values and t-values. These parameters are arranged in descending order of their sensitivity, suggesting that ALPHA_BF is the most sensitive parameter, while GW_DELAY is the least sensitive parameter. These parameters were then used in the process of calibration and validation.

Table 3: List of Final Sensitive Parameters found in Student t-test

Sensitivity Rank	**Sensitive Parameters**	**Description**	**t-Value**	**p-Value**
1	ALPHA_BF	Baseflow alpha factor (days)	19.16	0.00
2	CH_N_2	Main channel Manning's "n"	-13.57	0.00
3	CH_K_2	Main channel effective hydraulic conductivity (mm/hr.)	-11.25	0.00
4	GW_DELAY	Groundwater delay time (days)	-3.33	0.00

3.6.2 Streamflow Calibration using SUFI-2

After performing the global sensitivity analysis, calibration of the SWAT streamflow outputs was carried out. Calibration was performed from 2015 to 2016 with a warm-up period of 2 years (2013-2014). Several iterations were run. The final iteration, with 1000 simulations, was used to obtain the results for calibration.

Table 3 presents the list of parameters, calibrated by SUFI-2, along with their minimum, maximum, and final fitted values. The final fitted values were then used to write the parameters back into the original SWAT model baseline and future scenarios.

Table 4: List of parameters calibrated by SWAT-CUP

No.	**Calibrated Parameters**	**Description**	**Min. Value**	**Max. Value**	**Final Fitted Value**
1	ALPHA_BF	Baseflow alpha factor (days)	0.4	1	0.90
2	GW_DELAY	Groundwater delay time (days)	30	77	52
3	CH_N_2	Main channel Manning's "n"	0	0.3	0.09
4	CH_K_2	Main channel effective hydraulic conductivity (mm/hr.)	7	89	79

3.6.3 Streamflow Validation using SUFI-2

After achieving the desired results for calibration, the process of validation was started. The range of parameters, and the number of simulations, were kept analogous to the range of parameters used during the process of calibration.

3.7 Writing Calibrated Parameter back to the Original SWAT Model

After the successful calibration and validation of the simulated streamflow, the final fitted calibrated parameters (See Table 4), were written back into the original SWAT models of baseline and future scenarios using the manual calibration helper in SWAT. The manual calibration helper allows users to multiply, replace, or add a threshold to a parameter. The final fitted values served as threshold values and were used to replace old values of ALPHA_BF, CH_N2, CH_K2, and GW_DELAY, and both models were rerun.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 SWAT Model Calibration, Validation, and Uncertainty Analysis

In this section, I discuss the evaluation of calibrated parameters, the evaluation of model performance, the analysis of land-use change scenarios, the evaluation of model error, and the limitations of the study.

4.1.1 Evaluation of Calibrated Parameters

The calibrated parameters, ALPHA_BF, GW_DELAY, CH_N2, CH_K2, were found to have fitted values of 0.90 days, 52 days, 0.09, and 79 mm/h, as provided in Table 4. The sensitive parameters (ALPHA_BF and GW_DELAY) control processes that happen at a greater depth (Heuvelmans, Muys, & Feyen, 2006). The most sensitive parameter ALPHA_BF has a default range of 0-1. The value of 0 indicates no connection to groundwater (Baker & Miller, 2013). ALPHA_BF, with a value of 0.90 days, indicates a rapid response to recharge due to the presence of shallow soils (Malago et al., 2015).

The next sensitive parameter, GW_DELAY, with a calibrated value of 52 days, indicates the presence of deeper aquifer in the Chipola Basin (Liew et al., 2015).

The sensitive parameter CH_N2, with a calibrated value of 0.09, indicates the presence of weeds and brush in the channel. The last sensitive parameter CH_K2, with a calibrated value of 79 mm/h, indicates that the bed material of the Chipola Basin is composed of clean sand and gravel (Arnold et al., 2013).

4.1.2 Evaluation of Model Performance

Model's goodness of fit was evaluated using Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), and percent bias (PBIAS) during the processes of calibration and validation. NSE was selected as the primary objective function at the outlet 72 of the watershed against the USGS gauge station, while R^2 and PBIAS were calculated as a secondary function.

The calibration process returned an NSE value of 0.83 and an R^2 value of 0.84, both are considered "very good" for streamflow. The model underpredicted streamflow, as depicted by the positive value of PBIAS (5.8). This underestimation may be explained due to inability of the SWAT model to capture flood peaks. However, the lower value of PBIAS indicates that the results of the calibration results of streamflow are "very good." The values of statistical analysis produced by SUFI-2 are summarized in Table 5. The hydrograph produced by SUFI-2 during calibration is provided as Figure 10. The green region shows 95% prediction uncertainty (PPU) by the simulation. The p-factor of 0.71 suggests that 71% of the observed streamflow data could be bracketed by uncertainties, and the p-factor had a value of 0.74. Both the p-factor and r-factor are considered acceptable. These results suggest that SUFI-2 captured observed data very well during the process of calibration, and that calibrated values can be used for analysis of change in streamflow due to land-use change scenarios.

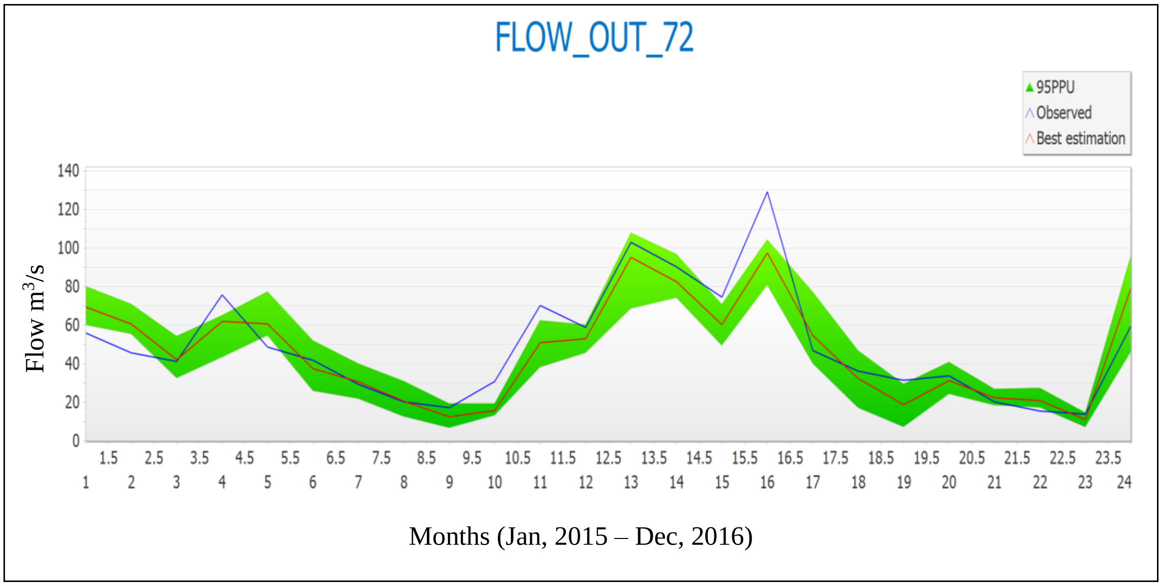


Figure 10: Calibration hydrograph

The validation process yielded an NSE value of 0.76, and R^2 yielded a value of 0.80, both of which are considered "very good" for streamflow. However, the results of PBIAS were not consistent with the calibration results, as the negative value of PBIAS indicated an overestimation of streamflow. The contrast of PBIAS between calibration and validation can be explained in terms of short data duration. Consistency of PBIAS results can be achieved by using long term streamflow data. However, a p-factor value of 0.63 and an r-factor value of 0.80 are considered adequate for the model. The low value of PBIAS also indicates that the results of the model are very good and can be used in the analysis of land-use change.

Table 5 summarizes the results of calibration and validation. The hydrograph produced by SUFI-2 during the process of validation is provided as Figure 11.

Table 5: Calibration and Validation Results of simulated streamflow

Method (SUFI2)	p-Factor	r-factor	NSE	R^2	PBIAS
Calibration (2015-2016)	0.71	0.74	0.83	0.84	5.8
Validation (2017-2018)	0.63	0.80	0.76	0.80	-11.2

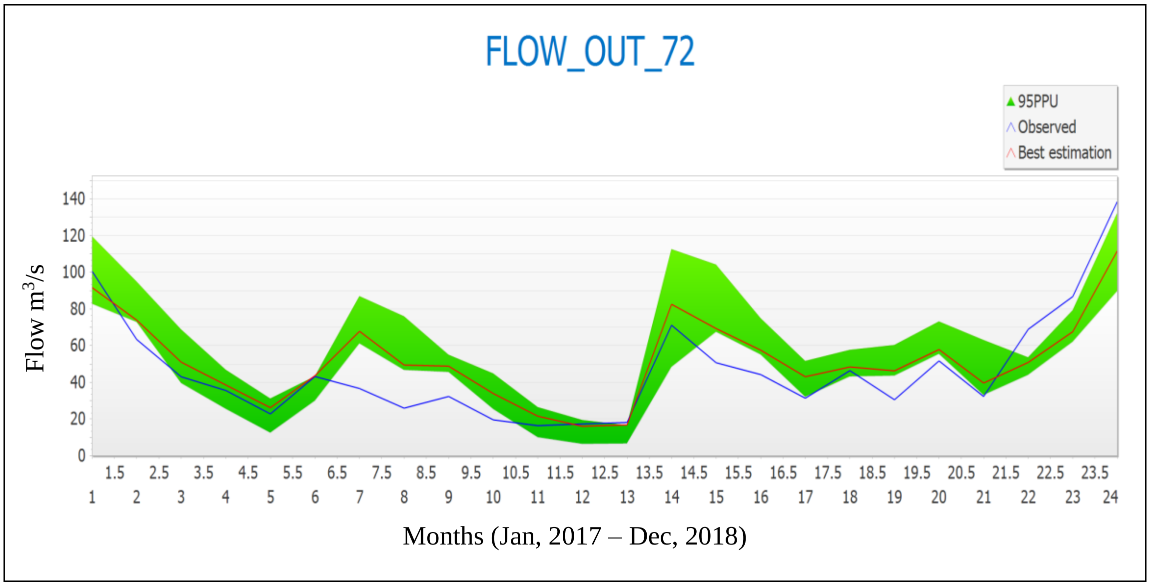
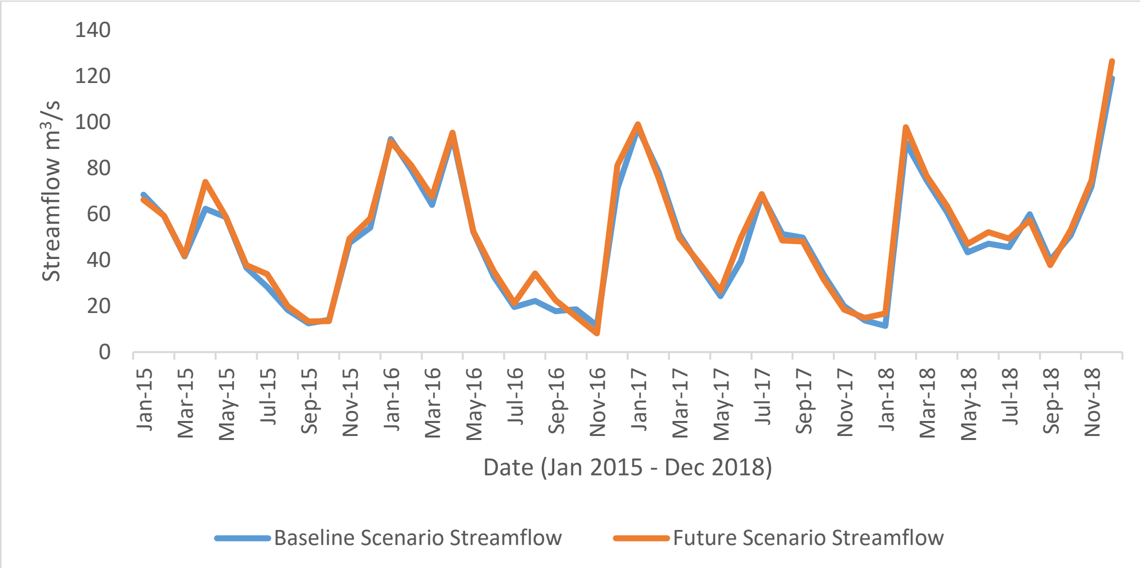


Figure 11: Validation hydrograph

4.1.3 Analysis of Land-use Change Scenarios

Streamflow calculations for the baseline scenario averaged 49.14 m^3/s. However, streamflow calculated for the future scenario averaged 51.14 m^3/s over four years. An analysis of land-use change scenarios depicted an overall average increase of 2% in the streamflow of the Chipola River over four years. The increase in streamflow can be attributed to an increase in urbanization from 6.68% to 25.82%. However, a 2% increase in the streamflow is not significant when compared to a total increase of 19.14% of urbanized area. The reason behind low streamflow increases lies in the fact that the Chipola Basin is heavily forested with a total forest cover of 29.45%. The forest cover is still 10.31% greater than the overall increased urbanized area of 19.14% and plays a role in minimizing the increased runoff from the urbanized areas.

Table 6 shows the monthly streamflow for two land-use scenarios and attached in Appendix C. Graph 1 shows a comparison of streamflow data for the baseline and future scenarios.



Graph1: Comparison of streamflow of baseline scenario and future scenarios

4.2 Evaluation of Model Error

Although the calibrated results of the SWAT model suggested that there would be a 2% increase in the streamflow of the Chipola River, it was necessary to consider the model error.

During the process of calibration, the model captured 71% of the observed data, as depicted by the p-factor (0.71) of the Nash-Sutcliffe efficiency (NSE). Model error (0.29), suggested that 29% of the observed streamflow data was not captured during the process of calibration.

Another source of the error could be in writing the calibrated parameters back into the original SWAT models using the manual calibration helper in the SWAT model. The manual calibration helper is subject to uncertainties as it does not always yield the exact results yielded by the SUFI-2. Therefore, it may be concluded that a 2% increase in the streamflow of the Chipola River may be subject to uncertainties.

4.3 Study Limitations

Several limitations were associated with this study and are detailed below.

This study required hourly-rainfall data for calculating runoff using the Green-Ampt method; however, hourly rainfall data were limited to only one weather station (Marinara). A lack of weather stations in the basin impacted the ability of the SWAT model to account for changing conditions and resulted in homogenous weather data reporting for the entire basin. Model performance could thereby be improved if hourly-rainfall data from multiple weather stations were available.

This study also simulated streamflow for only four years (2015-2018), as weather data for the year 2012 were not available. This resulted in a negative PBIAS for the calibration period (2015-2016) and a positive PBIAS for the validation period (2017-2018). This contrast of PBIAS in calibration and validation could have been avoided if weather data for the year 2012 were available. The availability of weather data for a longer duration would help to calculate streamflow for a longer duration and could therefore provide long term analysis of change in streamflow due to land-use change.

This study used the SWAT model to predict streamflow change over time, but the SWAT failed to capture the flood peaks. This failure of the SWAT model is associated with the fact that SWAT was not designed to capture flood peaks (Arnold et al., 1998a). The choice of a model capable of capturing flood peaks could further improve the results of this study.

Another limitation of this study is the non-availability of stream gauge data at the downstream of the Chipola River. Data of the stream gauge calibrated and validated for this study was located in sub-basin 72 of the Chipola Basin, suggesting that streamflow was calculated for only 72 of 100 sub-basins. Change in streamflow for the entire basin could be calculated if streamflow data were available at the downstream of the Chipola River. A stream gauge located at the downstream could give a more realistic calculation of the overall streamflow change of the Chipola River.

Lastly, this study attempted to predict future conditions of the streamflow by developing a hypothetical future land-use map. More accurate predictions be developed by using a more sophisticated technique, such as Cellular Automata (CA)-Markov chain model. CA Markov chain model is capable of producing better spatio-temporal maps of land-use change and it has been used in numerous studies (Hamad, Balzter, & Kolo, 2018). Parsa et al. (2016) used the CA-Markov model in the study area of Arasbaran biosphere reserve-Iran to create future land-use maps and reported that the model could be useful in policy design.

CHAPTER 5: SUMMARY, CONCLUSION, AND RECOMMENDATIONS

This research was performed in the study site of the Chipola River Basin using a semi-distributed model SWAT. This study had three objectives. The first objective was to quantify the potential impacts of land-use change on streamflow of the Chipola River by using an integrated hydrologic simulation model Soil and Water Assessment Tool (SWAT) in ArcGIS.

The SWAT model was run for monthly time-steps using both baseline and future scenarios for four years (2015-2018). The SWAT model did produce streamflow results for both scenarios; however, due to uncertainties associated with hydrologic models, the SWAT-simulated streamflow results could not be trusted. Therefore, it was necessary to calibrate and validate the results, which led to the second objective of this study.

The second objective of this study was to calibrate and validate the streamflow results of the SWAT model using the Sequential Uncertainty Fitting (SUFI-2) in SWAT Calibration and Uncertainty Fitting (SWAT-CUP).

SWAT streamflow results were calibrated (2015-2016) and validated (2017-2018) against observed streamflow data using the SUFI-2 algorithm in SWAT-CUP. Calibration and validation produced very good results for NSE, R^2 and PBIAS. Calibrated streamflow averaged 49.14 m^3/s and 51.14 m^3/s for the baseline scenario and for the future scenario, respectively. Results suggested that there would be an average increase of 2% in the streamflow of the Chipola River for four years (2015-2018). However, the 2% statistic was subject to uncertainties due to an associated error of 29% during the calibration process, and using manual calibration helper for writing calibrated parameters back into original SWAT models. Therefore, the null hypothesis, stating that there would be no change in the streamflow of the Chipola River due to increased urbanization, was accepted. Statistical results of calibration and validation also concluded that the SWAT model was reasonably capable of analyzing the impacts of land-use on streamflow of the Chipola River and could be applied to future studies of this basin.

Based on the results, it was also concluded that urbanization had a positive relationship with the streamflow of the Chipola River. Despite the increased urbanization in the Chipola Basin, an increase in streamflow was minimal with forest cover currently playing a positive role in controlling runoff from urban areas. An alternative land-use class assignment to future land-use map, or consideration of concentric or multi-nuclei expansion, may result in a significant increase in streamflow for the Chipola River. Developing future soil maps according to future land-use maps may also result in significant increases in streamflow for the Chipola River.

The third objective of was to give recommendations based upon results, for better land-use and water management decisions in the future. The following are the recommendations based upon the results of this study:

1) Results of this study suggest that urbanization is linked to an increase in the streamflow of the Chipola River; however, the increase is almost negligible. If land managers and planners plan for urbanization as designed in this study, Chipola River Basin would support urbanization effectively.
2) Results of this study lead to the conclusion that forest cover is playing an important role in preventing urban runoff. Therefore, it is recommended to protect the forest cover when planning for urbanization.

3) Although increased urbanization would result in minimal impact on the streamflow of the Chipola River, it is still necessary to take steps avoid this impact. Therefore, a recommendation is to design stormwater management practices that could reduce runoff from urbanized areas.
4) A final conclusion is that an alternate land-use class assignment, or alternate urbanization scheme, may result in a significant increase in the streamflow of the Chipola River. Therefore, effective land-use management and planning is recommended for the Chipola Basin in addition to designing storm water management systems and practices.

The results of this study provide a good understanding of the impacts of land-use change, specifically of urbanization, on the streamflow of the Chipola River. The outcomes of this research can help in the development of land management practices that include regulatory actions, monitoring activities, and land-use management and planning for protecting increased streamflow.

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APPENDICES

Appendix A

AL	Alabama
AAT	All-At-a-Time
ALPHA_BF	Baseflow Alpha-Factor
BF	Baseflow
BASINS	Better Assessment Science Integrating Point and Non-Point Sources
C˚	Celsius
CN	Curve Number
CH_N2	main channel Manning's "n"
CH_K2	channel hydraulic conductivity
DHSVM	The Distributed Hydrology Soil Vegetation Model
DEM	Digital Elevation Model
ESCO	soil evaporation compensation factor
FL	Florida
FAWN	Florida Automated Weather Network
GLUE	Generalized Likelihood Uncertainty Estimation
GW_DELAY	groundwater delay

GW_REVAP	groundwater "revap" coefficient
GIS	Geographic Information Systems
Ha	Hectares
HRUs	hydrological response units
HUC8	Hydrologic unit code 8
HYLUC	Hydrological Land-use Change
IHACRES	Identification of unit Hydrographs And Component flows from Rainfall, Evaporation, and Streamflow data
km^2	square kilometers
LULC	Land-use land cover
mm	Millimeter
m/s	meter per second
m^3/s	Cubic meter per second
MJ/m2	megajoule per square meter
MIKE-SHE	European Hydrological System Model
MCMC	Markov chain Monte Carlo
NSE	Nash Sutcliffe efficiency
NAM	Nedbor-Afstromnings Model
NLCD	National Land Cover Database
OAT	one-at-a-time
PBIAS	percent bias
PSO	Particle Swarm Optimization
ParaSol	Parameter Solution

PRMS	Precipitation Runoff Modelling System
R^2	coefficient of determination
RHESSys	Regional Hydro-Ecological Simulation System
SUFI-2	Sequential Uncertainty Fitting-2
SWIM	Soil and Water Integrated Model
SLURP	Simple Lumped Reservoir Parametric
SHETRAN	Systeme Hydrologique Europeen Transport
SW	Stormflow
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Procedures
TAC-D	Tracer Aided Catchment *model* – Distributed
TOPLATS	TOPMODEL-Based Land surface-atmosphere Transfer Scheme
TIGER	Topologically Integrated Geographic Encoding and Referencing
USGS NHD	United States Geological Survey National Hydrography Dataset
USEPA	United States Environmental Protection Agency
USGS NED	United States Geological Survey National Elevation Dataset
USGS	United States Geological Survey
UTM	universal transverse Mercator
USDA	United States Department of Agriculture
WASIM	Water balance-Simulation Model

Appendix B

Procedure for SWAT-CUP Calibration

SUFI-2 Project setup:

- Start
- New
- Next
- Described “TxtInOut” location
- Next
- SWAT version described “2012”
- Architecture Processor described “32 bit”
- Project type described “SUFI-2”
- Next
- Project name and location described

After setting up the project, following steps were followed:

Calibration Inputs

- **Par_inf.txt:** used to add parameters and define their min and max values. Number of parameters and no. of desired simulations was added. Such as no. of parameters “4”, no. of simulation “1000”.
- **“SUFI2_swEdit.def” file:** Starting and ending no. of simulations were defined. Such as starting no. of simulation “1”, ending no. of simulation “1000”.
- **“File.Cio” file:** Following changes were made in this file:

NYBR = 4, IYR = 2013, IDAF = 1, IDAL = 366, NYSKIP = 2

Where,

NYBR = Number of years simulated

IYR = Beginning year of simulation

IDAF = Beginning Julian day of simulation

NYSKIP = number of years to skip output printing/summarization

Observation

- **"Observed_rch.txt" file:** Following changes were made in this file:

number of observed variables defined = 1

FLOW_OUT_72 was defined to calibrated sub-basin 72

No. of data points = 24

Following observed data was copied:

1	FLOW_OUT_1_2015	55.98
2	FLOW_OUT_2_2015	45.70
3	FLOW_OUT_3_2015	41.26
4	FLOW_OUT_4_2015	75.78
5	FLOW_OUT_5_2015	48.70
6	FLOW_OUT_6_2015	41.85
7	FLOW_OUT_7_2015	29.39
8	FLOW_OUT_8_2015	20.29
9	FLOW_OUT_9_2015	17.29
10	FLOW_OUT_10_2015	30.89
11	FLOW_OUT_11_2015	70.28
12	FLOW_OUT_12_2015	58.90
13	FLOW_OUT_1_2016	103.02
14	FLOW_OUT_2_2016	90.30
15	FLOW_OUT_3_2016	74.59
16	FLOW_OUT_4_2016	129.24
17	FLOW_OUT_5_2016	46.89
18	FLOW_OUT_6_2016	36.22
19	FLOW_OUT_7_2016	31.49
20	FLOW_OUT_8_2016	33.81
21	FLOW_OUT_9_2016	20.27
22	FLOW_OUT_10_2016	15.53
23	FLOW_OUT_11_2016	13.91
24	FLOW_OUT_12_2016	59.52

Extraction

- **Var_file_rch.txt**

One variable was defined “FLOW_OUT_72.txt”

- **SUFI2_extract_rch.def file:** Following changes were made in this file
- number of variables to get = 1
- total number of reaches (subbasins) in the project = 100
- number of reaches (subbasins) to get for the first variable = 1
- reach (subbasin) numbers for the first variable = 72
- beginning year of simulation not including the warm up period = 2015
- end year of simulation = 2016
- time step (1=daily, 2=monthly, 3=yearly) = 2

Objective Function

- **Observed.txt file**
- number of observed variables = 1
- Objective function type = 5 (for NSE)
- this is the name of the variable and the subbasin number to be included in the objective function = FLOW_OUT_72
- Number of data points = 24
- Observed data was copied again in this file.
- **Var_file_name.txt**
    - FLOW_OUT_72.txt
- “Save All”
- “Calibrate”

- “Execute all”
- Pressed “Y”, and enter
- SUFI2_pre.bat finished quickly
- Process finished, close the window? Pressed ok
- Start the execution of SUFI2_Run.Bat. Pressed ok.
- After the process is finished. Close the window, pressed ok.
- Start the execution of SUFI2_post.Bat. Pressed ok.
- SUFI2_post.bat finished quickly
- Process finished, close the window? Pressed ok
- Do you want to save this iteration? Pressed yes and named the iteration with the desired name.
- Process of calibration was complete. Read outputs from Summary_stat.txt file.

Procedure for SWAT-CUP Validation

Procedure for validation is similar to calibration. Except following changes were made in the following files:

- **File.cio**

  NBYR = 6

  IDAL = 365

  NYSKIP = 4

- **“Observed_rch.txt” file:**

Following observed data for years 2017-2018 was added

1	FLOW_OUT_1_2017	100.58
2	FLOW_OUT_2_2017	63.40
3	FLOW_OUT_3_2017	43.04
4	FLOW_OUT_4_2017	35.59
5	FLOW_OUT_5_2017	22.81
6	FLOW_OUT_6_2017	43.21
7	FLOW_OUT_7_2017	36.67
8	FLOW_OUT_8_2017	25.96
9	FLOW_OUT_9_2017	32.34
10	FLOW_OUT_10_2017	19.58
11	FLOW_OUT_11_2017	16.41
12	FLOW_OUT_12_2017	17.38
13	FLOW_OUT_1_2018	18.17
14	FLOW_OUT_2_2018	71.16
15	FLOW_OUT_3_2018	50.69
16	FLOW_OUT_4_2018	44.26
17	FLOW_OUT_5_2018	31.38
18	FLOW_OUT_6_2018	46.41
19	FLOW_OUT_7_2018	30.55
20	FLOW_OUT_8_2018	51.71
21	FLOW_OUT_9_2018	32.31
22	FLOW_OUT_10_2018	68.92
23	FLOW_OUT_11_2018	86.79
24	FLOW_OUT_12_2018	138.58

- **SUFI2_extract_rch.def file**

Beginning year of simulation not including the warm up period = 2017

End year of simulation = 2018

- **Observed.txt file**

Data for years 2017-2018 was added

Appendix C

Date	Observed streamflow (m^3/s)	Baseline Scenario Streamflow (m^3/s)	Future Scenario streamflow (m^3/s)
Jan-15	55.98	68.38	66.23
Feb-15	45.70	59.08	59.2
Mar-15	41.26	41.55	41.83
Apr-15	75.78	62.25	74.05
May-15	48.70	58.71	58.9
Jun-15	41.85	36.73	37.88
Jul-15	29.39	28.42	33.93
Aug-15	20.29	18.36	20.02
Sep-15	17.29	12.48	13.27
Oct-15	30.89	14.08	13.44
Nov-15	70.28	47.49	49.42
Dec-15	58.90	54.09	58.15
Jan-16	103.02	92.59	91.52
Feb-16	90.30	79.3	81.24
Mar-16	74.59	64.05	67.55
Apr-16	129.24	93.73	95.49
May-16	46.89	52.3	52.37
Jun-16	36.22	32.86	35.21
Jul-16	31.49	19.61	21.25
Aug-16	33.81	22.29	34.16
Sep-16	20.27	17.76	22.5
Oct-16	15.53	18.68	15.42
Nov-16	13.91	11.53	8.141
Dec-16	59.52	71.13	81.24
Jan-17	100.58	97.5	99.04
Feb-17	63.40	78.38	75.62
Mar-17	43.04	51.34	49.69
Apr-17	35.59	37.31	38.43
May-17	22.81	24.33	26.69
Jun-17	43.21	39.57	49.76
Jul-17	36.67	68.25	68.67
Aug-17	25.96	51.3	48.52
Sep-17	32.34	49.83	48.14
Oct-17	19.58	33.78	31.67
Nov-17	16.41	19.95	18.51
Dec-17	17.38	13.72	14.85
Jan-18	18.17	11.39	16.76
Feb-18	71.16	91.16	97.85

Mar-18	50.69	74.64	76.69
Apr-18	44.26	60.85	63.42
May-18	31.38	43.38	47.05
Jun-18	46.41	47.19	52.18
Jul-18	30.55	45.62	49.33
Aug-18	51.71	59.93	57.32
Sep-18	32.31	39.96	37.86
Oct-18	68.92	50.81	53.16
Nov-18	86.79	72.05	74.66
Dec-18	138.58	119	126.5
Average	48.31	49.14	51.14