IMPACT OF WOOD PELLET PRODUCTION ON WATER AVAILABILITY: A CASE STUDY FROM NORTHEAST OCONEE RIVER BASIN IN GEORGIA

by

SURENDRA SHRESTHA

(Under the Direction of Puneet Dwivedi)

ABSTRACT

The export of wood pellets from southeastern United States to the European Union is continuously increasing. It is quite likely that the area under forest cover will increase to meet the rising demand for wood pellets at the expense of other competitive land uses in southeastern states. This research analyzes the impact of an increase in forest area on the hydrology of a local watershed located in the Northeastern Oconee River Basin in Piedmont Georgia. Using spatial modeling, suitable sites for loblolly pine (*Pinus taeda*) production were determined. The results of suitability analysis were merged with historical records of land use change to project an increase in area under loblolly pine for 2016, 2021, and 2026. Then, a hydrological model (SWAT) was used to predict any changes in water discharges till 2028 for 14 scenarios in the presence of evolving land use changes. Results suggest that changes in land use in conjunction with variable climatic conditions could decrease or increase streamflow by up to 29% and 31% and evapotranspiration by up to 3% and 4%, respectively. Results of this study improve our understanding of sustainability of wood pellet production in southeastern states.

INDEX WORDS: Wood Pellets, Land Use Change, Suitability Analysis, Watershed Hydrology, Sustainability

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

In 2007, the European Union policy makers decided to reduce carbon emissions of the energy sector to 20% below 1990 levels by 2020 (European Commission, 2015a; ReCS, 2016). This policy was agreed and legislated by the Council and Parliament through the ‘Climate and Energy Package’ by the end of 2008 (European Commission, 2015a). To obtain the set target of carbon reduction, the European Union decided to meet 20% of its energy consumption from different renewable energy sources, including solid biomass by 2020 (European Commission, 2012, 2015a). The European Union’s Emissions Trading System has set a cap on the total amount of greenhouse gases that the factories, companies, and other installations in the system can emit. Under this cap, companies can trade emissions allowances with one another (European Commission, 2015b). As a result, several power companies in the European Union have decided to use wood pellets to replace the coal as a means of producing heat and electricity (Goetzl, 2015; IER, 2015; Zeller, 2015) so that they can sell their carbon allowances to other companies who are falling short in meeting their carbon reduction targets.

The European Union is importing wood pellets from the southeastern United States and Pacific Canada to meet the total demand of wood pellets for electricity generation (Galik & Abt, 2015). As a result, wood pellet production is continuously increasing in the United States, in general and in southeastern states, in particular (Wong & Bredehoeft, 2014). For example, the production capacity of wood pellets in the United States has increased by more than four-fold from less than 3 million metric tons in 2008 to over 12 million metric tons in 2014 (Goetzl, 2015).

Similarly, the export of wood pellets from the United States to the European Union and rest of the world has increased from 1.45 million metric tons in 2012 to 2.9 million metric tons in 2013 (Figure 1.1) i.e., an increment of more than 100% in just a year (Wong & Bredehoeft, 2014). The southeastern states are producing about 99% of total wood pellets exported from the United States to the European Union (Wong & Bredehoeft, 2014).

Though the carbon saving potential of wood pellets is controversial (New York Times, 2015), there are several studies that suggest that the use of wood pellets as a source of energy could save carbon emissions relative to the electricity derived from fossil fuels. For example, Roeder et al. (2015) examined the carbon savings from the combustion of imported wood pellets from forest residues to generate electricity relative to coal-fired electricity generation in the United Kingdom. It was found that electricity derived from imported wood pellets saved about 83% of carbon emissions related to coal-fired electricity. Similarly, Dwivedi et al. (2011) assessed the global warming impact of wood pellets in two cases: 1) when the wood pellets were exported from the southern United States for electricity production in The Netherlands, and 2) when the same wood pellets were used in Florida for electricity generation instead of export. The global warming impact of wood pellets in both cases was assessed using the life cycle assessment. It was found that about 73% of carbon emissions were saved for every unit of electricity generated in The Netherland from the imported wood pellets relative to the coal-based electricity. This value was found to be 82.4% when the wood pellets were utilized within the Florida. Moreover, a recent study by Dwivedi et al. (2014) reported that at least 50% carbon emissions could be saved when imported wood pellets were used for electricity generation in the United Kingdom relative to a unit of grid-based electricity. Similarly, Wang et al. (2015) found that the relative savings in carbon emissions from wood pellets used for electricity generation and imported from the southeastern states could be as high as 85% compared to coal-based electricity after accounting for not only direct carbon emissions related with wood pellets but also carbon emissions related with indirect market and land use effects induced by changes in prices of forest and agricultural products over the 2007–2032 period. These existing studies clearly indicate that significant amounts of carbon emissions could be saved from transatlantic wood pellet trade.

Utilization of forest biomass to meet the demand for wood pellet has the potential to influence current forest management regimes, profitability of forest landowners, and traditional wood consuming sectors like paper mills (Abt et al., 2014). Among the southeastern states, Georgia, Alabama, and Florida have large forest resource base, as about 31% of total timberlands i.e., about 19 million acres in these states are planted pine acres mostly owned by private landowners (USDA Forest Service, 2011). In the last decade, the total area under pine plantations decreased in Georgia and Florida due to lower round wood prices (USDA Forest Service, 2011). However, prices of pulpwood are expected to rise with the increasing demand of pulpwood for manufacturing of wood pellets. These rising pulpwood prices will encourage existing landowners to plant pine on their forestlands (Abt et al., 2012). As a result, it is very likely that more land will come under forestry from other competing land bases especially in Georgia, Florida, and Alabama as these states produce about 31.2% of total pulpwood in the country (Piva et al., 2014).

Land use change is considered a primary factor in the context of global environmental change (Houghton, 1994). Field based studies provide detailed descriptions of interactions between several environmental variables and land use changes. However, field studies alone are not sufficient for the predictions of future pattern of change (Petit et al., 2001). Land use change can be best predicted through modeling using the tool of Geographic Information System (GIS), as it takes into account the linkages between the land use change and dynamic forces behind it.

Several studies have used GIS to focus on various aspects of sustainable bioenergy development. For example, Ranney and Cushman (1980) established a link between woody biomass productivity and land availability for biomass production from short rotation woody crops in the southern United States. Similarly, Graham et al. (2000) developed a GIS based model for allocation of suitable sites for switchgrass (*Panicum virgatum*) in 11 southern states based on the production cost and other factors like soil erosion, nutrient loss, runoff, and pesticide movement off the site. Recently, Nepal et al. (2014) developed a spatially-explicit model to identify the amount and spatial distribution of economically feasible sites for establishing dedicated energy crops under various market and policy scenarios in Kentucky. However, no woody species were included in any of these analyses.

Monitoring the spatial patterns of land use change is essential to understand its impact on people and resources simultaneously. This is especially true for water resources as land use changes could significantly affect hydrology of a watershed (Robertson et al., 2011) due to changes in evapotranspiration and infiltration rates (Trimble et al., 1987; Bosch et al., 2006) leading to changes in water demand or supply at the same time. The increase or decrease in water demand coupled with changes in traditional land uses could affect water quality as well (DeFries & Eshleman, 2004).

A number of studies have established the relation between land cover change and watershed hydrology (Grace, 2005; Schoonover et al., 2006; Raini, 2009; Cruise et al., 2010; Isik et al., 2013; Öztürk et al., 2013; Wagner et al., 2013) suggesting that changes in land cover to forests, because of increased evapotranspiration, can lead to significant decrease in streamflow (Bosch et al., 2006). For example, Trimble et al. (1987) studied the impact of reforestation on streamflow in 10 large and populated contiguous river basins with a total area of 54,020 km² in

Alabama, Georgia, and South Carolina. Those river basins had undergone 10 to 28% of the land use change from cropland to forest during the period 1919 to 1967. This study reported a 4 to 21% decrease in annual stream discharge and attributed this decrease to increased forest cover. Grace (2005) reviewed several studies which focused on watersheds located in 13 southern states to understand the impact of active forest management on water availability. It was found that water yield increased in all watersheds where harvesting sites were present and ranged from 69 to 210 mm per year. Cruise et al. (2010) assessed the impact of changing landscapes on the hydrology of streams in the watersheds (< 2500 km^2) of Alabama, Georgia, and Tennessee. Landsat Thematic Mapper data was used to determine the land cover change at three points in time - 1980, 1990, and 2010. Large river basins (e.g., Alabama River basin, Tennessee River basin, and Chattahoochee River basin) were not included in the analysis to detect hydrological impacts of land use changes at a finer scale. A total of 12 watersheds that ranged from 2,292 km^2 to 166 km^2 were selected. Results showed that the watersheds with largest land cover change from agriculture to forestry (20% or more) have significant reduction in the streamflow (Cruise et al., 2010).

Isik et al. (2013) developed a hybrid model based on Artificial Neural Networks and Soil Conservation Service Curve Number to predict changes in daily streamflow in response to changing land use and soil characteristics. The study was done in 10 watersheds of Harris and Muscogee counties of Georgia where watershed sizes ranged from 3.6 to 26.2 km^2. Land use, hydrological soil groups, and climate variables such as precipitation and temperature were used in the model in order to replicate the hydrological response of a watershed (Isik et al., 2013). The model predicted increased average streamflow for pasture and urban dominant scenarios while more stable hydrology with decreased streamflow for forest dominated scenarios (Isik et al., 2013).

These studies indicate that if certain land uses move to forest, it could impact watershed hydrology with decreased streamflow due to an increase in interception and evapotranspiration.

This study was carried out to investigate the impact of demand for wood pellets on land use change and then to determine impact of changed land use on the hydrology of a local watershed located in the Northeastern part of the Oconee River Basin in Piedmont Georgia. The main aim of this research is to fill a critical gap in our understanding on Bioenergy-Land Use Change-Water Availability nexus in the presence of climatic variability. This study was done in two phases which are discussed in subsequent chapters. First, a GIS based suitability model was developed to identify suitable sites for loblolly pine (*Pinus taeda*) – a key forest species in the southern United States covering an area of 229,420 km^2 (Oswalt et al., 2014). We also determined the future rate of land cover change based on the historical rate of change, which was then integrated with the outputs of suitability analysis to project land use changes in the selected watershed for years 2016, 2021, and 2026. Second, the impact of land use and climate change on the local hydrology was evaluated using 14 sub-scenarios under four land use and climate change scenarios: 1) Base Scenario (BAU), 2) Land Use Change only (LU), 3) Climate Change only (CC), and 4) Land Use and Climate Change combined (LUCC). This study identified suitable sites for loblolly pine plantation using suitability analysis in ArcGIS. Results showed that both land use and climate change significantly affected the surface hydrology (evapotranspiration, ground water, runoff, and streamflow) of the watershed. Results of this study will help us in understanding the sustainability of wood-based energy sources, in general or wood pellets, in particular in a comprehensive manner in the context of southeastern United States.

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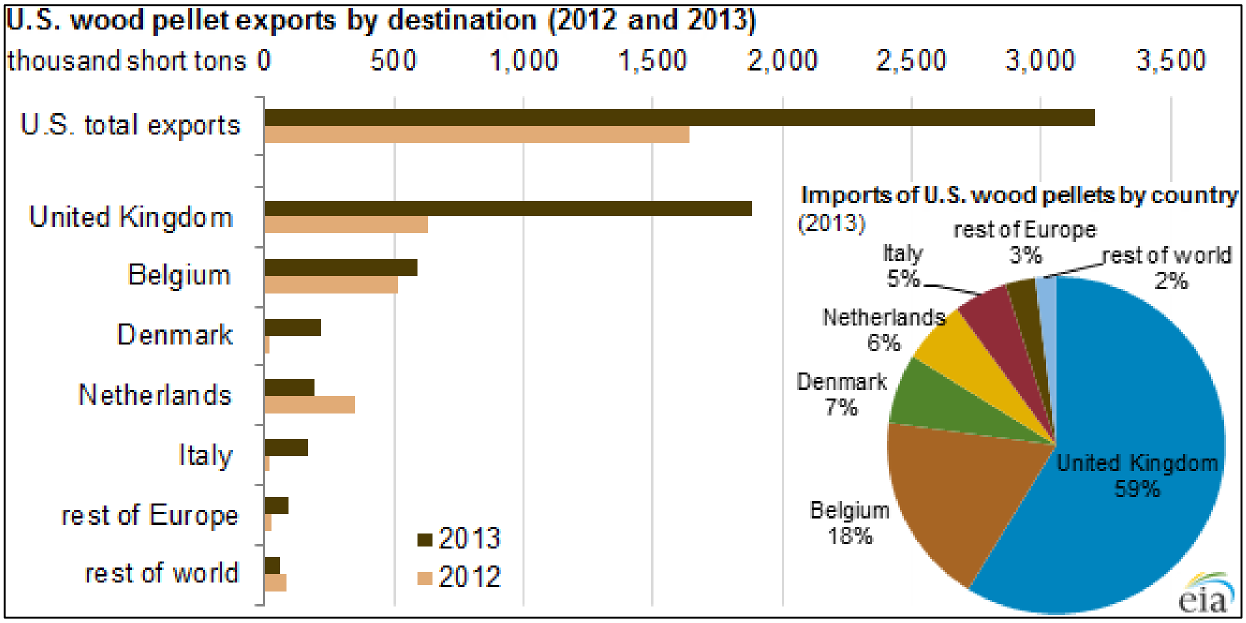

Figure1.1: United States wood pellet exports by destination, 2012 and 2013.

CHAPTER 2

INTEGRATING SITE SUITABILITY ANALYSIS WITH HISTORIC LAND COVER DYNAMICS FOR DETERMINING FUTURE LAND USE CHANGES IN THE CONTEXT OF SUSTAINABLE BIOENERGY DEVELOPMENT

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Abstract

The export of wood pellets from southeastern states to the European Union is continuously increasing. In order to meet the growing demand for wood pellets, it is quite likely that more land will move into forestry from other competitive land uses. This study determines the impact of an increase in demand for wood pellets on land use changes. We performed suitability analysis to identify suitable sites for loblolly pine plantation in Northeast Oconee River Basin land cover. The results show that 932 km^2 of land (38% of the watershed) was suitable for loblolly pine plantation. We integrated suitability analysis with the historical rate of land use change to project an increase in area under loblolly pine for 2016, 2021, and 2026. The land use conversion relative to 2011 were 3%, 5%, and 6.6% for years 2016, 2021, and 2026 respectively. This model was developed as a general tool and can be applied to any spatial scale and various geographical regions at a relatively short time.

INDEX WORDS: wood pellets, land use change, suitability analysis, southeastern US

Introduction

In 2007, the European Union policy makers introduced new energy policy goals to reduce greenhouse gas (GHGs) emissions of the energy sector to 20% below 1990 levels by 2020 (European Commission, 2015a; ReCS, 2016). This policy was agreed and legislated by the Council and Parliament through the 'Climate and Energy Package' at the end of 2008 (European Commission, 2015a). A policy target i.e., sourcing 20% of total energy consumed from different renewable energy sources by 2020 was set (European Commission, 2012, 2015a). The European Union emissions trading system has set a cap on the total amount of certain GHGs that the factories, companies, and other installations in the system can emit. Under this cap, companies either receive or buy the emission allowance and can trade such allowances with one another (European Commission, 2015b). As a result, several power companies in the European Union have decided to use wood pellets to replace the coal as a means of producing heat and electricity (Goetzl, 2015; IER, 2015; Zeller, 2015) so that they can sell their carbon allowances to other companies who are falling short in meeting their reduction target.

The European Union has become a net importer of wood pellets to meet the growing demand for electricity generation from solid biomass (Lamers et al., 2012; Lamers et al., 2015). The part of the total wood pellets required by the European power companies has been fulfilled by imports from the southeast United States and western Canada (Galik & Abt, 2015). As a result, wood pellet production is continuously increasing in the United States, in general and in southeastern states, in particular (Wong & Bredehoeft, 2014). For example, the production capacity of wood pellets in the United States has increased by more than four-fold from less than 3 million metric tons in 2008 to over 12 million metric tons in 2014 (Goetzl, 2015). Similarly, the wood pellet export from the United States to the European Union and rest of the world has increased from 1.9 million metric tons in 2012 to 3 million metric tons in 2013 and 4 million metric tons in 2014 (Figure 2.1) i.e., an increment of more than 100% in just two years (EIA, 2015). The southeastern states are producing about 99% of the total wood pellets exported from the United States to various countries in the European Union (Wong & Bredehoeft, 2014).

The majority of the existing studies have analyzed the potential reduction in the GHG emissions due to the use of wood pellets as a source of electricity generation (Dwivedi et al., 2011; Abt et al., 2012; Dwivedi et al., 2014; Galik & Abt, 2015; Roeder et al., 2015; Wang et al., 2015). Dwivedi et al. (2011) assessed the global warming impact of wood pellets in two cases: 1) when the wood pellets were exported from the Southern United States for electricity production in The Netherlands and 2) when the same wood pellets were used within Florida for electricity generation instead of export. The global warming impact of wood pellets in both cases was assessed using the life cycle assessment. It was found that about 73% of GHG emissions were saved for every unit of electricity generated in The Netherland from the imported wood pellets relative to the coal-based electricity. This value was found to be 82.4% when the wood pellets were utilized within the Florida. Similarly, Dwivedi et al. (2014) conducted research on the potential carbon savings of transatlantic wood pellet trade using a simulation-based landscape approach combined with life cycle assessment. It was reported that at least 50% GHG emissions could be saved when imported wood pellets are used for electricity generation in the United Kingdom relative to a unit of grid-based electricity. Moreover, the recent study conducted by Galik and Abt (2015) on the GHG savings related with exported wood pellets from the US South reported that the use of pellets can achieve over 100% savings in cumulative emissions compared to coal after accounting for induced land use changes. Recently, Wang et al. (2015) reported that the relative savings of GHG emissions from wood pellets used for electricity generation and imported from the southeastern states could be as high as 85% compared to that of coal-based electricity after accounting for not only direct life-cycle GHG intensity of pellets but also for the accompanying indirect market and land use effects induced by changes in prices of forest and agricultural products over the 2007–2032 period. The majority of existing studies clearly indicate that significant amounts of GHG emissions could be saved from transatlantic wood pellet trade.

Utilization of forest biomass to meet the demand for wood pellets has potential to influence current forest management regimes, profitability of forest landowners, and traditional wood consuming sectors like paper mills (Abt et al., 2014). Among the southern states, Georgia, Alabama, and Florida have large forest resource bases with more than 31% of the timberland in this region in pine plantations (mostly loblolly pine), the majority of which are owned by private owners (USDA Forest Service, 2011). In the last decade, the total area under pine plantations decreased in southeastern states due to lower round wood prices (USDA Forest Service, 2011). Similarly, between 2008 and 2010, the pulpwood production in most of the southeastern states decreased considerably. For example, pulpwood production in Georgia decreased by 1%, whereas it decreased by 4, 5, and 2% in Alabama, North Carolina, and South Carolina respectively (Piva et al., 2014). However, with the increasing demand for pulpwood to manufacture wood pellets for meeting foreign demand, prices of pulpwood are expected to rise which will probably encourage existing landowners to plant pine (Abt et al., 2012). As a result of which, it is very likely that more land will come under forestry from other competing land uses especially in Georgia, Florida, and Alabama as these states together produce about 31.2% of the total pulpwood in the country (Piva et al., 2014)

Land use change is considered to be a primary factor in the study of global environment change (Houghton, 1994). Field based studies provide a detailed description of the interaction between environmental variables and the driving forces of land use change. However, field studies alone are not sufficient for predictions of the future pattern of change (Petit et al., 2001). To better understand and predict the change process, it is essential to monitoring the spatial patterns of land use. Land use change can be best predicted through modelling using the tool of Geographic Information System (GIS), as it takes into account the existing link between the land use change and dynamic forces behind it. Several ecologists and conservation scientists use GIS based models that use known locations to predict habitat suitability and the associated distribution of the species (Evans et al., 2010).

Ranney and Cushman (1980) established a link between woody biomass productivity and land availability for biomass production from short rotation woody crops in the southern United States. Similarly, Graham et al. (2000) developed a GIS based model for allocation of suitable sites for switchgrass (*Panicum virgatum*) in 11 southern states based on production cost and other factors like soil erosion, nutrient loss, runoff, and pesticide movement off the site. Moreover, Evans et al. (2010) developed a suitability modeling approach to identify suitable areas for biofuel feedstock production for two major US biofuel crops, corn and switchgrass based on the use of two presence-only species distribution models: Maxent and Support vector machines. Analysis indicated that both modeling approaches predicted county-scale increases in corn production from 2006 to 2007 well. It was also concluded that presence-only models are powerful tools to predict the relative land suitability for biofuel feedstock production across geographical regions and may also provide important insight into increased biofuel demand related land use change patterns (Evans et al., 2010). Recently, Nepal et al. (2014) developed a spatially-explicit model to identify the amount and spatial distribution of economically feasible sites for establishing dedicated energy crops under various market and policy scenarios in Kentucky. However, no woody species were included in any of these analysis.

In this study, we developed a GIS based suitability modeling to identify sites for growth of loblolly pine (*Pinus taeda*) based on different suitability factors i.e. slope (Slope), distance to road (DisRoad), distance to city (DisUrban), distance to water (DisWater), and distance to evergreen forest (DisFor). We also determined the future rates of change based on historical conversion rates and global demand of wood pellets, which were then combined with the suitability model to simulate the potential land use change in space and time.

Study Area

The selected watershed is located in the North-East Oconee River Basin. The selected watershed occupies about 2438.5 km^2 i.e. 17.7% area of the Oconee River Basin (13798 km^2). The selected watershed includes 10 counties i.e., Hall, Gwinnett, Walton, Jackson, Barrow, Oconee, Oglethorpe, Clarke, Banks, and Madison (Figure 2.2). The selected watershed has three wood-consuming mills including a recently announced wood pellet mill which will consume about a million short ton of small-diameter wood products and mill residues to manufacture pellets for export purposes. The mean slope and elevation of the selected watershed is 4.36° (σ = 3.02°) and 248.2 m (σ = 45.48 m), respectively. In 2011, the major land cover types present in the selected watershed were Deciduous Forests, Pasture/Hay, Developed-Open Space, Evergreen Forest, and Developed-Low Intensity occupying 34.8, 2.1, 11.4, 7.7, and 7.1% of total land area, respectively (Table 2.1). For all land cover types which occupied more than 5% of total land in 2001, the maximum increase is observed for land cover types Developed – Low Intensity (26.3%) followed by Developed – Open Space (17.6%) between 2011 and 2001. For the same time period, maximum decrease is observed for Evergreen Forest (12.6%) followed by Deciduous Forest (7.3%) and Pasture/Hay (6.9%). Table 2.2 indicates that 2.2, 2.5, 2.3, and 5.6% of total area under Deciduous Forest, Evergreen Forest, Mixed Forest, and Shrub/Scrub has moved into Developed-Open Space since 2001 indicating that the majority of the first level of urban development is primarily on former forestlands in the selected watershed. This is also true for Grassland/Herbaceous and Pasture/Hay land cover types located in the watershed. However, the total area under agricultural lands has not changed very much between 2001 and 2011.

Materials and Methods

We used suitability analysis to identify the potential sites for loblolly pine plantation. We also determined the historical rate of change for different land uses. Finally, we integrated the suitability analysis and historical rate of change in land use in a dynamic model to determine the land use for 2016, 2021, and 2026 in the presence of additional demand of loblolly pine due to recently announced wood pellet mill in the watershed. Figure 2.3 shows the schematic flow of the suitability analysis and land use change modeling.

Data Source

The data inputs for suitability analysis include Digital Elevation Model (DEM), National Land Cover Data (NLCD), Road layer, and Wood mills layer. These GIS dataset layers were obtained from different sources (Table 2.3). The output of the suitability analysis was used for predicting the land use change.

Suitability Modeling

Suitability modeling involves calculating suitable sites based on several drivers of change. The suitability model involved four steps: 1) identify suitability factors, 2) Scale suitability factors, 3) weight suitability factors, and 4) calculate Overall Suitability Index (OSI).

1. Identifying suitability factors for suitability analysis

The starting point of suitability analysis was to define the characteristics that make the land suitable for loblolly pine plantations. For this analysis, we considered five driving factors which are given below:

1. Distance from the existing Evergreen Forest (DisFor),
2. Distance from the water resources (DisWater),
3. Distance from the major roads and highways (DisRoad),
4. Distance from the existing developed areas such as major towns (DisUrban), and
5. Slope (Slope)

2. Scaling the Suitability Factors

We scaled and obtained normalized Index (NI) value for each pixel within each suitability factor from 0 to 1 using the following equations:

$$\text{Normalized Index (NI)} = (P_{Abs} - P_{Min})/(P_{Max} - P_{Min})$$

Where, P_{Abs} = Absolute pixel value and P_{Max} and P_{Min} are maximum and minimum pixel value for the corresponding favorable classes.

3. Ranking and Weighting Suitability Factors

To establish a logical assessment of optimal suitability, certain factors were considered to be more important than others. The suitability factors were weighted based on how important they were to the overall analysis. These were the subjective rankings and weights based on judgement and knowledge of the area.

4. Overall Suitability Index (OSI)

Overall Suitability Index (OSI) was calculated by integrating the integrated index of a variable with their corresponding weight and was given by following equation:

$$OSI = NI_{DisFor} \text{ X } 0.25 + NI_{Slope} \text{ X } 0.25 + NI_{DisRoad} \text{ X } 0.2 + NI_{DisUrban} \text{ X } 0.2 + NI_{DisWater} \text{ X } 0.1$$

The OSI values were further classified into three suitability categories viz. High, Medium, and Low based on natural breaks classification. Those pixels with OSI value above 0.560876 were assigned to High suitable category, whereas pixels with OSI value between 0.485165 and 0.560876 were assigned to Medium suitability category. Similarly, pixels with OSI value less than 0.485165 were assigned to Low suitability category.

Historical and Future Change in Land Cover

We used two input data sets of the study area, one for historical estimates and one for future estimates. The historical data set covers the period from 2001 to 2011 and the future data set covers the periods from 2012 to 2028. The historical data contains the transition matrix (Table 2), which is basically the estimates of the number (or percent) of pixels that have undergone change from one land cover class to another between the years 2001 and 2011. The historical land cover area and changes in land cover estimates are presented in last two columns of Table 2.1 and in Table

2.2 respectively. The transition matrix (Table 2.2) indicates that the most of the conversion to Evergreen Forest (42) was from land covers Shrub land (52), Grassland (71), and Hay/Pasture (81) at the rate of 15.6, 1.5, 1.1, and 0.1% respectively indicating that when the demand of wood pellets increases land covers Shrub land, Grassland, and Pasture/Hay are the potential land uses that are highly likely to be converted to evergreen forest.

With due consideration to the historical rate of land use conversion in our study area and increasing global demand of wood pellets, we determined the rate of change for each site suitability category of each land cover class present in the study (Table 2.4).

Land Use Change Projection

The future rate of change based on the historical transition rate was used as input in the land use change model to allocate a certain percent of land parcel from land covers Evergreen forest (42), Shrub land (52), Grassland (71), and Pasture/Hay (81) for loblolly pine plantation. Figure 2.4 shows how the different land covers undergo transition over time. Using the rate of change, we estimated the number of cells for each land cover undergoing transition for each time period (Table 2.5).

Results

Site Suitability

The final output of the suitability analysis for the study area has three suitability categories. They are High, Medium, and Low suitable. Figure 2.5 shows spatial distribution of land under each suitability category for each of the land covers that are present in the watershed. The distribution of suitability categories is throughout the area. Although the most suitable sites are dispersed throughout the study area, most of them are clustered at the southernmost part of watershed where most of the Evergreen forest exists and at the northern corner of watershed which are far away from the major city area like Athens. This is likely because more weight was given to those sites that were far from the urban areas and at close proximity to the evergreen forest in the model. Very low suitable areas are represented by water bodies (NLCD land cover classes 11, 90, and 95) and developmental areas (NLCD land cover classes 21, 22, 23, and 24). Figure 2.6 shows the spatial distribution of land for each suitability category under four the land covers that we considered in our study. Not Analyzed includes the land covers that were not considered in our study, such as water bodies, barren land, agricultural land and developed areas. The percentage of the total land under each category was highest under Medium suitability category, followed by Low and High. Based on land covers that we used for our analysis i.e. Evergreen forest (42), Shrub land (52), Grassland (71), and Pasture/Hay (81), the High, Medium, and Low suitable areas were found to be 6.7% (162.5 km^2), 22.6% (548.5 km^2), and 8.6% (209.3 km^2) of the total watershed (Figure 2.7).

To prevent competition with food production and the conversion of natural forest, our analysis was restricted to the land covers identified as Hay/Pasture, Shrub land, Evergreen Forest, and Grassland covering an area of 923.48 km^2.

Land Cover Change

Spatial based land use change models are used to address two questions: first, where the changes are most likely to occur (spatial location of change) and second, what are the rates at which these changes are likely to occur (quantity of change) (Veldkamp & Lambin, 2001). Land use change models can easily deal with the first question, as it takes into account the determinants of change. However, quantification of change is driven by the demand of the land-based commodities (Stephenne & Lambin, 2001). After determining the rate of change for each suitability category, we determined the land cover change. Figures 2.8a, 2.8b, and 2.8c show the spatial distribution of the changed pixels under each suitability category, based on the future rate of change (Table 2.4), for years 2016, 2021, and 2026. The spatial distribution of the changed pixel showed that the changes occurred on grid cells that are closed to the wood pellet mill facility located near Athens. This is mostly due to the fact that the allocation of the cells for conversion to evergreen forest was based on the distance from the wood pellet mill. Figure 2.9a shows the map of land cover of the watershed in 2011 and Figures 2.9b, 2.9c, and 2.9d show the output of the land use change model i.e. land cover map for 2016, 2021, and 2026 respectively. The allocated land cover conversions for pine plantation relative to 2011 were 2.9%, 4.95%, and 6.56% for years 2016, 2021, and 2026 respectively (Figure 2.10).

Discussion

The increasing demand of wood pellets for energy production are challenging land change scientists to consider the location of bioenergy crops within current land use pattern. This study was designed to assess site suitability for the production of woody biomass for wood pellets production by using GIS-based suitability modeling and to quantify the land use change by allocating the certain area of land for pine plantation each year on the basis of future rate of change. We have provided the methodology to estimate the spatial distribution of available land available for loblolly pine plantation. The suitability model was successful at identifying sites where loblolly pine can be grown for woody biomass production. A large portion of suitable sites were scattered throughout the study area. Some of the most suitable sites were relatively distant from the newly announced wood pellet mill, as this mill is located near the Athens area. However, most of the changed grid cells were centered on pellet mill. This is likely because allocation of cells for change was based on distance from the existing wood pellet mill.

A total of 923 km² was taken into consideration for suitability analysis to establish loblolly pine in our study area, which represents 38% of the watershed area. Most of the allocation of land for conversion happened from the land cover Hay/Pasture, which accounted for 40.8, 43.6, and 51.5% of total conversion in years 2016, 2021, and 2026. To meet the increasing demand of wood pellets, more of this land use can be used for bioenergy production. Moreover, government incentive such as tax breaks and subsidy might increase landowners' willingness to grow more woody-biomass, thus increasing the area available for biomass production.

Based on our assessment of a sub-basin of Oconee watershed as a case study for more detailed analysis, we show that there is great land area potential for biomass production for wood pellets in the southeastern United States. The main limitation of our approach is that we did not use the production cost as a factor for suitability analysis. This was due to the fact that the pixels were located within 50 km from the announced wood pellet mill. This model was developed as a general tool that can be applied to any spatial scale and to various geographical regions, thus can help guide research of site suitability of bioenergy crops.

Conclusions

We used different relevant factors to determine suitability of loblolly pine production in the study area. The model was successful in identifying sites where loblolly pines can be grown for woody biomass production. This study only considered four land cover classes for suitability analysis. A total of 923 km², 38% of the watershed area, was considered suitable for the analysis to establish loblolly pine. Out of 38%, Medium suitable covers 16.3%, followed by High (14.3%) and Low (7.3%). We also determined the future rate of change based on the historical transition rates. The final output of the suitability analysis was used as an input in a land use change model where it was combined with future rate of change to simulate potential land use changes over time and space. Based on the land use change model, we obtained land use maps for 2016, 2021, and 2026 which were used as inputs in hydrological model to determine potential changes in streamflow till 2028. This model was developed as a general tool that can be applied to any spatial scale and to various geographical regions, thus can help guide research of site suitability of bioenergy crops.

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Table 2.1: Land cover details of the selected watershed.

Land Cover Class	Land Cover (km^2)		Land Cover (%)		Change (%) in Land Cover
	2001	2011	2001	2011	2011-2001
Open Water (11)	16.5	17.2	0.7	0.7	4.2
Developed, Open Space (21)	235.6	277	9.7	11.4	17.6
Developed, Low Intensity (22)	138	174.3	5.7	7.1	26.3
Developed, Medium Intensity (23)	28.1	56.5	1.2	2.3	101.2
Developed, High Intensity (24)	9.6	15.9	0.4	0.7	65.6
Barren Land (31)	19.8	14.8	0.8	0.6	-25.2
Deciduous Forest (41)	914.2	847.6	37.5	34.8	-7.3
Evergreen Forest (42)	214.3	187.2	8.8	7.7	-12.6
Mixed Forest (43)	24.7	21.4	1	0.9	-13.4
Shrub/Scrub (52)	5.7	33.2	0.2	1.4	482.5
Grassland/Herbaceous (71)	188.9	188.3	7.7	7.7	-0.3
Pasture/Hay (81)	553.1	514.8	22.7	21.1	-6.9
Cultivated Crops (82)	2.1	2	0.1	0.1	-4.8
Woody Wetlands (90)	87.3	85.4	3.6	3.5	-2.1
Emergent Herbaceous Wetlands (95)	0.6	3	0	0.1	400

Source: U.S. Department of Agriculture/National Resource Conservation Service.

Table 2.2: Transition matrix showing changes in land cover types (%) between 2001 and 2011 in the selected watershed.

		Land Cover 2011															
		11	21	22	23	24	31	41	42	43	52	71	81	82	90	95	Total
Land Cover 2001	11	95	1.2	1.1	0.5	0	0.3	0.2	0	0	0.1	0.2	0.3	0	0.1	1.1	100
	21	-	95.8	0.9	2.9	0.4	-	-	-	-	-	-	-	-	-	-	100
	22	-	-	97.1	1.8	1.1	-	-	-	-	-	-	-	-	-	-	100
	23	-	-	-	99.6	0.4	-	-	-	-	-	-	-	-	-	-	100
	24	-	-	-	-	100	-	-	-	-	-	-	-	-	-	-	100
	31	1.3	5.6	9.2	7.3	1.3	61.6	6	1.5	-	3.7	1.4	-	-	0.3	0.7	100
	41	0.1	2.2	1.5	0.8	0.1	0.1	91.7	-	-	1.7	1.7	0.1	-	-	-	100
	42	-	2.5	2	1.3	0.3	0.2	0.6	85.6	-	3.5	4	0.1	-	-	-	100
	43	-	2.3	1.7	0.8	0.2	0.1	0.2	0.3	86.4	3.8	3.7	0.3	-	0.1	0.2	100
	52	0.4	5.6	3.1	1.8	0.3	0.4	2.5	15.6	0.1	69.5	0.8	-	-	-	-	100
	71	0.3	3.4	2.7	1.1	0.2	0.3	3	1.1	-	1.9	85.5	-	-	0.1	0.5	100
	81	-	2.9	2.1	1	0.2	0.1	0.2	0.1	-	0.2	0.2	92.9	-	-	-	100
	82	-	1.6	1.1	1.3	0.7	0.6	1.4	-	-	0.8	0.6	-	92	-	-	100
	90	0.1	1	0.4	0.1	-	-	0.1	-	-	0.1	0.1	-	-	97	1.1	100
	95	-	0.6	0.3	-	-	-	3	-	-	1.9	-	-	-	22.5	71.7	100

Land Cover Types: Open Water (11); Developed, Open Space (21); Developed, Low Intensity (22); Developed, Medium Intensity (23); Developed, High Intensity (24); Barren Land (31); Deciduous Forest (41); Evergreen Forest (42); Mixed Forest (43); Shrub/Scrub (52); Grassland/Herbaceous (71); Pasture/Hay (81); Cultivated Crops (82); Woody Wetlands (90); and Emergent Herbaceous Wetlands (95).

Table 2.3: Data inputs and their sources

Data layers	Source
DEM	USDA/NRCS (2015)
Land cover	USDA/NRCS (2015)
Road	Elizabeth Cramer (personal communication)
Wood Mills	Elizabeth Cramer (personal communication)

Table 2.4: Suitability category with their respective historical and future rate of change

Allocated Rate of Change (%)								
	Evergreen Forest		Shrub land		Grassland		Pasture/Hay	
Suitability Category	Historical	Future	Historical	Future	Historical	Future	Historical	Future
High	2.1	4	8.6	3	0.6	2	0.03	2
Medium	1.4	3	6.9	2	0.4	1.5	0.02	1.5
Low	0.5	2	0.52	1	0.1	1	0.01	1

Table 2.5: Total number of pixels at transition each year.

	Land Cover Class															
	High				Medium				Low				Very Low			
Year	81	71	52	42	81	71	52	42	81	71	52	42	81	71	52	42
2012	2917	1133	258	4330	2158	849	182	1842	1439	514	80	647	693	224	20	62
2013	2859	1110	253	4157	2125	836	179	1786	1424	509	80	634	690	223	20	61
2014	2802	1088	247	3990	2093	823	176	1733	1410	504	79	621	686	222	20	61
2015	2746	1066	243	3831	2062	811	174	1681	1396	499	78	609	683	220	20	60
2016	2691	1045	238	3678	2031	799	171	1630	1382	494	77	596	679	219	20	59
2017	2637	1024	233	3530	2001	787	168	1582	1368	489	76	585	676	218	20	59
2018	2584	1003	228	3389	1971	775	166	1534	1354	484	76	573	673	217	20	58
2019	2533	983	224	3254	1941	764	163	1488	1341	479	75	561	669	216	19	58
2020	2482	964	219	3123	1912	752	161	1443	1327	475	74	550	666	215	19	57
2021	2432	944	215	2999	1883	741	159	1400	1314	470	73	539	663	214	19	56
2022	2384	925	211	2879	1855	730	156	1358	1301	465	73	528	659	213	19	56
2023	2336	907	206	2763	1827	719	154	1317	1288	460	72	518	656	212	19	55
2024	2289	889	202	2653	1800	708	152	1278	1275	456	71	507	653	211	19	55
2025	2243	871	198	2547	1773	697	149	1240	1262	451	71	497	649	210	19	54
2026	2199	854	194	2445	1746	687	147	1202	1250	447	70	487	646	209	19	54
2027	2155	836	190	2347	1720	677	145	1166	1237	442	69	478	643	208	19	53
2028	2112	820	187	2253	1694	666	143	1131	1225	438	68	468	640	207	19	53
2029	2069	803	183	2163	1669	656	141	1097	1213	433	68	459	637	205	18	52
2030	2028	787	179	2077	1644	647	138	1065	1201	429	67	450	633	204	18	52

Land Cover Types: Evergreen Forest (42); Shrub/Scrub (52); Grassland/Herbaceous (71); Pasture/Hay (81)

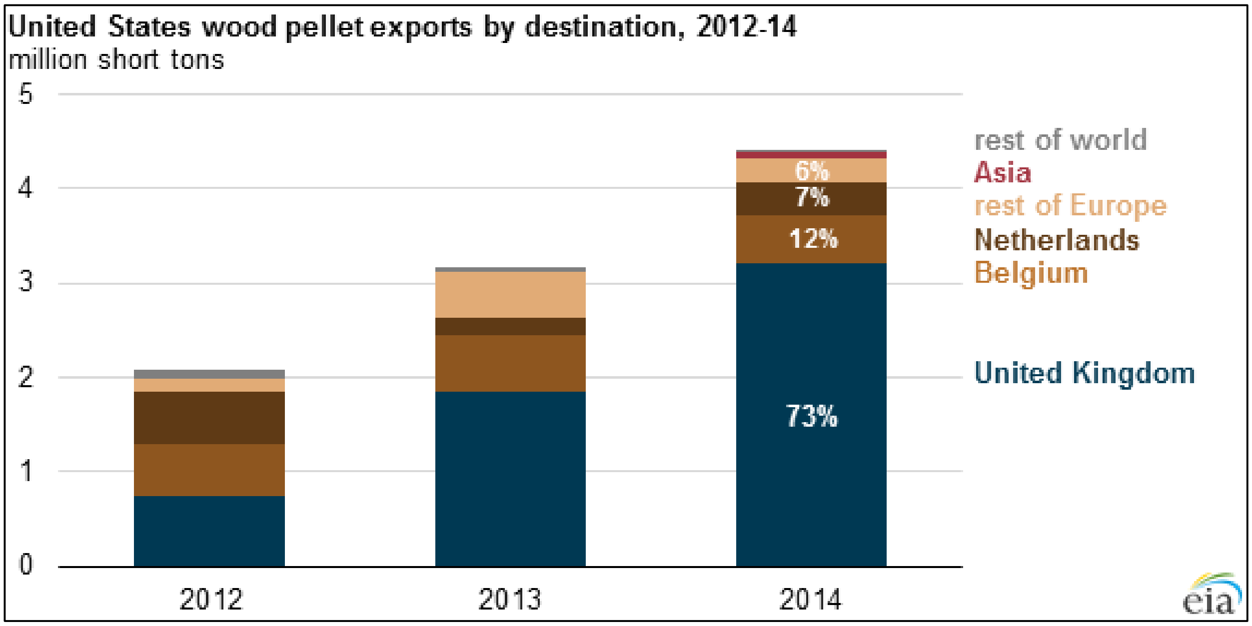

Figure 2.1: United States wood pellet exports by destination, 2012-2014.

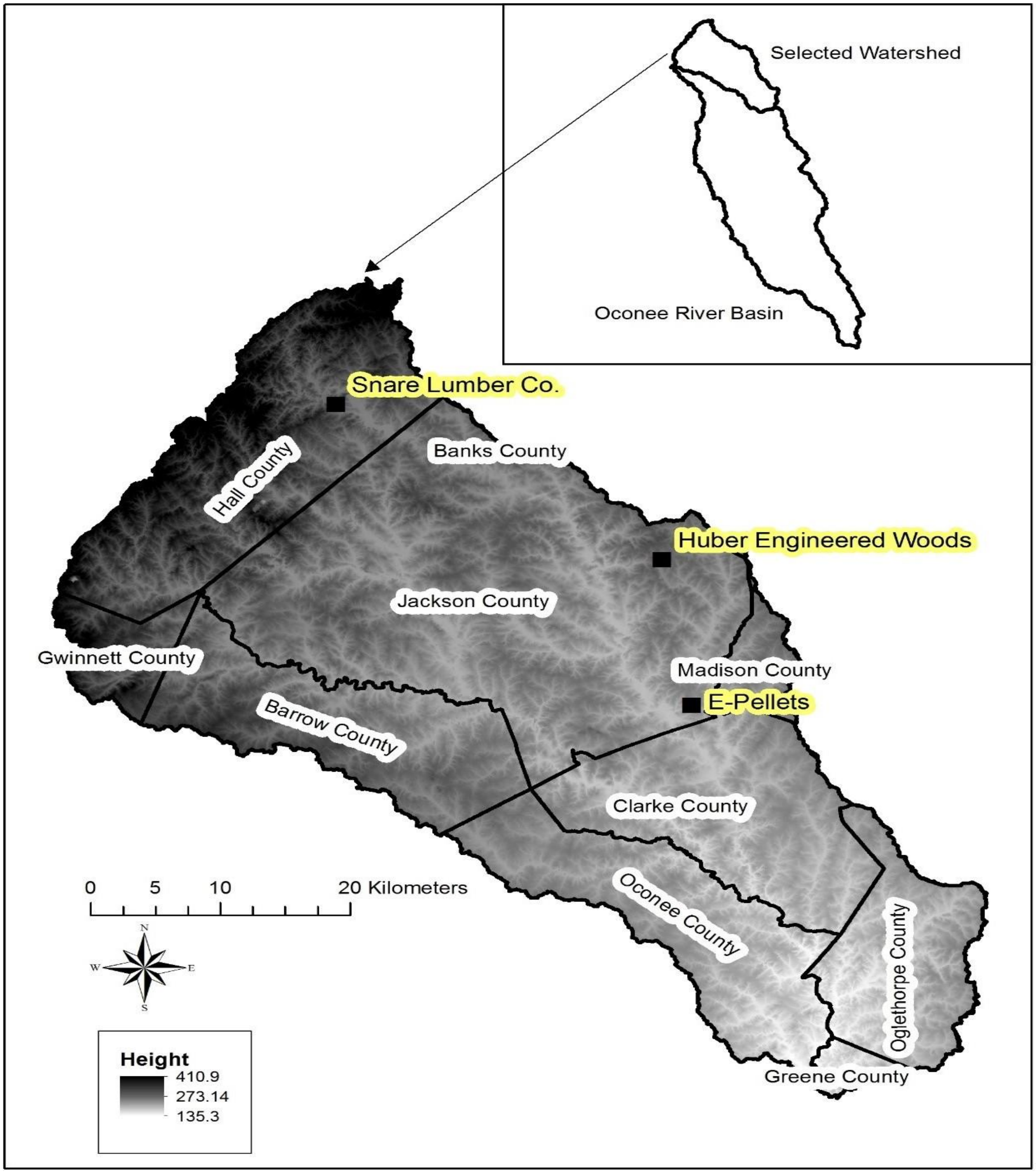

Figure 2.2: Location of the selected watershed in the Oconee River Basin

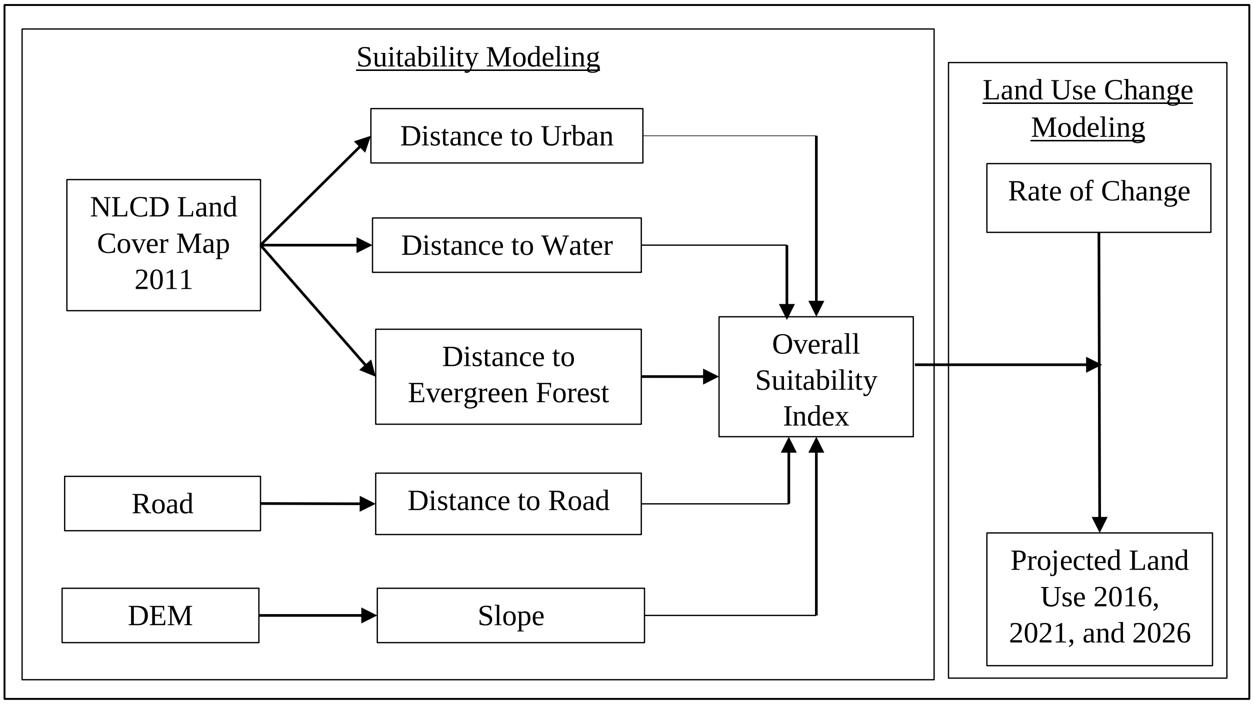

Figure 2.3: Flow Chart of suitability analysis and land use change modeling.

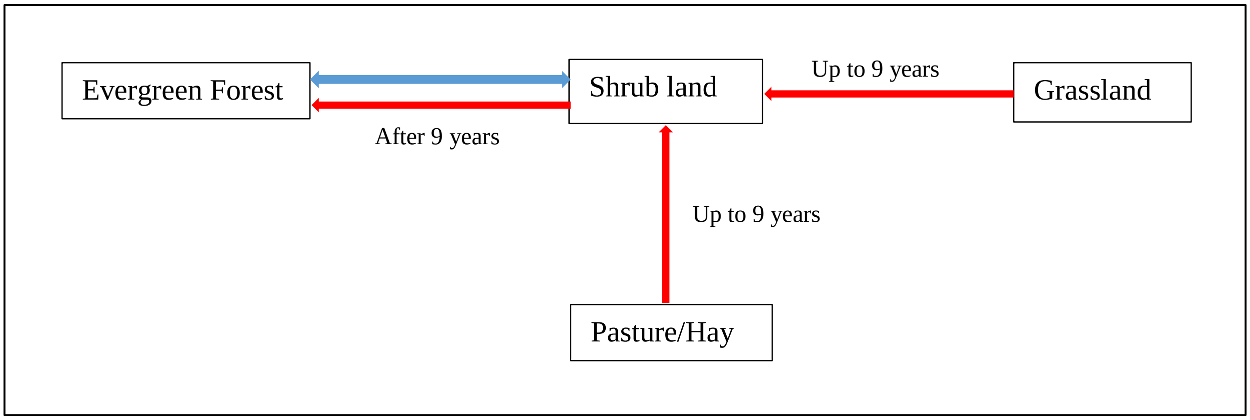

Figure 2.4: Transition among different types of land cover. The arrow with heads in both directions indicates transition in each direction and those with head in one direction indicate transition in one direction.

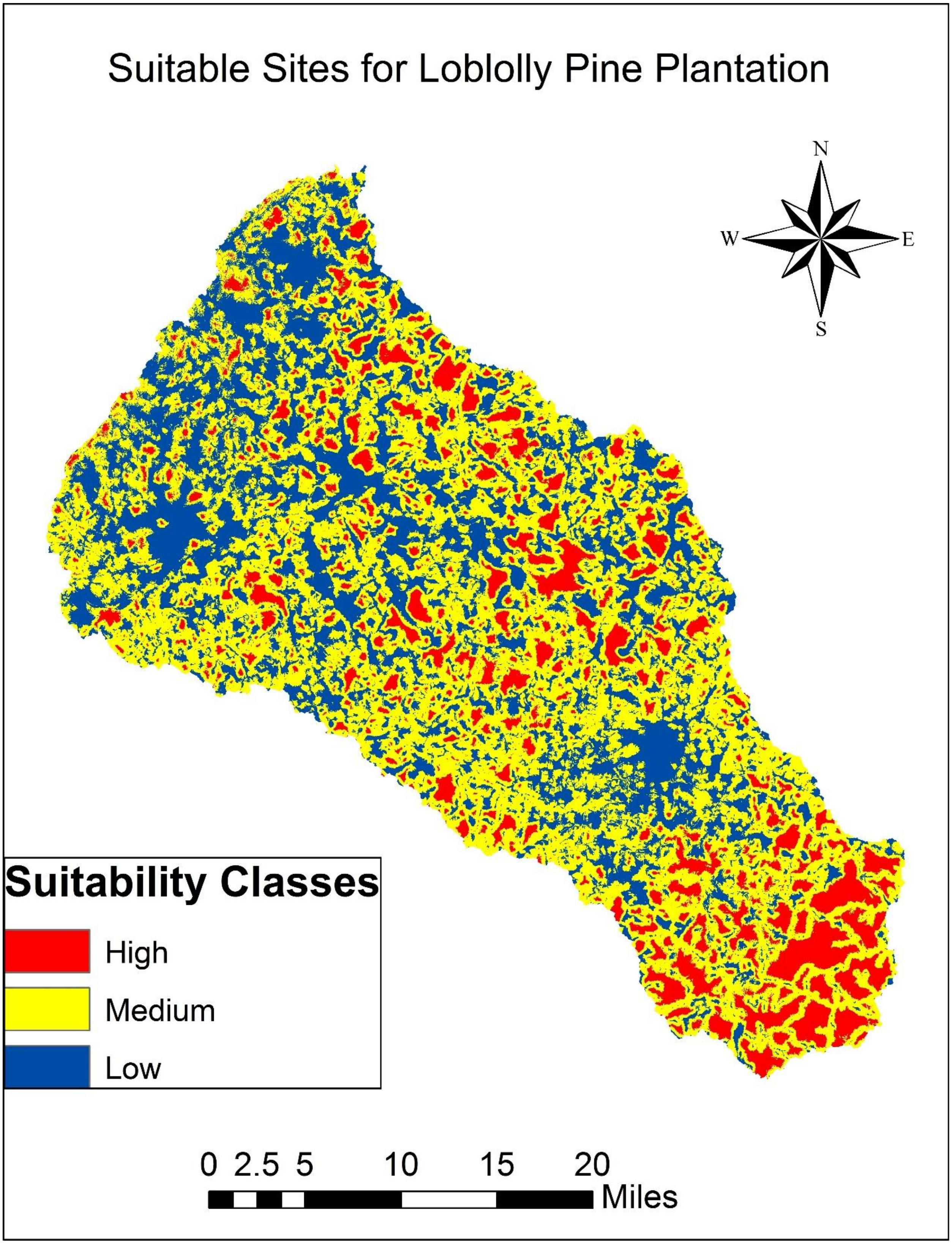

Figure 2.5: Suitability map of loblolly pine plantation.

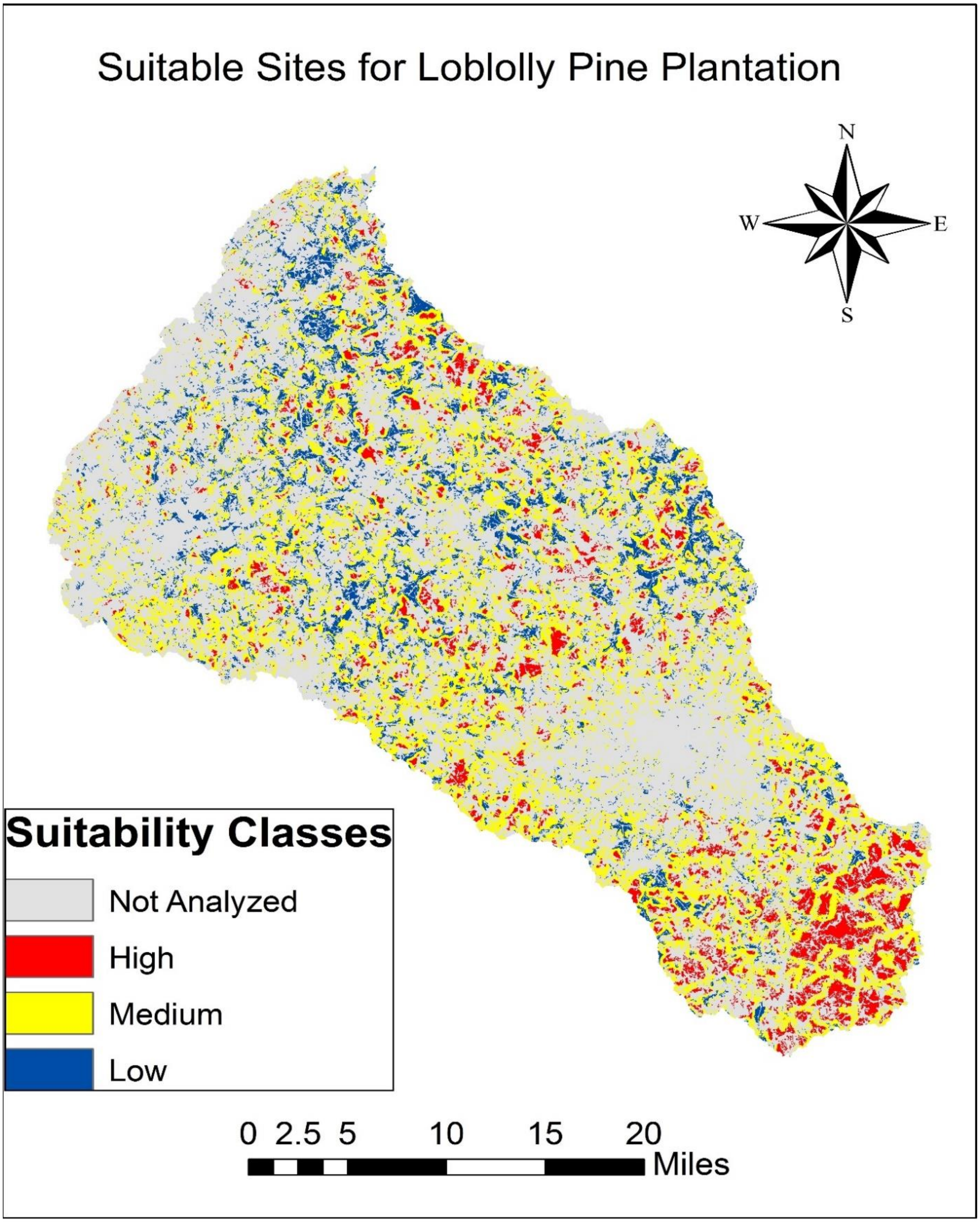

Figure 2.6: Suitability map of loblolly pine under four land covers in the watershed.

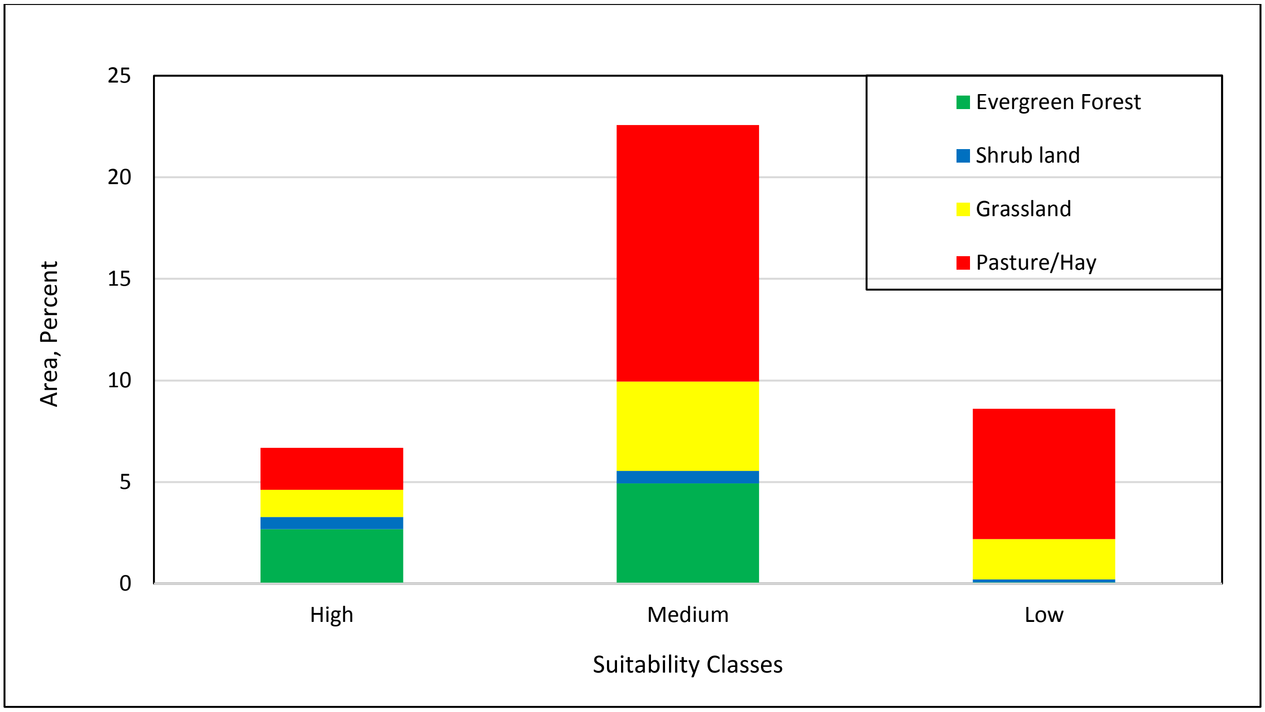

Figure 2.7: Site suitability distribution for loblolly pine under land covers evergreen forest, shrub land, grassland, and pasture/hay.

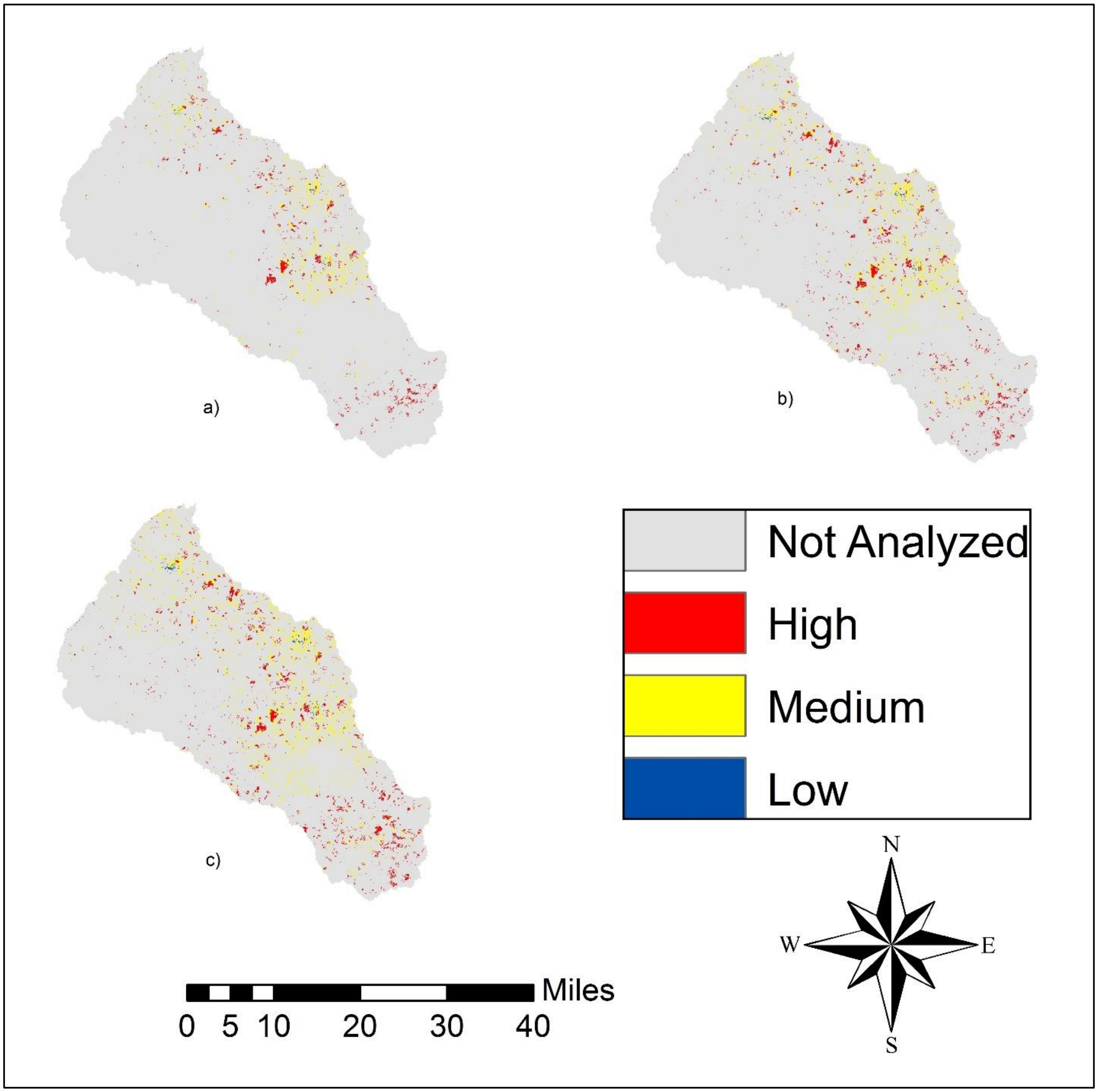

Figure 2.8: Map showing allocation of suitable sites for pine plantation in (a) 2016, (b) 2021, and (c) 2026.

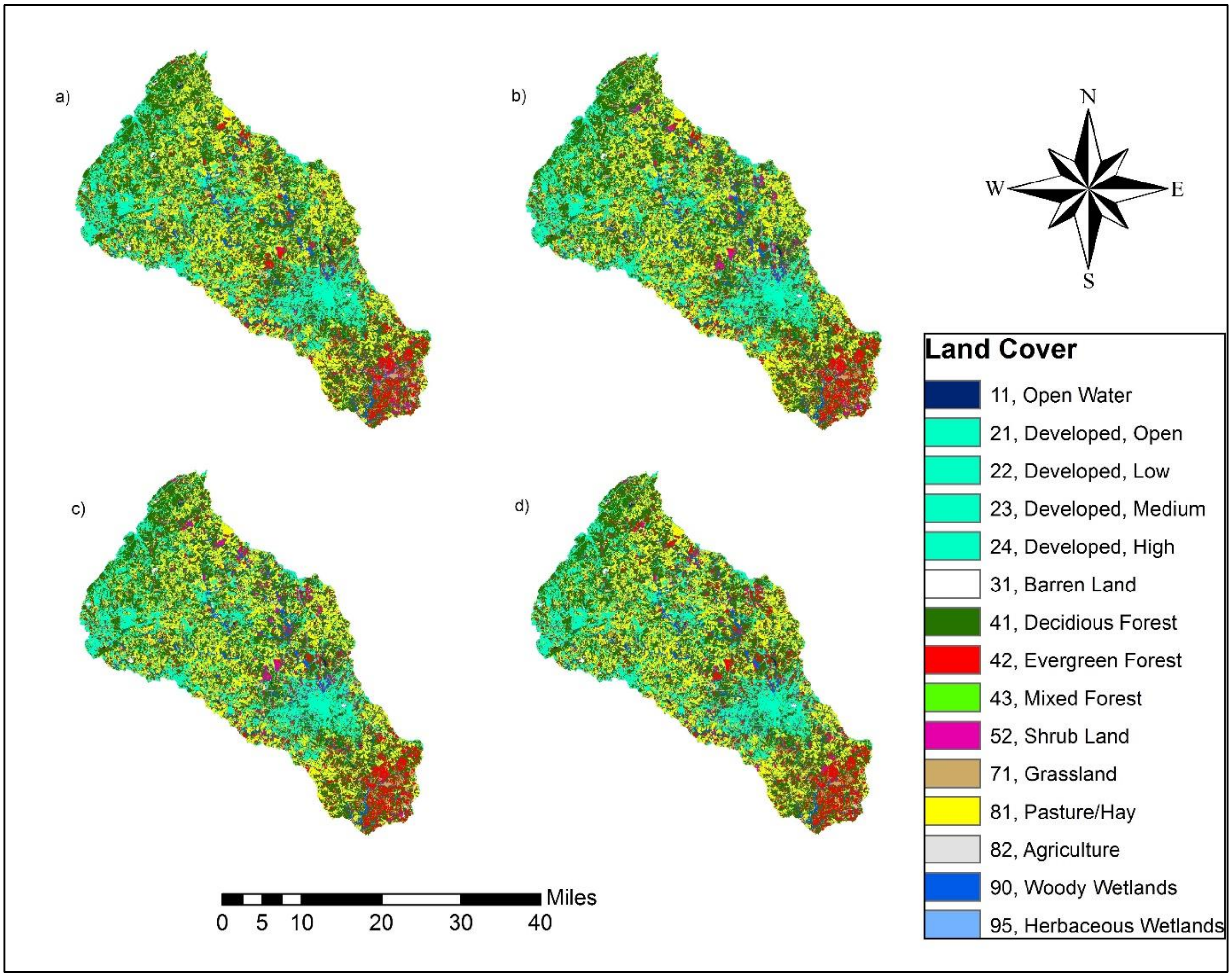

Figure 2.9: Land use maps for a) 2011, b) 2016, c) 2021, and d) 2026.

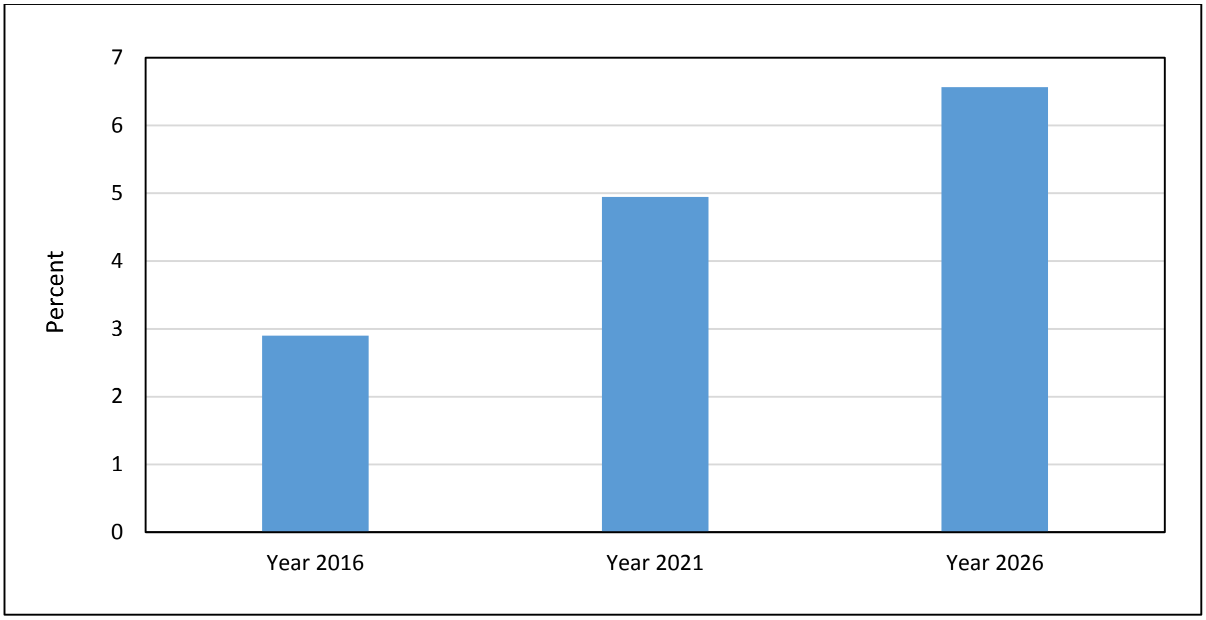

Figure 2.10: Change in land use for years 2016, 2021, and 2026 relative to 2011.

CHAPTER 3

ASSESSING HYDROLOGICAL IMPACT OF LAND COVER AND CLIMATE CHANGE SCENARIOS IN THE NORTHE-EAST OCONEE RIVER BASIN OF GEORGIA

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[1] Shrestha, S. and Dwivedi, P. 2016. To be submitted to *Journal of the American Water Resources Association*.

Abstract

Land use and climate are two main factors that can significantly influence the hydrological cycle in a watershed. Understanding the impacts of land use and climate changes is of great importance for land use planning and sustainable water resource management. This study investigates the impacts of land use change (in the context of growing wood pellet demand) and climate variability on the surface hydrology (evapotranspiration, ground water, runoff, and streamflow) of a sub-basin located in northeast corner of Oconee river basin of Georgia using Soil and Water Assessment Tool. Three different land covers for 2016, 2021, and 2026 and climate scenarios were used as inputs in the hydrological model. The Nash-Sutcliffe model efficiency coefficient and R^2 value were 0.78 and 0.82 for calibration and 0.81 and 0.89 for validation. The results show that 65 to 75% of the precipitation was lost to evapotranspiration. The impact of land use and climate change on evapotranspiration was not much. Land use change increased ground runoff by 0.4 and increased runoff by 1.7 to 2.7%, while the combination of land use and climate change changed runoff depth by -28 to 30% and streamflow by -30 to 31%. This indicates that impact of climate change on surface hydrology is more pronounced than the land use change in the study site.

INDEX WORDS: wood pellets, land use change, climate change, surface hydrology, SWAT

Introduction

Land use change is considered a primary factor in the context of global environmental change (Houghton, 1994). Quantifying land use explains how humans have utilized the land resources over time (Pielke et al., 2002). Monitoring the spatial patterns of land use dynamics is essential to understand its impact on people and resources simultaneously. This is especially true for water resources as land use changes could significantly affect various components of the hydrologic budget such as evaporation, surface runoff, infiltration, and groundwater recharge (Trimble et al., 1987; DeFries & Eshleman, 2004; Bosch et al., 2006; Öztürk et al., 2013). The increase or decrease in water demand coupled with changes in traditional land uses could affect water quality as well (DeFries & Eshleman, 2004).

A number of studies have established the relation between land cover change and watershed hydrology (Grace, 2005; Schoonover et al., 2006; Raini, 2009; Cruise et al., 2010; Isik et al., 2013; Öztürk et al., 2013; Wagner et al., 2013) suggesting that changes in land cover to forests, because of increased evapotranspiration, can lead to significant decrease in streamflow (Bosch et al., 2006). For example, Trimble et al. (1987) studied the impact of reforestation on streamflow in 10 large and populated contiguous river basins with a total area of 54,020 km^2 in Alabama, Georgia, and South Carolina. Those river basins had undergone 10 to 28% of the land use change from cropland to forest during the period 1919 to 1967. This study reported a 4 to 21% decrease in annual stream discharge and attributed this decrease to increased forest cover.

Grace (2005) reviewed several studies which focused on watersheds located in 13 southern states to understand the impact of active forest management on water availability. It was found that water yield increased in all watersheds where harvesting sites were present and ranged from 69 to 210 mm per year. Cruise et al. (2010) assessed the impact of changing landscapes on the hydrology of streams in the watersheds (< 2500 km^2) of Alabama, Georgia, and Tennessee. Landsat Thematic Mapper data was used to determine the land cover change in three different years (1980, 1990, and 2010). Large river basins (e.g., Alabama River basin, Tennessee River basin, and Chattahoochee River basin) were not included in the analysis to detect hydrological impacts of land use changes at a fine scale. A total of 12 watersheds that ranged from 166 to 2,292 km^2 were selected. Results showed that the watersheds with largest land cover change from agriculture to forestry (20% or more) had significant reduction in streamflow (Cruise et al., 2010).

Isik et al. (2013) developed a hybrid model based on Artificial Neural Networks and Soil Conservation Service Curve Number to predict changes in daily streamflow in response to changing land use and soil characteristics. The study was done in 10 watersheds of Harris and Muscogee counties of Georgia where watershed sizes ranged from 3.6 to 26.2 km^2. Land use, hydrological soil groups, and climate variables such as precipitation and temperature were used in the model in order to replicate the hydrological response of a watershed (Isik et al., 2013). The model predicted increased average streamflow for pasture and urban dominant scenarios while more stable hydrology with decreased streamflow for forest dominated scenarios (Isik et al., 2013). These studies indicate that the forest cover leads to less streamflow and higher evapotranspiration compared to other land use types such as agriculture, pasture, and grassland. This is due to factors such as interception of precipitation by vegetation canopy, increased infiltration capacity and soil porosity by dense network of roots, and increased evapotranspiration.

The accurate prediction of land use impact on the dynamic water balance of a watershed requires development of integrated models that combine land use models and hydrological models. Several studies have emphasized the advantages of combining the land use models and hydrological models to accurately assess the impact of land use change on watershed hydrology.

Choi and Deal (2008) connected a cellular, dynamic, spatial urban growth model and a semi-distributed continuous hydrology model using a Hydrological Simulation Program to quantitatively predict streamflow in response to possible future urban growth at a basin scale in the United States. Zhang et al. (2012) combined an integrated land use change model (CLUE-S) with hydrological model to assess hydrological process for historical and potential land-cover change in Southwest China. Wijesekara et al. (2012) combined a land use cellular automata (CA) model and the distributed physically based MIKE-SHE/MIKE-11 hydrological model to assess the impact of land use changes on hydrological processes in the Elbow River watershed in southern Alberta, Canada.

Land cover change accompanied by systematic changes in climatic variables (e.g. precipitation and temperature) may induce notable alteration in stream discharge. Climate change affects volume, peak rate, and timing of surface runoff and streamflow through alteration in amount, intensity, and distribution of regional precipitation and temperature (Neff et al., 2000; Groisman et al., 2001; Novotny & Stefan, 2007; Wang et al., 2008). There are two methods to study the effect on the hydrological cycle. The first method is based on meteorological data where different climate change scenarios are set up based on historical meteorological data and then used for hydrological simulation in hydrological model (Wang et al., 2008). The second method is to simulate climate using a climate model, such as a General Circulation Model (GCM) and then use the output of climate model as input to the hydrological model for hydrological simulation (Arnell & Reynard, 1996). The later method has been widely used for hydrological simulation (Buytaert et al., 2009; Hay et al., 2011; LaFontaine et al., 2015). The study of land use and climate change on water resources is mainly focused on estimating the relative change in streamflow which is considered to be useful in decision-making processes for water-resource management (Kepner et al., 2004; Li et al., 2009; Shaw et al., 2014; Chen et al., 2015; Niraula et al., 2015).

The objective of this study is to quantify the impacts of land use change and climate variability on runoff, evapotranspiration, and streamflow. In this study, we developed a coupled land use hydrological model to analyze the impact of 14 different land uses and climate scenarios on the hydrological process for the NE sub-catchment of the Oconee River basin in Georgia.

Study Area

The selected watershed is located in the North-East Oconee River Basin. The selected watershed occupies about 2438.5 km^2 i.e. 17.7% area of the Oconee River Basin (13798 km^2). The selected watershed includes 10 counties i.e., Hall, Gwinnett, Walton, Jackson, Barrow, Oconee, Oglethorpe, Clarke, Banks, and Madison. The selected watershed has three wood-consuming mills including a recently announced pellet mill (Figure 3.1). The mean slope and elevation of the selected watershed is 4.36° ($\sigma = 3.02°$) and 248.2 m ($\sigma = 45.48$ m), respectively. In 2011, the major land cover types present in the selected watershed were Deciduous Forests, Pasture/Hay, Developed-Open Space, Evergreen Forest, and Developed-Low Intensity occupying 34.8, 2.1, 11.4, 7.7, and 7.1% of the total land area, respectively (Table 2.1). For all land cover types which occupied more than 5% of the total land in 2001, the maximum increase was observed for land cover types Developed – Low Intensity (26.3%) followed by Developed – Open Space (17.6%) between 2011 and 2001. For the same time period, the maximum decrease wass observed for Evergreen Forest (12.6%) followed by Deciduous Forest (7.3%) and Pasture/Hay (6.9%). Table 2.2 indicates that 2.2, 2.5, 2.3, and 5.6% of total area under Deciduous Forest, Evergreen Forest, Mixed Forest, and Shrub/Scrub has moved into Developed-Open Space since 2001 indicating that the majority of first level of urban development was primarily on former forestlands in the selected watershed. This is also true for Grassland/Herbaceous and Pasture/Hay land cover types located in the watershed. However, total area under agricultural lands did not change much between 2001 and 2011.

Materials and Methods

Soil and Water Assessment Tool (SWAT), a physically based hydrological model, was used for the simulation of streamflow. Land use change results along with climate variability were combined with the hydrological model to determine streamflow under different land use and climate change scenarios (Figure 3.2).

SWAT

SWAT, developed by the USDA Agriculture Research Service (ARS), is a complex, conceptual watershed-scale model that predicts the impact of land management practices on water, sediment, and chemical yields from agricultural lands in large, complex watersheds (Arnold et al., 1998; Neitsch et al., 2011). ArcSWAT, an ArcGIS extension, was used for running the model to predict the discharge. In SWAT, the watershed is subdivided into sub-basins based on climate forcing (precipitation and air temperature). SWAT creates subdivisions within the sub-basins using land use, soil, slope, and climate data which are referred as ‘Hydrological Response Units’ (HRU). Each HRU is assumed to be uniform in terms of soil, land use, and slope. Based on precipitation, runoff, evapotranspiration, percolation, and return flow, for each HRU, a water budget is computed (Lin & Radcliffe, 2006). The water balance equation in the SWAT for an HRU is given by the following expression (Arnold et al., 1998)

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

where SW_t (mm) is the final soil water content on day i, SW_o (mm) is the initial soil water content on day i, t is the time in days, R_{day} (mm) is the amount of rainfall on day i, Q_{sur} (mm) is the amount of surface runoff on day i, E_a (mm) is the amount of evapotranspiration on day i, W_{seep} (mm) is the amount of water entering the vadose zone from the soil profile on day i, and Q_{gw} (mm) is the amount of base flow or return flow on day i.

In recent years, the Soil and Water Assessment Tool (SWAT) model has been used successfully in many countries. SWAT is widely used for precipitation runoff analysis (Arnold et al., 1993; Bingner, 1996), climate change effect on hydrological processes (Eckhardt & Ulbrich, 2003; Van Liew & Garbrecht, 2003; Wang et al., 2008), and land use change effect on hydrology (Wang et al., 2008; Öztürk et al., 2013).

SWAT Data Inputs

The basic data inputs were Digital Elevation model (DEM), soils, land use, and climate. These data were obtained from various sources. The National Elevation Dataset, developed by USGS Earth Resource Observation and Science Data Center, was downloaded to get the DEM data for the study site with spatial resolution of 30 meters (USDA/NRCS, 2015). The soil information obtained from the SSURGO soil database was used as soil input in the SWAT model. The SSURGO soil database was obtained from USDA Natural resource Conservation Service. The SWAT/SSURGO soil database was downloaded from the SWAT webpage and contains all the soil attributes related to SSURGO soil values in the United States (Texas A&M University and USDA–ARS, 2015). The land use/cover data was obtained from the National Land Cover Database which is a product created by the Multi-Resolution Land Characteristics (MRLC) Consortium

(USDA/NRCS, 2015). To predict the discharge for future period till 2028, we used land covers obtained from suitability modelling (Chapter 2). Similarly, weather data (mean precipitation, maximum temperature, and minimum temperature) were obtained from the weather stations that are located in and around the study area (Figure 3.1).

Evaluating the effect of land use change and climate variability

To evaluate the effect of land use change and climate variability on watershed hydrology, we used a one factor at a time approach (i.e., changing one factor at a time while holding others constant). For the land use and climate change combined scenarios, we used multi factor at a time approach. The effect of land use and climate change were quantified by comparing the SWAT outputs of the four broad scenarios as follows:

1) Base scenario (BAU): 2011 land cover and 2001-2014 climate.

2) Land use change only scenario (LU): 2016, 2021, and 2026 land cover and 2001-2014 climate. We used land use maps of 2016, 2021, and 2026 to represent the land use patterns of 2015-2020, 2021-2025, and 2026-2028 respectively.

3) Climate change only scenario (CC): 2011 land use and 2015-2028 projected changed climate (PCC here after). We ran four different scenarios using 2011 land cover under this broad scenario as below:

- 1°C rise in temperature (LUT1+)
- 2°C rise in temperature (LUT2+)
- 10% increase in precipitation (LUP10+)
- 10% decrease in precipitation (LUP10-)

4) Land use and climate change combined scenario (LUCC): 2016, 2021, and 2026 land use and 2015-2028 PCC.

We ran 8 different scenarios using 2016, 2021, and 2026 land cover under this broad scenario as below:

- Land use change and 1°C rise in temperature (LUCCT1+)
- Land use change and 2°C rise in temperature (LUCCT2+)
- Land use change and 10% increase in precipitation (LUCCP10+)
- Land use change and 10% decrease in precipitation (LUCCP10-)
- Land use change, 1°C rise in temperature, and 10% increase in precipitation (LUCCT1+P10+)
- Land use change, 2°C rise in temperature, and 10% increase in precipitation (LUCCT2+P10+)
- Land use change, 1°C rise in temperature, and 10% decrease in precipitation (LUCCT1+P10-)
- Land use change, 2°C rise in temperature, and 10% decrease in precipitation (LUCCT2+P10-)

We set up different climate change scenarios based on historical meteorological data. We plotted the long term historical meteorological data from Ben Epps Climate station to get the potential temperature and precipitation estimate for 2015-2028 period. The temperature increased by about 1°C and precipitation decreased by about 10% over several decades (Figures 3.3 and 3.4). LaFontaine et al. (2015) statistically downscaled three GCMs (CCSM3-, PCM-, and GFLD-based simulation) using the ARRM downscaling procedure to project maximum and minimum temperature and precipitation for a river basin in southeast U.S. It was reported that maximum and minimum daily temperatures were increased and ranged between 2.5 and 4°C for IPCC high emission scenario (A1Fi) and between 0.5 and 1.5°C for the lower emission scenario. Similarly, CCSM3 and PCM-based simulations projected median precipitation to increase by about 10-15% for both emission scenarios while GFLD-based simulation showed a median decrease of approximately 8% for the high emission scenario and an increase of approximately 3% for the low emission scenario. Based on this study and historical meteorological record, we used 1°C and 2°C rise in temperature and ± 10% change in precipitation under climate change scenario.

SWAT Parameter Inputs

The selection of parameters for the SWAT model that affect the watershed hydrology was based on a literature review (Van Liew et al., 2007; Cibin et al., 2010; Arnold et al., 2012; Oliver et al., 2014). The list of parameters that were used for model simulations are shown in the Table 3.1.

SWAT Calibration and Validation

Calibration and validation of the SWAT hydrological model was performed using a computer program called ‘SWAT Calibration and Uncertainty Program 2012’ (SWAT-CUP 2012). SWAT-CUP allows for sensitivity analysis, calibration, validation, and uncertainty analysis of SWAT models by linking several optimization procedures to SWAT (Abbaspour, 2014). In SWAT-CUP, the uncertain model parameters’ value are systematically changed; the model is run with the changed parameter value; and the required outputs are extracted (Abbaspour, 2014). The Sequential Uncertainty Fitting Version 2 (SUFI-2) algorithm was used in this study for the calibration and validation of the SWAT model and to evaluate the goodness-of-fit of the model.

Percent Bias (PBIAS), R^2 value, and Nash-Sutcliffe (NS) model efficiency coefficient were used to assess the goodness-of-fit and uncertainty of the model streamflow. PBIAS and NS model efficiency coefficient are given as:

$$PBIAS = (\Sigma Q_{obs} - \Sigma Q_{sim})*100/ \Sigma Q_{obs}$$

$$NS = 1 - [\Sigma(Q_{obs} - Q_{sim})/ \Sigma(Q_{obs} - Q_{avg})]$$

where, Q_{obs}, Q_{avg}, and Q_{sim} are observed (measured), arithmetic average, and SWAT simulated streamflow. The optimal value of PBIAS is 0. The lower magnitude values indicate accurate model simulation, while positive values indicate model underestimation bias and negative values indicate model overestimation bias. The value of NS model efficiency coefficient ranges from $-\infty$ to 1. An efficiency of 1 corresponds to a perfect match of observed and predicted values. If $NS=0$, predictions are as good as the mean of the observed data. If $NS<0$, observed mean is a better predictor than the model (Grunwald & Frede, 1999). The R^2 value ranges from 0 to 1, where 1 represents a perfect fit and 0 represents no fit at all (Ott & Longnecker, 2001).

SWAT Simulations

The model was allowed to warm up for three years before 2001 and calibrated on the monthly time step for the 7-year period from 1 January 2001 to 31 December 2007. After calibration, the model was run for another seven years from 1 January 2008 to 31 December 2014 for validation using the SWAT parameters that were obtained from the final calibration of the model.

After validating the model, we used those calibrated parameters values to run the hydrological model in ArcSWAT to observe the effect of land use and climate change on the streamflow. We ran the model for a 14-year period from 1 Jan. 2015 to 31 Dec. 2028 in the presence of evolving land covers: 2016, 2021, and 2026 with 14 different simulations under four different climate and land use change scenarios: 1) Base Scenario (BAU), 2) Land use change only (LU), 3) Climate change only (CC), and 4) land use and climate change combined (LUCC).

Results

SWAT Calibration and Validation

Initially, 19 parameters pertaining to watershed hydrology were calibrated in the SWAT model for the year 1 January 2001 to 31 December 2007. At the end of calibration, only 7 model parameters were found to be sensitive to the streamflow. Table 3.2 gives the final values of the adjusted parameters to calibrate streamflow and the *p* values associated with them. Based on the *p* values of sensitivity associated with the parameters, TRNSRCH, CH_K2, GW_REVAP, GWQMN, SOL_K, SOL_AWC, and CH_N2 were the most sensitive parameters (in order of decreasing sensitivity), as their p-values were less than level of significance of the model i.e. 0.05. Figure 3.5a and 3.5b give the plot of the USGS observed streamflow, SWAT best simulation flow, and the 95% prediction uncertainty band for calibration and validation periods respectively. In the beginning of the simulation, the simulated streamflow was close to the USGS observed streamflow which indicates that the warm up period used in the SWAT model i.e. three years from 1 March 1998 to 31 December 2000 was adequate to equilibrate the base flow and soil moisture.

For the calibration and validation procedure, SWAT simulated monthly flow was compared to the observed average monthly flow at the USGS station number 02218300 on the Oconee River near Penfield, GA. Regression analysis yielded an R^2 of 0.82 and 0.89 for calibration and validation of the SWAT model indicating a good model fit (Figure 3.6a and 3.6b). Table 3.3

gives the NS coefficients and R^2 values for the SWAT simulation that were obtained from SWAT-CUP using SUFI-2 algorithm. For calibration, the NS coefficient, R^2 value, PBIAS were 0.78, 0.82, and 7.28% respectively. For validation, the NS coefficients, R^2 value, and PBIAS were 0.81, 0.89, and 3.57 respectively. According to Moriasi et al. (2007), for a model fit for streamflow to be considered as satisfactory, the monthly NS value has to be >0.5. Our result showed a good fit of the SWAT simulation for both calibration and validation periods.

Land Use and Climate Change Impact on Evapotranspiration and Ground Water

The calibrated SWAT model was run from 1 January 2015 to 31 December 2028 using 14 different scenarios under four broad scenarios in the presence of evolving land covers: 2016, 2021, and 2026 to determine the impact of potential land use change accompanied by climate change on the local watershed hydrology. Table 3.4 shows the results of average annual evapotranspiration (ET) and ground water depth simulated by SWAT under the four scenarios. Result showed that the majority of precipitation was lost through ET which accounted for 65-75% across all four scenarios. Overall, land use change and climate variability did not produce marked changes in the water loss through ET. The highest gain in ET was with the land use change, 2°C rise in temperature, and 10% decrease in precipitation (LUCCT2+P10-) simulation under land use and climate change combined scenario, which increased by 3.5% (28.5mm) relative to base scenario (Table 3.4). Similarly, the highest loss in ET was with land use change and 10 % decrease in precipitation (LUCCP10-) simulation under combined scenario, which accounted for 2.8% (22.7 mm) loss relative to base scenario. Figure 3.7 is a plot of average monthly ET throughout the basin which shows only small alterations due to land use and climate change across 14 different scenarios. During winter (December and February), the ET is at its minimum due to low temperature. ET starts to increase between March and May. From June to August, ET reaches its peak due to high temperature and high rainfall and starts to fall from September. Similarly, there was very little impact of land use change on ground water depth (Table 3.4). Ground water was highly impacted by the change in climate and the impact was much more pronounced when accompanied by land use change. The groundwater depth increased under CCP10+, LUCCP10+, LUCCT1+P10+, and LUCCT2+P10+ scenarios by 24-29%, while it decreased under CCP10-, LUCCP10-, LUCCT1+P10-, and LUCCT2+P10- scenarios by 27-30% relative to base scenario.

Land use and Climate Change Impact on Runoff Depth and Stream Discharge

As with ET and groundwater, the impact of land use and climate change on runoff and stream discharge was assessed by running the SWAT model from 1 January 2015 to 31 December 2028 for four different land use and climate change scenarios. Table 3.5 shows the annual mean runoff simulated by SWAT under different land use and climate change scenarios. The difference between BAU and LU indicated the influence of land use change over the period of time. Compared to BAU, the simulated runoff in LU decreased by 0.6 mm (0.4%) and streamflow increased by 1.7 to 2.7%, indicating very low impact of land use change on both runoff and streamflow. The difference between BAU and CC indicated the influence of climate change. Results showed the slight change in runoff and streamflow in scenarios with changed temperature (CCT1+ and CCT2+), where runoff decreased 1.2 mm (0.8%) and 2.6 mm (1.8%) and streamflow decreased by 1.8 to 2.8%. Runoff changed by 29.1% and -26.4% and streamflow by 30% and -28.6% under CCP10+ and CCP10- scenarios respectively. Under LUCC, the greatest increase in runoff and streamflow was in LUCCP10+ i.e. 42.2 mm (29.2%) and 30.5% respectively and the greatest decrease was in LUCCT2+P2- i.e. 40.3 mm (28%) and 30.4% respectively (Table 3.5).

In order to understand how precipitation and temperature affect the streamflow, we used correlation analysis between precipitation and streamflow and temperature and streamflow. The streamflow was positively correlated with precipitation with a coefficient of 0.88, while streamflow was negatively correlated with temperature with a coefficient of 0.73. The correlations between annual precipitation, temperature, and streamflow were statistically significant, as the p-value associated with them were less than 0.05, the level of significance (Table 3.6). The results show that the streamflow was better correlated with precipitation than with temperature. Figure 3.8 shows the regression between precipitation and streamflow and between temperature and streamflow. The R^2 value between precipitation and streamflow and between temperature and streamflow were 0.77 and 0.54, which indicates a good fit.

Discussion

This study analyzed impact of projected land use and climate change on stream flow in the Upper Northeast Oconee River Basin. For this study, the land use projection was developed separately and was integrated with the hydrological model. To ascertain the hydrologic impacts of land use and climate changes, we used the SWAT model for 14 different sub-scenarios under four scenarios of land use and climate change. In general, the method proved to be effective in simulating the streamflow. The validation period confirmed the performance statistics from the calibration period. For the NE Oconee River Basin, our results showed that land use and climate change, particularly change in precipitation, over the next two decades would have significant impact on the streamflow in the study area.

Generally speaking, forest cover produced lower streamflow and soil water and higher evapotranspiration than other land use types (Trimble et al., 1987; DeFries & Eshleman, 2004; Bosch et al., 2006; Li et al., 2009). The major portion of the precipitation is lost to ET. The results in Table 9 show that the total precipitation loss to ET was 65-75%, which is consistent with the findings of other reported studies (Li et al., 2009; Yang et al., 2012; Bhattarai et al., 2015). Several studies have established the impact of land use and climate change on ET (Bosch et al., 2006; Thodsen, 2007; Cruise et al., 2010). This study found that the land use and climate change had very low impact on ET and ground water recharge (Table 3.4). Actual ET response to land use and climate changes was shown to be more variable for the CC and LUCC scenarios compared to LU scenario. Decreased ET was noted for the LU scenario, which could be attributed to the harvest of Evergreen Forest. Similarly, the results showed increased ET for most of the simulations under CC and LUCC scenarios. Increased temperature and changes in precipitation are the primary sources for this result. The results of change in ET under different land use and climate change scenarios were found to be -3 to 4%. This result is comparable with the result from similar studies by Christensen et al. (2004); Thodsen (2007); and Li et al. (2009). In contrast, more pronounced impacts of land use and climate change were noticed on groundwater storage. The impact of land use on ground water was low compared to the climate. The resulting changes were always positive for land use change. As evergreen forest was projected to harvest, most of the water that would have gone to ET now went to surface runoff or to groundwater flow. When land use and climate changes were combined, the gain in ground water flow increased by up to 29%, which is similar to the results reported by Li et al. (2009).

Similar to other studies (Booth et al., 2002; Schoonover et al., 2006; Wang et al., 2008; Hurkmans et al., 2009; Qi et al., 2009; Price et al., 2011; Isik et al., 2013; Öztürk et al., 2013; LaFontaine et al., 2015; Niraula et al., 2015), this study found that land use change affects streamflow. More specifically, Trimble et al. (1987) studied the impact of reforestation on streamflow in 10 large and populated contiguous river basins in Alabama, Georgia, and South

Carolina. The results reported 4 to 21% decrease in annual stream discharge. Also, the study of Schoonover et al. (2006) showed that the land use changes played a crucial role in driving the hydrological process in watershed hydrology. Our results (Table 3.5) showed some effects of land use changes on the streamflow under the land use of 2016, 2021, and 2026, as some of the evergreen forests were changed to shrub. However, contrary to other studies, this impact seems to be relatively small. There could be two reasons for this result. First, many of the existing studies were conducted in urbanizing watershed. Second, we only considered land cover types Evergreen forest, Shrub land, Grassland, and Pasture/Hay for conversion keeping other land covers constant over the period of time. Also, it took 10 years for other competitive land covers to come under forestry cover. At the same time, we also harvested the forest area each year for woody biomass production. Consequently, the hydrologic effects of land use changes in the watershed are not as pronounced as we typically expected based on existing studies.

Based on this study, we found that that climate change can significantly affect both runoff and streamflow (Table 3.5), as found in many of the previous studies (Christensen et al., 2004; Novotny & Stefan, 2007; Li et al., 2009; Harding et al., 2012; Chen et al., 2015; LaFontaine et al., 2015). The relative change in streamflow due to climate variability in this study was up to 30% in the simulations with 10% increase in precipitation and as much as -29% in the simulations with 10% decrease in precipitation, which is relatively high compared to other studies: 5-13% by Hundecha and Bardossy (2004) and 13% by Wang et al. (2008). However, some other studies have predicted higher relative change in streamflow such as, 47% by Li et al. (2009); 68% by Chen et al. (2015); and between -65% and 114% using Outlet calibrated model by Niraula et al. (2015). Overall, the streamflow projection analysis found that the impact of climate variability on projected streamflow was relatively higher compared to the impact of land use change, a result which is consistent with the results of studies by Chen et al. (2005) and Öztürk et al. (2013).

In order to find out how the runoff and streamflow responds to the changing temperature, under the same precipitation condition, we simulated the runoff for the period 2015 to 2018 using the SWAT model by increasing the maximum and minimum temperature by 1°C and 2°C (Scenario 3). Results showed that both runoff and streamflow decreased with increased temperature under the same precipitation condition. Runoff decreased by 0.8 and 1.8% and streamflow decreased by 1.8 and 2.8% when temperature increased by 1°C and 2°C respectively (Table 3.5). Similarly, we modeled the runoff using SWAT to find out how the runoff and streamflow responds to the changing precipitation, when the temperature remains constant by changing the precipitation by ±10%. The results indicated that both runoff and streamflow increased with the increased precipitation and decreased with decreased precipitation under the same temperature condition. The runoff and streamflow increased by 29% and 30% respectively when precipitation increased by 10% and decreased by 26.4% and 28.6% respectively when the precipitation decreased by 10% (Table 3.5). This result clearly indicates that the changes in precipitation result in greater percent changes in streamflow which is consistent with the findings of Wang et al. (2008).

Conclusions

Soil and Water Assessment Tool (SWAT) was used to predict the effect of potential land use and climate change on the hydrological cycle of a watershed located in the northeast corner of Oconee river basin in the piedmont region of Georgia. Sensitivity analysis was undertaken to determine the most appropriate parameters that affect watershed hydrology. Out of 19 parameters, seven parameters were found to be significant in terms of *p*-value associated with them. The calibrated SWAT model was run from 1 Jan. 2015 to 31 Dec. 2028 using 14 sub-scenarios under four land use and climate change scenarios to simulate the hydrological response to land use change and climate change till 2028. The study indicated that 65-75% of precipitation was lost to evapotranspiration. The relative change in evapotranspiration due to land use change was very low, where it decreased by 0.2%. The greatest change was observed on LUCCT2+P10+ scenario with the value of 3.5% increase relative to base scenario. In contrast, the ground water depth changed by 24-29% due to land use and climate change relative to base scenario. The relative change in streamflow due to land use change was between 1.7 to 2.7%. The greatest increase and decrease in streamflow was found in land use and climate change combined scenario, which accounts for 30.5% and 29.8% respectively. Overall, the climate variation played a more pronounced role than land use in influencing surface hydrology in this watershed. Under the same precipitation condition, the mean annual basin streamflow decreased by 0.8 and 1.8% when the temperature increased by 1°C and 2°C respectively. Similarly, under the same temperature condition, the mean annual basin streamflow increased by 30% when precipitation increased by 10% and decreased by 28.6% when precipitation decreased by 10%. Through this study, it is clear that the future changes in land use and climate, particularly decrease in precipitation, will very likely exacerbate the shortage of clean water, affecting water delivery for communities, reservoir operations, and energy production.

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Table 3.1: Parameters used for SWAT model calibration.

SWAT Parameter	Description	Fitted Value	*P* value of sensitivity
GW_DELAY	time for water leaving the bottom of the root zone to reach the shallow aquifer (days)	158.778	0.8**
GWQMN	threshold depth of water in the shallow aquifer required for return flow to occur (mm)	576.883	<0.0001
CH_K2	main channel hydraulic conductivity (mm h^{-1})	0.854	<0.0001
CH_N1	Manning's "n" value for tributary channels	0.345	0.53*
CH_N2	Manning's "n" value for the main channel	0.068	0.001
GW_REVAP	Groundwater re-evaporation coefficient	0.047	<0.0001
REVAPMN	Threshold water depth in the shallow aquifer for revap, (mm)	276.486	0.41*
SOL_AWC	available soil water capacity (mm H2O mm^{-1} soil)	0.357	<0.0001
SOL_K	saturated hydraulic conductivity (mm h^{-1})	0.715	<0.0001
TRNSRCH	fraction of transmission losses from main channel that enter deep aquifer	0.267	<0.0001
CN2	Curve number for moisture condition II	-0.168	0.22*
ALPHA_BF	baseflow recession constant	-0.063	0.95*
ALPHA_BNK	baseflow alpha factor for bank storage (days)	0.087	0.08*
CH_K1	Effective hydraulic conductivity in tributary channel alluvium	9.15	0.15*
ESCO	soil evaporation compensation factor	0.532	0.57*
EPCO	Plant uptake compensation factor	0.319	0.23*
GW_SPYLD	Specific yield of the shallow aquifer (m^3/m^3)	0.236	0.83*
RCHRG_DP	Recharge to deep aquifer	0.055	0.28*
SURLAG	surface runoff lag coefficient	9.162	0.22*

*Deleted after second iteration, **Deleted after third iteration

Table 3.2: Sensitivity results for the parameters for streamflow.

SWAT Parameter	Description	Fitted Value	*P* value for sensitivity
GWQMN	threshold depth of water in the shallow aquifer required for return flow to occur (mm)	576.883	<0.001
CH_K2	main channel hydraulic conductivity (mm h^{-1})	0.854	<0.001
CH_N2	Manning's "n" value for the main channel	0.068	0.001
GW_REVAP	groundwater re-evaporation coefficient	0.046	<0.001
SOL_AWC	available soil water capacity (mm H_2O mm^{-1} soil)	0.357	<0.001
SOL_K	saturated hydraulic conductivity (mm h^{-1})	0.715	<0.001
TRNSRCH	fraction of transmission losses from main channel that enter deep aquifer	0.267	<0.001

Table 3.3: Monthly Nash-Sutcliffe model efficiency coefficients (NS) and R^2 values for calibration and validation periods.

Simulation Period	Monthly Stream flow		
	NS	R^2	PBIAS (%)
2001-2007 (Calibration)	0.78	0.82	7.28
2008-2014 (Validation)	0.81	0.89	3.57
2001-2014 (Base Scenario)	0.77	0.84	4.24

Table 3.4: Simulated average annual groundwater and evapotranspiration under different land use and climate change scenarios.

Scenarios	Climate	Land use	Precipitation (mm)	Ground Water			Evapotranspiration		
				Simulation (mm)	Change (mm)	Percent (%)	Simulation (mm)	Change (mm)	Percent (%)
Base Scenario (BAU)									
	2015-2028 Projected Climate	2011	1185.5	205.9	0.0	0.0	823.1	0.0	0.0
Land use change only (LU)									
		2016	1185.5	207.7	1.9	0.9	821.7	-1.4	-0.2
	2015-2028 Projected Climate	2021	1185.5	207.0	1.1	0.5	821.9	-1.2	-0.1
		2026	1185.5	207.2	1.3	0.7	822.1	-1.0	-0.1
Climate change only (CC)									
CCT1+	2015-2028 PCC	2011	1185.5	201.3	-4.6	-2.2	829.6	6.5	0.8
CCT2+	2015-2028 PCC	2011	1185.5	199.8	-6.0	-2.9	833.0	9.9	1.2
CCP10+	2015-2028 PCC	2011	1303.6	263.3	57.4	27.9	839.0	15.9	1.9
CCP10-	2015-2028 PCC	2011	1066.1	148.7	-57.2	-27.8	801.6	-21.5	-2.6

Table 3.4 (Continued)

Scenarios	Climate	Land use	Precipitation, mm	Ground Water			Evapotranspiration		
				Simulation (mm)	Change (mm)	Percent (%)	Simulation (mm)	Change (mm)	Percent (%)
Land use and climate change combined (LUCC)									
LUCCT1+	2015-2028 PCC	2016	1185.5	203.1	-2.8	-1.4	828.3	5.2	0.6
		2021	1185.5	202.4	-3.5	-1.7	828.3	5.2	0.6
		2026	1185.5	202.5	-3.4	-1.6	828.7	5.6	0.7
LUCCT2+	2015-2028 PCC	2016	1185.5	201.5	-4.4	-2.1	831.9	8.8	1.1
		2021	1185.5	200.9	-4.9	-2.4	831.8	8.7	1.1
		2026	1185.5	200.9	-5.0	-2.4	832.4	9.3	1.1
LUCCP10+	2015-2028 PCC	2016	1303.6	265.4	59.5	28.9	837.6	14.5	1.8
		2021	1303.6	264.4	58.6	28.5	837.8	14.7	1.8
		2026	1303.6	264.8	59.0	28.6	838.0	14.9	1.8
LUCCP10-	2015-2028 PCC	2016	1066.1	150.2	-55.6	-27.0	800.3	-22.8	-2.8
		2021	1066.1	149.7	-56.1	-27.3	800.4	-22.7	-2.8
		2026	1066.1	149.8	-56.1	-27.3	800.6	-22.5	-2.7
LUCCT1+P10+	2015-2028 PCC	2016	1303.6	259.6	53.8	26.1	845.8	22.7	2.8
		2021	1303.6	258.8	52.9	25.7	845.8	22.7	2.8
		2026	1303.6	259.1	53.2	25.8	846.2	23.1	2.8
LUCCT2+P10+	2015-2028 PCC	2016	1303.6	256.4	50.5	24.5	851.2	28.1	3.4
		2021	1303.6	255.6	49.8	24.2	851.2	28.1	3.4
		2026	1303.6	255.8	49.9	24.2	851.6	28.5	3.5
LUCCT1+P10-	2015-2028 PCC	2016	1066.1	146.8	-59.1	-28.7	805.0	-18.1	-2.2
		2021	1066.1	146.4	-59.5	-28.9	804.9	-18.2	-2.2
		2026	1066.1	146.2	-59.6	-29.0	805.4	-17.7	-2.2
LUCCT2+P10-	2015-2028 PCC	2016	1066.1	146.3	-59.6	-28.9	807.3	-15.8	-1.9
		2021	1066.1	145.9	-60.0	-29.1	807.1	-16.0	-1.9
		2026	1066.1	145.6	-60.2	-29.3	807.8	-15.3	-1.9

Table 3.5: Simulated average annual runoff under different land use and climate change scenarios.

Scenarios	Climate	Land use	Precipitation, mm	Runoff		SWAT Streamflow	
				Simulation (mm)	Change (%)	Monthly Average (cms)	Change (%)
Base Scenario (BAU)							
	2015-2028 Projected Climate	2011	1185.5	144.5	0.0	26.2	
Land use change only (LU)							
		2016	1185.5	143.9	-0.4	26.6	1.7
	2015-2028 Projected Climate	2021	1185.5	144.6	0.1	26.8	2.6
		2026	1185.5	144.1	-0.3	26.9	2.7
Climate change only (CC)							
CCT1+	2015-2028 PCC	2011	1185.5	143.3	-0.8	25.7	-1.8
CCT2+	2015-2028 PCC	2011	1185.5	141.9	-1.8	25.4	-2.8
CCP10+	2015-2028 PCC	2011	1303.6	186.6	29.1	34.0	30.0
CCP10-	2015-2028 PCC	2011	1066.1	106.4	-26.4	18.7	-28.6

Table 3.5 (Continued)

Scenarios	Climate	Land use	Precipitation, mm	Runoff		SWAT Streamflow	
				Simulation (mm)	Change (%)	Monthly Average (cms)	Change (%)
Land use and climate change combined (LUCC)							
LUCCT1+	2015-2028 PCC	2016	1185.5	142.7	-1.2	26.9	2.8
		2021	1185.5	143.4	-0.7	25.8	-1.5
		2026	1185.5	142.9	-1.1	25.7	-1.6
LUCCT2+	2015-2028 PCC	2016	1185.5	141.3	-2.2	25.5	-2.5
		2021	1185.5	142.0	-1.7	25.5	-2.4
		2026	1185.5	141.5	-2.1	25.5	-2.6
LUCCP10+	2015-2028 PCC	2016	1303.6	185.8	28.6	34.1	30.5
		2021	1303.6	186.6	29.2	34.1	30.4
		2026	1303.6	186.0	28.8	34.1	30.4
LUCCP10-	2015-2028 PCC	2016	1066.1	105.9	-26.7	18.8	-28.3
		2021	1066.1	106.5	-26.3	18.8	-28.3
		2026	1066.1	106.1	-26.6	18.7	-28.4
LUCCT1+P10+	2015-2028 PCC	2016	1303.6	184.2	27.5	33.5	28.1
		2021	1303.6	185.1	28.1	33.5	28.1
		2026	1303.6	184.4	27.6	33.5	28.0
LUCCT2+P10+	2015-2028 PCC	2016	1303.6	182.5	26.3	33.1	26.5
		2021	1303.6	183.3	26.9	33.1	26.5
		2026	1303.6	182.6	26.4	33.1	26.4
LUCCT1+P10-	2015-2028 PCC	2016	1066.1	105.2	-27.2	19.4	-25.7
		2021	1066.1	105.8	-26.8	18.4	-29.6
		2026	1066.1	105.4	-27.1	18.4	-29.8
LUCCT2+P10-	2015-2028 PCC	2016	1066.1	104.2	-27.9	18.2	-30.2
		2021	1066.1	104.7	-27.5	18.3	-30.2
		2026	1066.1	104.3	-27.8	18.2	-30.4

Table 3.6: Correlation between precipitation and streamflow and between temperature and streamflow.

	Correlation Coefficient (*p*-value)	
	Temperature	Precipitation
Streamflow	-0.73 (0.002)	-
Streamflow	-	0.88 (<0.001)

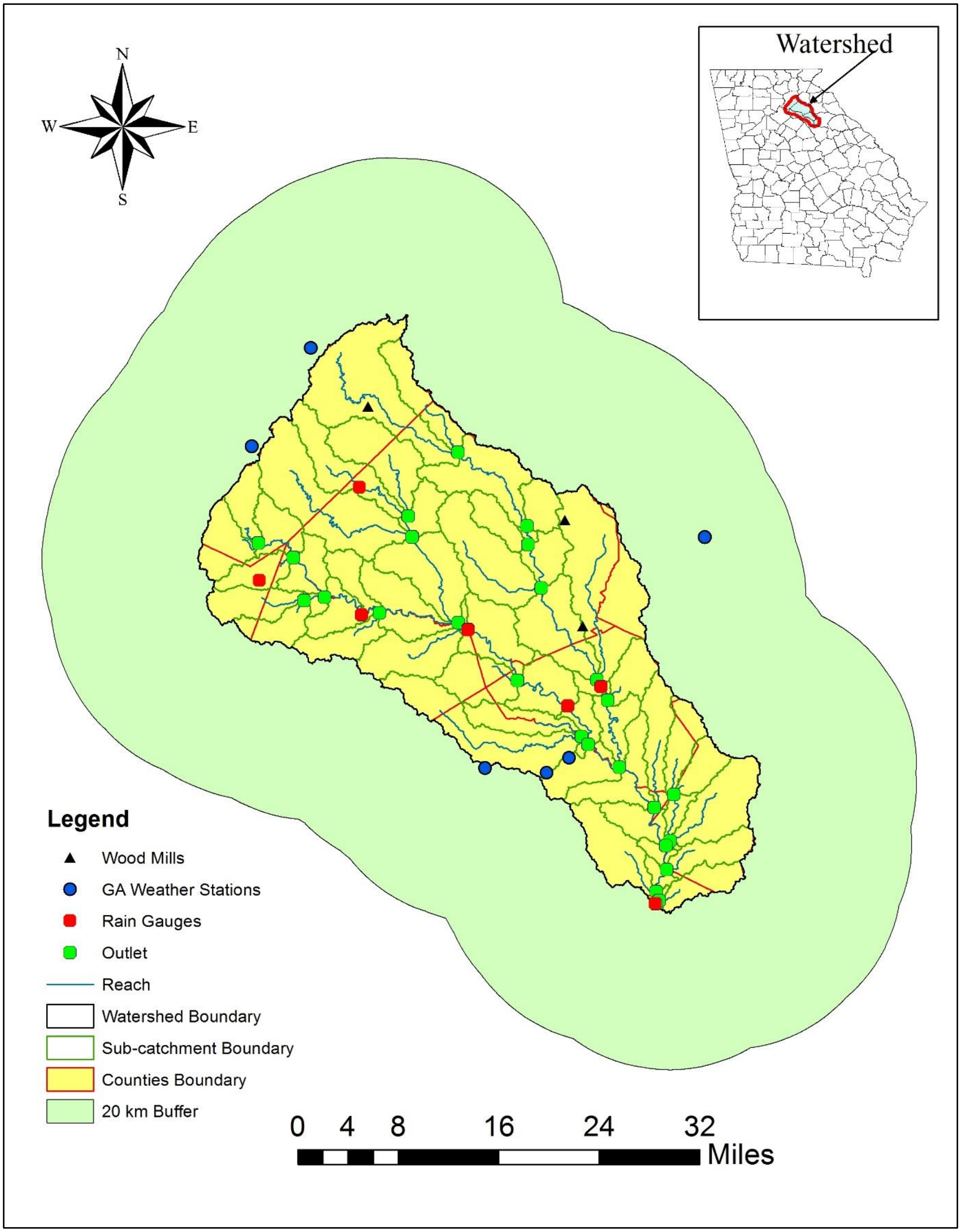


Figure 3.1: Location of wood mills, rain gages, and weather stations.

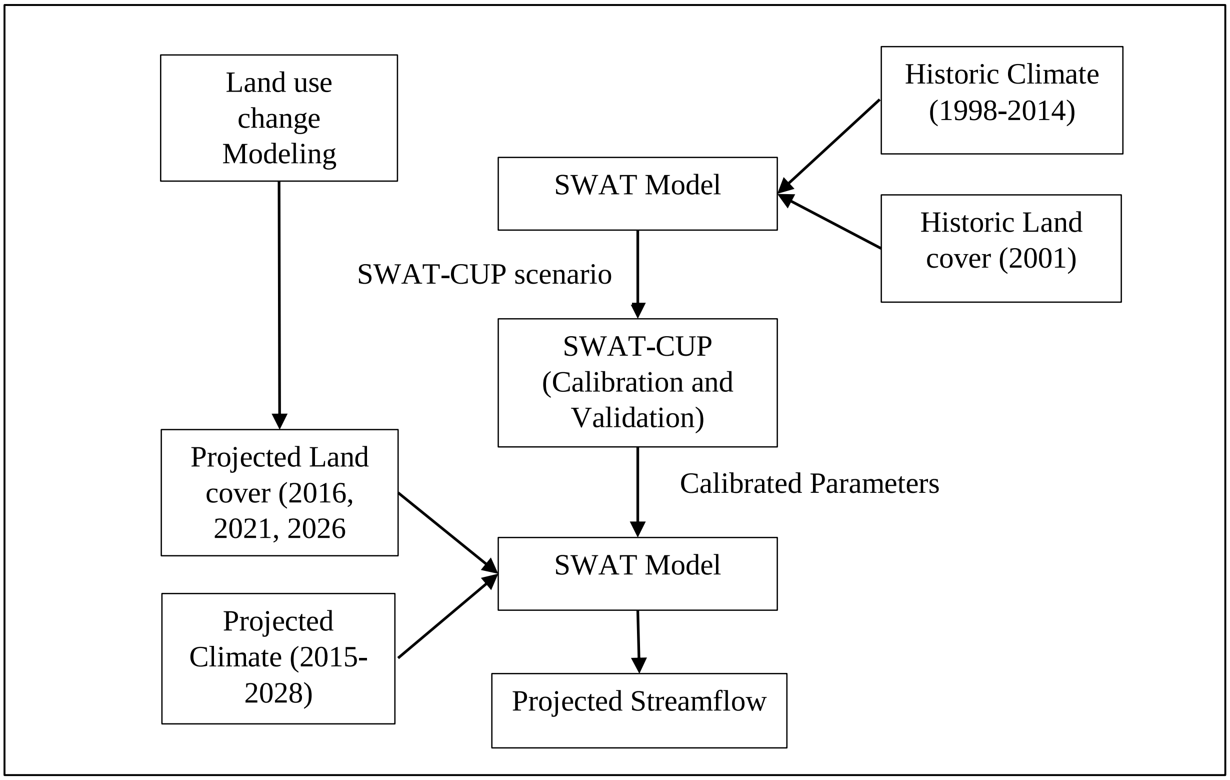


Figure 3.2: Diagram showing the linkage of climate and land cover dynamics to the watershed modeling.

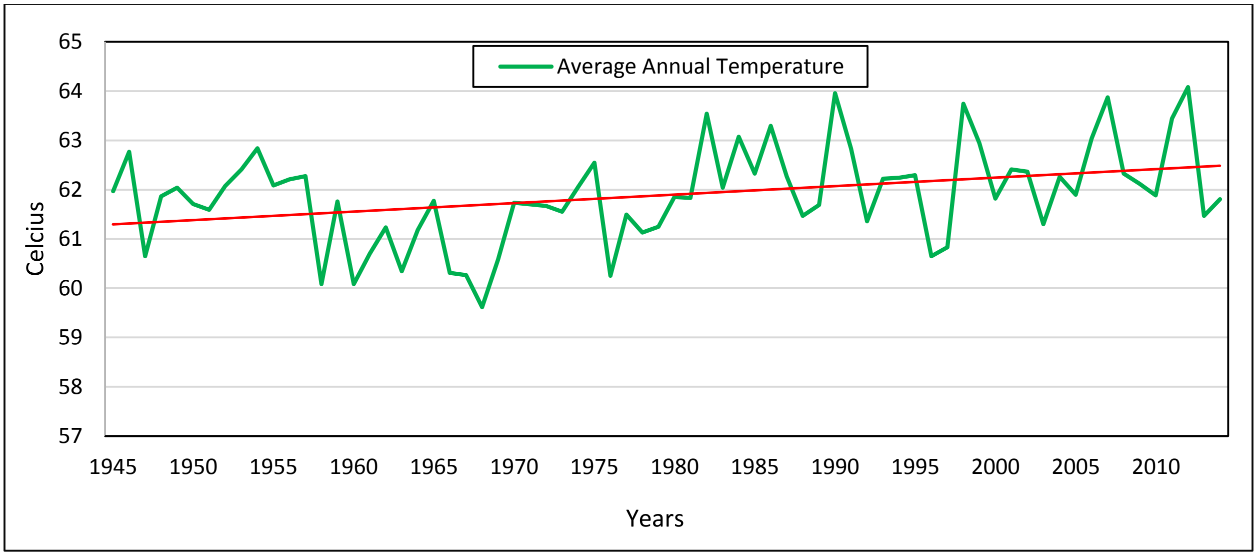


Figure 3.3: Historical average annual temperature data obtained from Ben Apps Climate station.

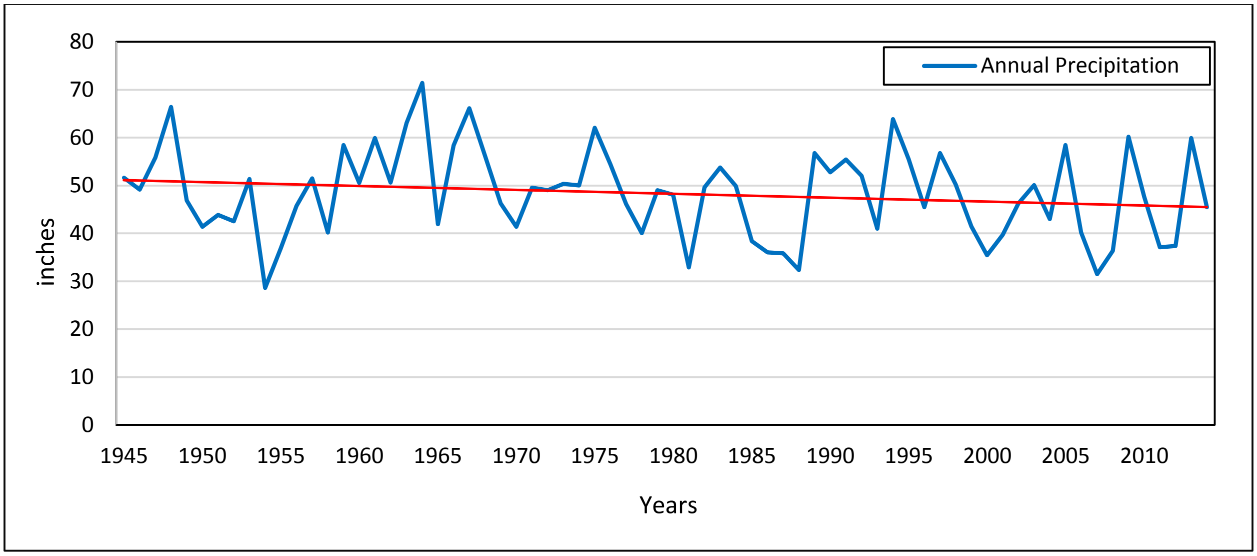
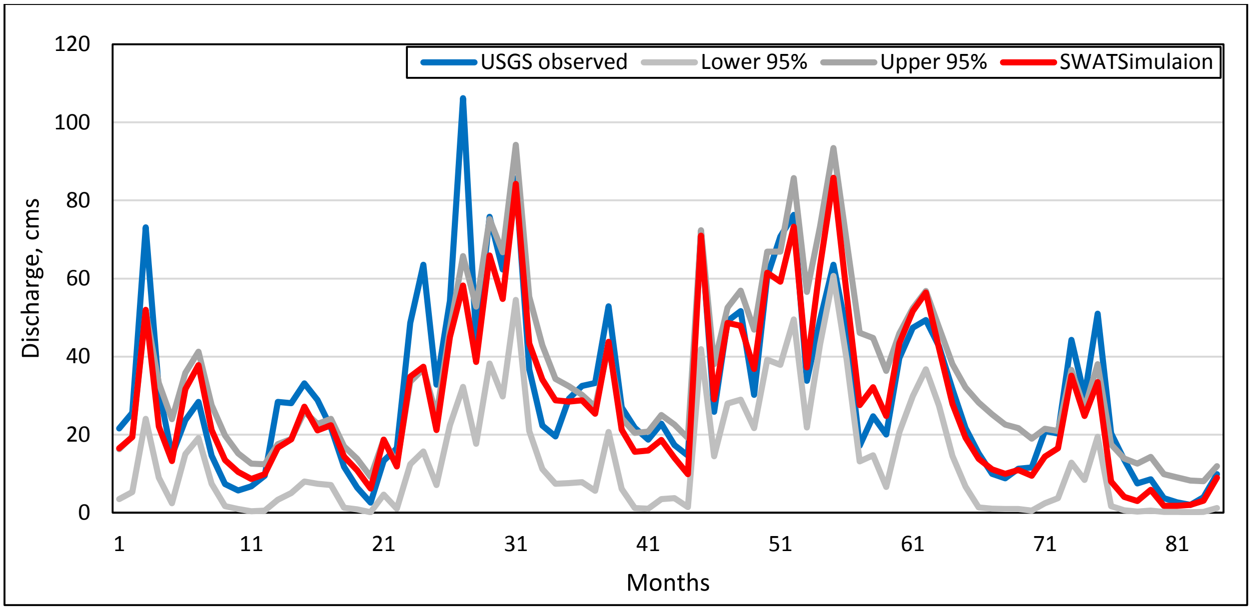


Figure 3.4: Plot of historical annual precipitation data obtained from Ben Apps Climate station.



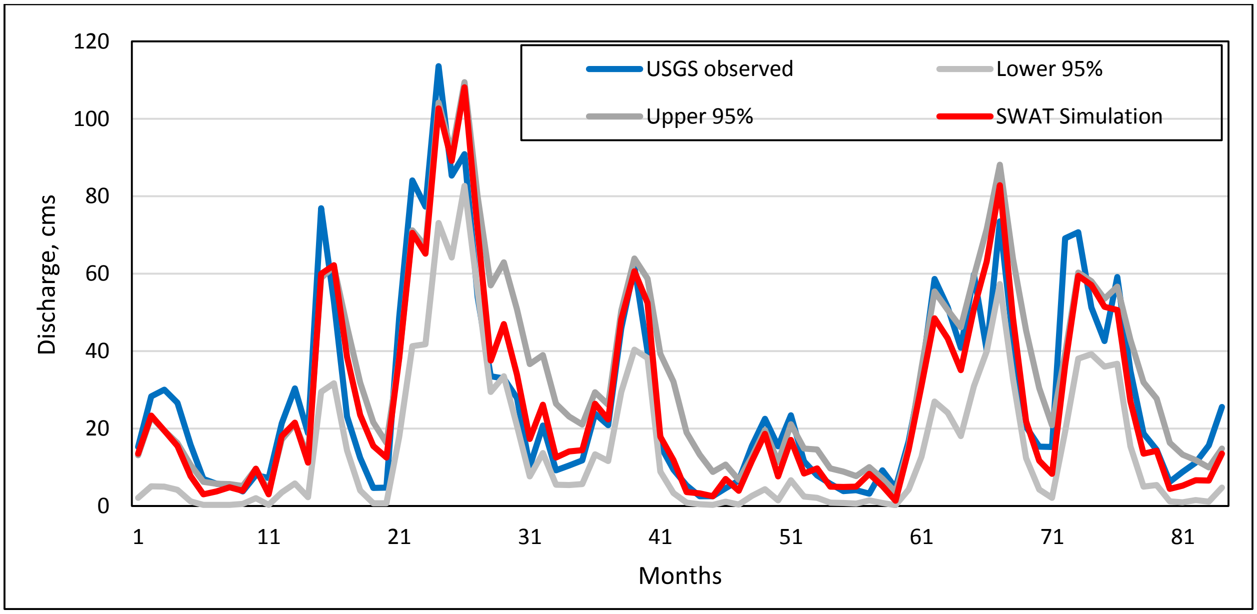
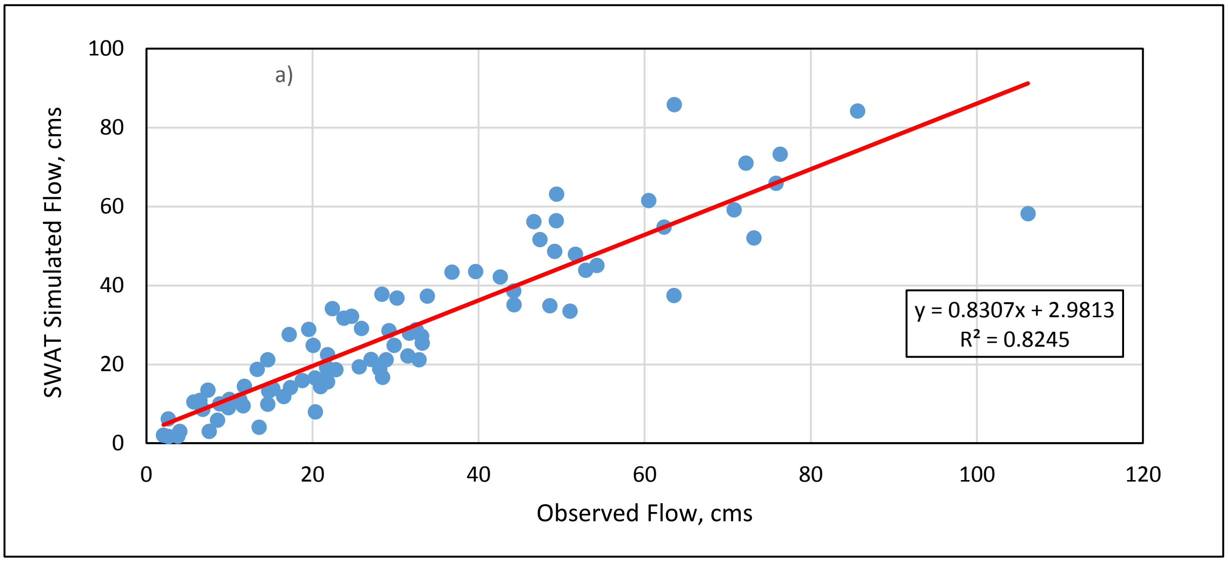


Figure 3.5: Plot of the observed USGS flow, SWAT best simulated flow, and upper and lower 95% prediction uncertainty band for the sub-watershed for (a) calibration period (1 Jan. 2001 to 31 Dec. 2007) and (b) validation period (1 Jan. 2008 to 31 Dec. 2014).



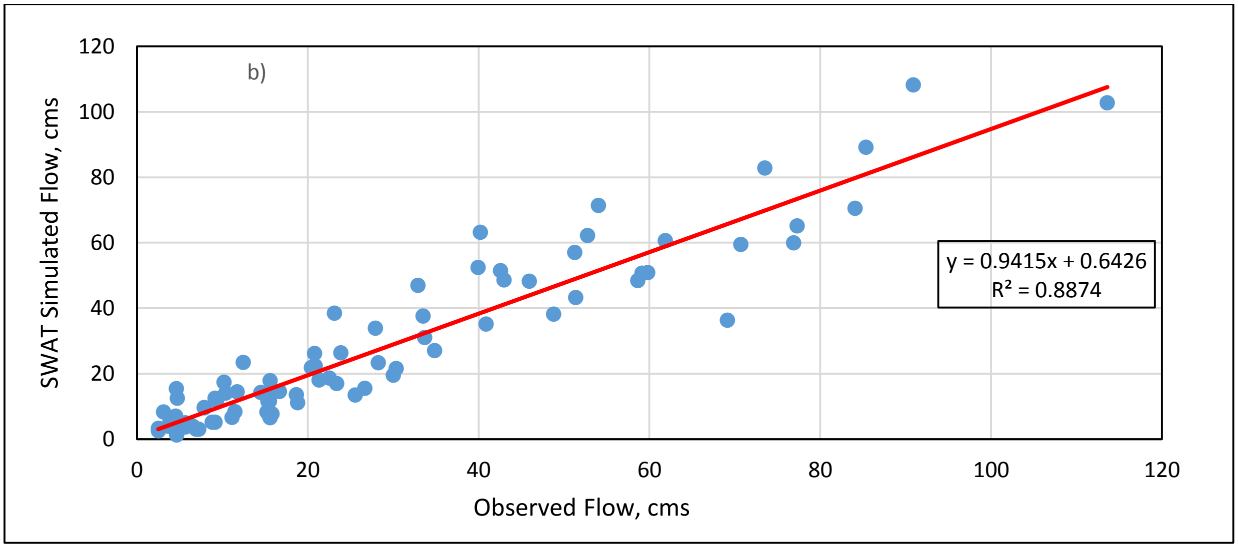


Figure 3.6: Regression of SWAT simulated monthly flow and USGS observed average monthly flow for (a) calibration period (1 Jan. 2001 to 31 Dec. 2007) and (b) validation period (1 Jan. 2008 to 31 Dec. 2014).

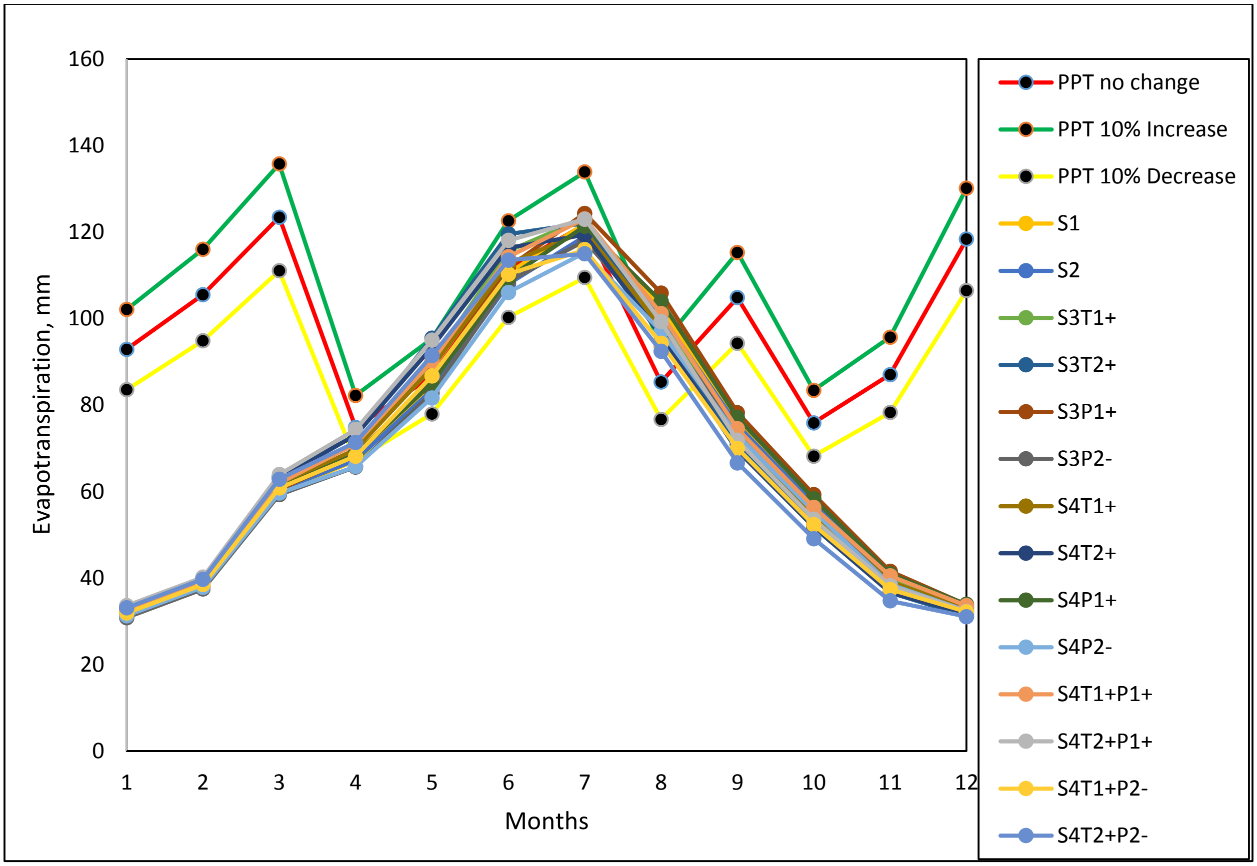


Figure 3.7: Mean monthly observation of evapotranspiration in the NE Oconee River Basin. Scenario types: Base Scenario (BAU), Land use change only (LU), 1 ^{0}C temperature rise (CCT1+), 2 ^{0}C temperature rise (CCT2+), 10% precipitation increase (CCP10+), 10% precipitation decrease (CCP10-), Land use change and 1 ^{0}C temperature rise (LUCCT1+), Land use change and 2 ^{0}C temperature rise (LUCCT2+), Land use change and 10% precipitation increase (LUCCP10+), Land use change and 10% precipitation decrease (LUCCP10-), Land use change, 1 ^{0}C temperature rise and 10% precipitation increase (LUCCT1+P10+), Land use change, 2 ^{0}C temperature rise and 10% precipitation increase (LUCCT2+P10+), Land use change, 1 ^{0}C temperature rise and 10% precipitation decrease (LUCCT1+P10-), and Land use change, 2 ^{0}C temperature rise and 10% precipitation decrease (LUCCT1+P10-).

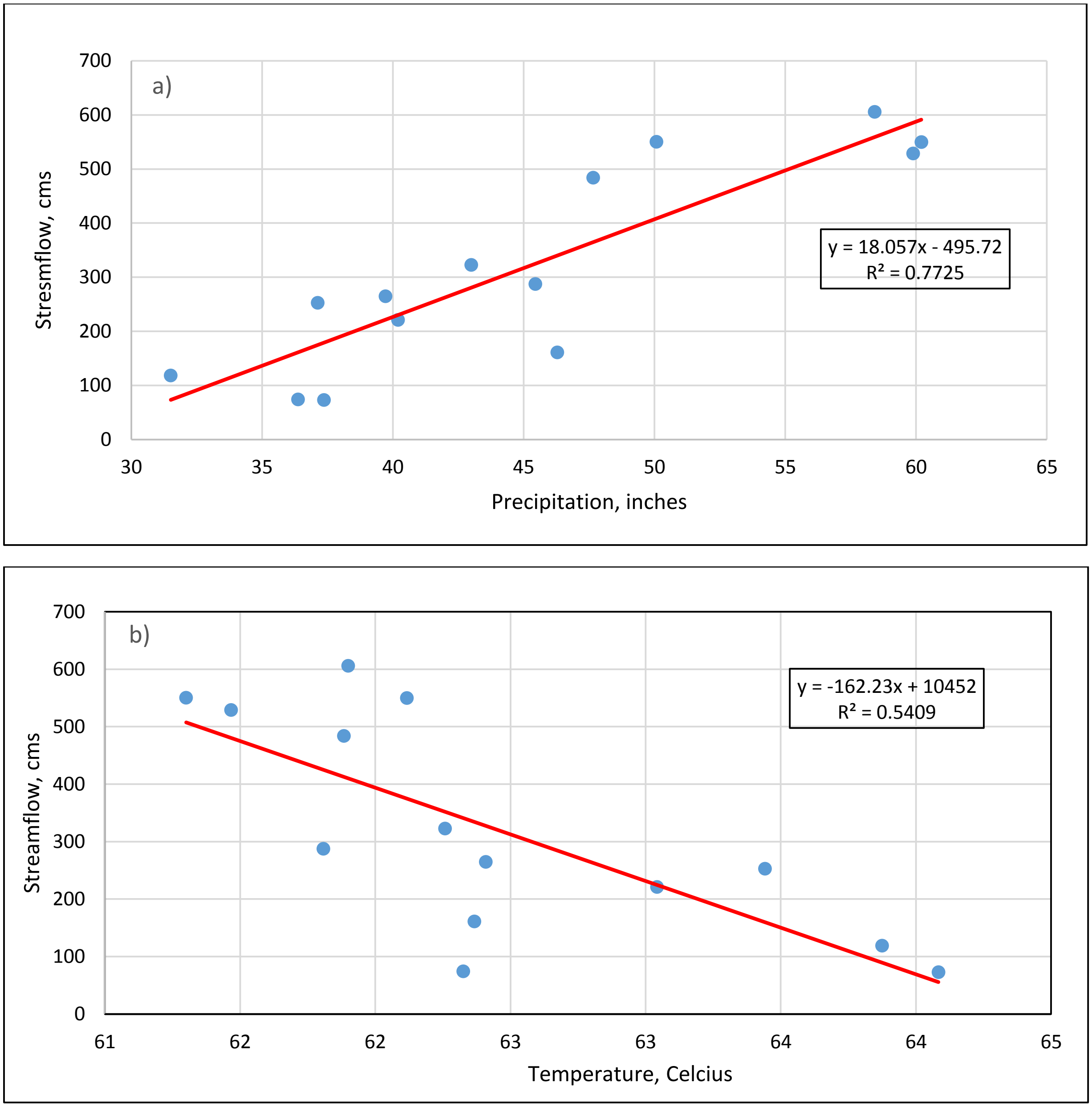


Figure 3.8: Regression of (a) annual streamflow and annual precipitation and (b) streamflow and annual temperature.

CHAPTER 4

CONCLUSIONS

We used suitability analysis as a tool for modeling relative land suitability for wood pellet production based on several suitability factors. The model was successful in identifying sites where loblolly pines can be grown for woody biomass production. This study only considered four land cover classes for suitability analysis. A total of 923 km², 38% of the watershed area, was identified suitable to establish loblolly pine. The suitability analysis was then combined with a land use change model to simulate potential land use changes over time and space. Based on the land use change model, we obtained land use maps for 2016, 2021, and 2026. The outputs of land use change model were then used as inputs in hydrological model (SWAT) to predict the effect of potential land use and climate change on the hydrological cycle of a watershed located in the northeast corner of Oconee river basin in the piedmont region of Georgia. Sensitivity analysis coupled with model calibration and validation were undertaken to determine the most appropriate parameters that affect watershed hydrology in the SWAT. Out of 19 parameters, seven parameters were found to be significant in terms of *p*-value associated with them. The calibrated SWAT model was run from 1 Jan. 2015 to 31 Dec. 2028 under four broad scenarios using 14 different scenarios to simulate the hydrological response to land use change and climate change till 2028.

The study indicated that the majority of precipitation was lost to evapotranspiration (65-75%). The relative change in evapotranspiration due to land use change was very low, where it decreased by 0.2%. When the temperature increased by 2°C and precipitation increased by 10%, ET increased by 3.5%. In contrast, the ground water depth changed by 24-29% due to land use and climate change relative to base scenario. The relative change in streamflow due to land use change was between 1.7 to 2.7%. The greatest increase and decrease in streamflow was found in land use and climate change combined scenario, which accounts for 30.5% and 29.8% respectively. Overall, the climate variation played a more pronounced role than land use in influencing surface hydrology in this watershed. Under the same precipitation condition, the mean annual basin streamflow decreased by 0.8 and 1.8% when the temperature increased by 1°C and 2°C respectively. Similarly, under the same temperature condition, the mean annual basin streamflow increased by 30% when precipitation increased by 10% and decreased by 28.6% when precipitation decreased by 10%. This study will guide the current debate on the overall sustainability of using small-diameter wood products for meeting growing demand of wood pellets in the southeastern United States.