Land Use Land Cover Change Projection for use in Municipal Water Resource Planning in the Saugahatchee Watershed

by

Rajesh Ramchandra Sawant

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

Auburn, Alabama
May 07, 2012

Keywords: Land Use Land Cover Change, Remote Sensing, GIS, GeOBIA

Approved by

Luke Marzen, Chair, Professor of Geography
Toni Alexander, Associate Professor of Geography
Charlene Lebleu, Associate Professor of Landscape Architecture

Abstract

The present work analyzes land use land cover changes in the Saugahatchee watershed through the use of remotely sensed satellite imagery. Urban growth has effect on the land use pattern in the local as well as in the surrounding region. Various models of land use change are extensively used for forecasting urban growth and future land use patterns. Modeling land use conversion patterns is the first step to understand the urban growth process. This work develops a land transformation model of urban growth to forecast land use changes in the saugahatchee sub-watershed surrounding Auburn-Opelika metropolitan area in the state of Alabama. This work uses GIS and image processing software namely ERDAS Imagine to process land use data and performs logistic regression analysis. Logistic regression is used to model land use change pattern in the area under investigation. The modeling is done in the GIS environment and spatial output of the model is fed into biophysical models, SWAT, to help determine the impact that LULC has on water quality and quantity and help resource manager evaluate future scenario of development.

Acknowledgments

I express my gratitude to my advisor, Dr. Luke Marzen, who suggested this research work and generously gave, continued guidance and support during the course of this work. I highly appreciate valuable suggestions of my committee members, Dr. Toni Alexander and Professor Charlene LeBleu, for this work.

My sincere thanks to the faculty, staff, and fellow students at the Department of Geology and Geography for making my study at the Auburn University a wonderful and enriching experience. My special thanks to Sherry Faust for her wholehearted administrative support in the department of Geography. My admiration for the unreserved support extended by my wife, Pallavi during the ups and down I experienced at the Auburn University. Finally it is the grace of the God that has helped me fulfill my aspirations.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ADEM	Alabama Department of Environmental Management
GIS	Geographic Information Systems
LULC	Land Use Land Cover
LUCC	Land Use Land Cover Change
GeOBIA	Geographic Object Based Image Analysis
RS	Remote Sensing
SWaMP	Saugahatchee Watershed Management Plan
SWAT	Soil Water Assessment Tool

CHAPTER 1

INTRODUCTION

1.1 Study background:

Changes in landscape development patterns occur in time and space due to complex interactions of physical, biological and social factors. Landscapes are influenced by human land use and the resultant landscape is a mosaic of landscape patches which vary in size, shape and spatial arrangement (Turner, 1987). Land use is a term used to describe human uses of the landscape through conversion and modification. Land use includes a variety of human uses such as urban or rural settlement, agriculture, transportation infrastructure, and recreation. Change in a land use often results in a change in the land cover. Land cover is characterized by climate and topography and includes number of categories like, forest, savannah, tundra, desert, etc. Land use changes over time in natural and human environments can result from processes of development. Conversion is a change from one land use to another. For example, forest clearance for pasture, wetland drainage for agriculture, and cropland conversion to urban settlement all constitute conversion. Modification is an alteration of the existing land cover that does not convert it to a different cover type such as, thinning of forest, intensification of cultivation, redevelopment of urban infrastructure (Meyer and Turner, 1994; Meyer, 1996).

In the past decade the land use land cover change (LULCC) Project, an international initiative to study changes in land use and land cover (LULC), has gained great momentum in its efforts to understand driving forces of land use change through comparative case studies. The project has developed diagnostic models of land-cover change, and produced regionally and globally integrated models (Geist and Lambin, 2001). The strong interest in LULC results from the direct relationship of LULC to many of the earth's fundamental characteristics and processes. This includes the productivity of the land, species diversity, and biochemical and hydrological cycles amongst many others. Land cover is continually shaped and transformed by land use changes such as, when a forest is converted to pasture or crop-land. Land use change often causes land-cover change. The underlying driving forces can be traced to a number of economic, technological, cultural and demographic factors and often, humans are recognized as a dominant force in local and global environmental change (Moran, 1993; Turner et al., 1994; Lambin et al., 2001). Understanding LULC is essential for many natural resource management and planning decision. It is important to have timely and precise information about LULC change detection of earth's surface for understanding relationships and interactions between human and their environment for better management of decision making (Lu et al., 2004).

Geospatial technologies such as Geographical Information System (GIS) and Remote Sensing (RS) have made it possible to develop spatially-explicit models of the social and environmental implications of LULCC. These models can define and test relationships between environmental and social variables using a combination of existing data (census data, LULC maps, and RS data), and field observations (ecological measurements; and surveys). These spatial models of LULC change drivers and their associated impacts can be used to evaluate cause and effects in LULC change observed in the past and are also extremely useful tools for offering forecasts of future land use changes and their effects on the environment and in the case of this proposed study; effects on water quality and quantity. Models of LULC change based on political, economic, environmental and other drivers can then be used to explore the impacts of policy decisions and other factors using scenario analysis and modeling techniques to make sustainable land management decisions (Heisterman et al., 2006).

From the methodological point of view the implementation of a GIS and RS with the support spatial analysis models facilitate the study of these spatial transformations, contributing to the understanding of these changes. This understanding will enable resource managers to visualize future scenarios that can be evaluated to assess their impact on water resources and thus will help to formulate appropriate developmental policies for sustainable development (Heisterman et al., 2006).

1.2 Statement of the Problem:

Through use of land, as reflected by water usage, human beings have appropriated as much as 40 percent of the net primary productivity of the earth. Changes in land are likely to alter ecosystem services. By altering ecosystem services, changes in land use and cover affect the ability of biological systems to support human needs (Vitousek et al., 1997). These changes in land use make places and people vulnerable to the changes in functions of economic and socio-political systems.

The Auburn-Opelika metropolitan area is one of the fastest growing Metropolitan Statistical Area (MSA) in Alabama (U.S. Census Bureau, 2009) and therefore has experienced rapid land cover change (Reutebuch et al., 2008). The metropolitan area encompasses the Saugahatchee sub-watershed which was identified to include two stream segments that the Alabama Department of Environmental Management (ADEM) has classified as impaired. The two impaired stream segments namely, Pepperell Branch and Saugahatchee Creek (Yates reservoir embayment) listed under 303d list of ADEM (see Figure 1) are polluted due to nutrient and organic enrichment flowing from industrial, municipal, non-irrigated crop production and pasture grazing uses. Land use changes associated with urbanization and forestry/agricultural land conversions within the Saugahatchee watershed have been shown to impact the water quality substantially and this study proposes to address some of these concerns (ADEM, 2010).

This study models and interprets urbanization patterns in Saugahatchee watershed, encompassing City of Auburn and Opelika in the State of Alabama, using a GIS and RS methods coupled with a logistic regression model to assess LULC change and the impacts on water quantity and quality. Analysis of future LULC change within the Saugahatchee sub-watershed is important in view of water quality and its supply for the community. Land use models are useful to better our understanding of the drivers of change, as well as associated consequences of changes and feedbacks. Land use models provide tools to predict and project changes in the land and the resultant consequences of such changes (Heistermann et al., 2006).

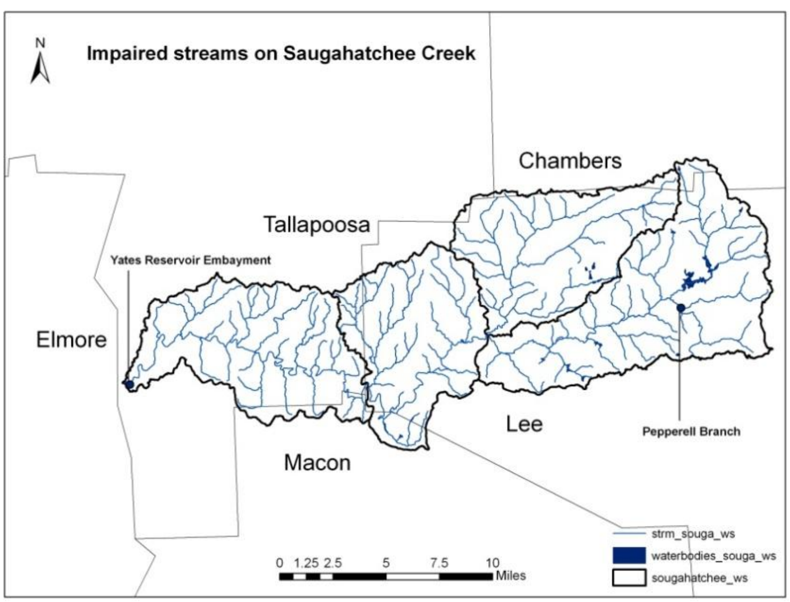


Figure 1.1 Saugahatchee sub-watershed showing two impaired streams on Saugahatchee creek.

1.3 Study Area:

The study site, Saugahatchee sub-watershed, is in the Lower Tallapoosa River Sub-Basin. Saugahatchee Creek has been identified as a high priority watershed by the Lower Tallapoosa Clean Water Partnership, the Alabama Soil and Water Conservation Committee, US Environmental Protection Agency and the Alabama Department of Environmental Management. (SWaMP, 2005). Figure 2 depicts various land uses in 2007 in Saugahatchee Watershed.

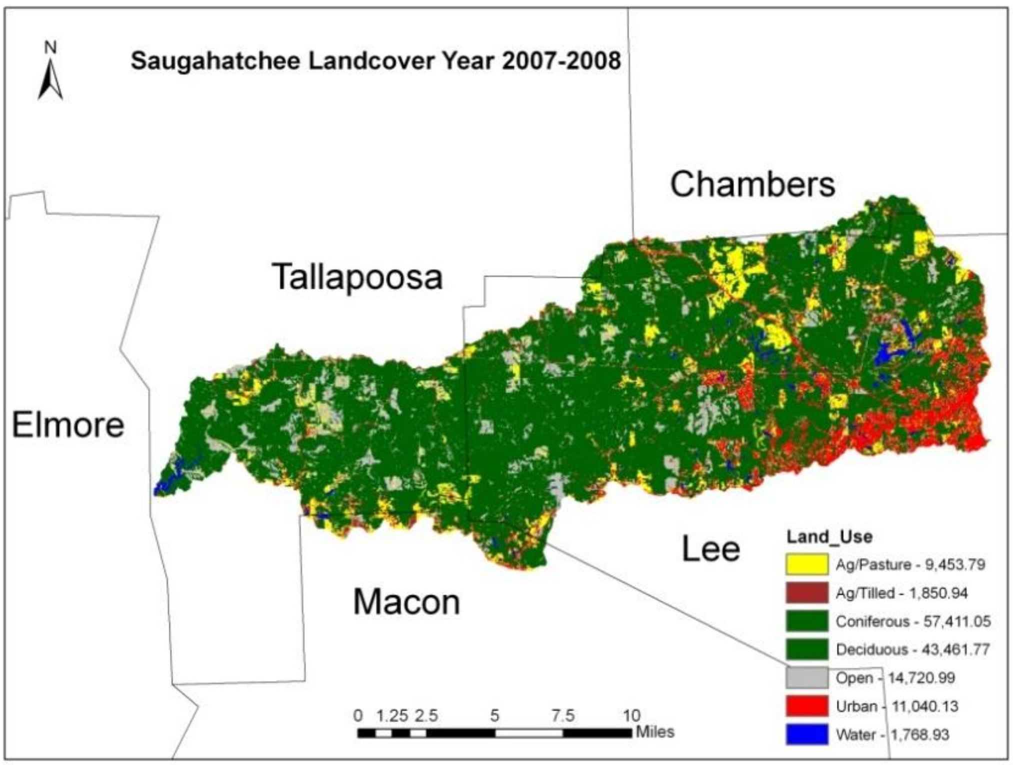


Figure 1.2 LULC (acres) within the Saugahatchee sub-watershed in the year 2007

According to a study done by Reutebuch et al. (2008) the area under forest cover is 72% of watershed area and urban development, mainly observed in southeastern part of the watershed occupies 7.9% of watershed area. Other predominant activity observed in the watershed is pastureland covering 10.5% of the area. It is posited that increasing Urban land use and pasture land have impact on the water quality and quantity in the watershed. Increasing impervious surfaces contribute to increases in surface runoff and pollutants, such as oil, sediments, and nutrients in runoff water. Conversion of forest to pasturelands also increases sediments and nutrient loads in the Saugahatchee creek (SWaMP, 2005).

1.4 Aim and Objectives:

The aim of this study is to analyze historical land use trends and evaluate various methods to detect, quantify, analyze, and forecast land use changes in the Saugahatchee Watershed. The study proposes to evaluate future land use scenarios and their impact on water quality and quantity.

The following are the specific objectives of the thesis:

- Quantify and examine the characteristics of land use change over the study area using RS and GIS analysis and ancillary information
- Compare Pixel Based and Object Based image classification
- Examine spatial transitions between different Land use categories
- Develop a model to predict and assess future land use changes and their impact on the water quality.
- Evaluate impact of future land use scenario on hydrologic changes in the watershed using biophysical models such as SWAT.

1.5 Research Questions:

The underlying basis of this study is that there have been considerable LULC changes in the Saugahatchee sub-watershed which have had a detrimental impact on the water quality in portions of the watershed.

In this investigation the following research questions are posed:

- Can improvements be made to traditional multi-spectral Pixel Based land use land cover classification through Object Based Image Analysis?
- What are the changes in land use and land cover in the study areas that are having the most substantial impact on water quality?
- What is the spatial and temporal extent of the land use and land cover change and where have the highest rates of changes have occurred?
- What are the major driving forces for the land use and land cover changes?
- What will be the extent of the land use and land cover changes in the future?
- What is the impact of future development scenarios on the water quality and quantity?

1.6 Thesis Outline:

Chapter1:

Introduction:

Statement of the Problem

Chapter3:

Multiple Logistic Regression and GIS to Model Land Use Change in Saugahatchee Watershed:

Introduction

Logistic Regression

Data and Methods

Results and Discussion

Logistic Regression Modeling

Model Validation

Land Use Land Cover Projection

Conclusion

Chapter4:

Use of SWAT for Assessing Water Quality and Quantity Impact of Land Use Change in the Saugahatchee Watershed:

Introduction

Data and Methods

Results and Discussion

Conclusion

Chapter5:

Summary

1.7 Methodology:

Various geospatial methodologies are used in this study to process, quantify, analyze and model the land use change. Image analysis of Landsat 5TM imagery is done by implementing traditional pixel-based classification methods utilizing unsupervised classification and cluster busting methods utilizing ERDAS Imagine 9.3. The results are compared with object oriented image analysis (OBIA) in Definiens 8.0 by developing a set of rules to hierarchically classify image segments. ArcGIS 9.3 version is used for spatial analysis of the land use changes. For the modeling part, this study has developed GIS based multi-criteria evaluation and logistic regression analysis to forecast land use change. This modeling is developed in the GIS environment and provides spatial outputs which are fed into biophysical models, SWAT, to help determine the impact that LULC change has on water quality and quantity which ideally may help resource managers evaluate and assess development scenarios.

1.8 Significance of the Study:

One of the major impacts of land use and land cover change is a loss of silviculture/ agriculture land through various development projects. Municipal developments in a watershed have substantial impact on the surface water quality and supply. Therefore, land use change studies are important tools for planners and decision makers to address the impact of urban growth. The proposed study is expected to provide resource managers with information on the condition and dynamics of the land use change in the Saugahatchee watershed through the use of remotely sensed satellite imagery for such analysis. The study shall provide tools to model land use changes and evaluate future development scenarios. The study underscores use of analytical tools for planners and decision makers to predict and compare impacts of different management options/policies. The study shall offer information related to dynamics of natural resources and may provide a basis for further research on assessing impacts of future land use on water quality and quantity in watersheds.

CHAPTER 2

REMOTE SENSING IMAGE ANALYSIS AND CLASSIFICATION OF LAND USE LAND COVER IN THE SAUGAHATCHEE WATERSHED

2.1 Introduction:

Human land-use activities impact the environment. Changes in land are likely to alter ecosystem services. By altering ecosystem services, changes in land-use and land-cover impacts the ability of biological systems to support human needs (Vitousek et al., 1997). Monitoring of land cover and its change thus is of critical importance. Remotely sensed data are widely used in land cover mapping, and monitoring of our environment. Remotely sensed (RS) satellite imagery and aerial photography have been widely used in many studies in urban area analysis and in various scientific research studies aiding in resource management decisions. It facilitates spatio-temporal analysis of our environment and the impact of human activities on it (Zhou et al., 2004). RS data provide a view of spatio-temporal patterns for a particular time period associated with change in a landscape, and thus are found useful for studying landscape dynamics and modeling of changes in the landscape (Yeh and Li, 1997; Longley, 2002; Herold et al., 2003). RS imagery analysis has been commonly used for change detection analysis (Im et al., 2008) and has potential use in management and planning of urban areas through gaining an understanding of land-use information (Herold et al., 2002).

The methods employing remote sensing techniques for analysis of urban land-use information have evolved from the very basic visual interpretation into a complex computer based analysis. However, automatic delineation of urban areas and differentiation of land cover types is still a challenge (Erbek et al., 2004; Lo and Choi, 2004; Qian et al., 2005). At present, the extraction accuracy of built-up areas is still unsatisfactory, which usually varies around 70%-80% for Landsat imagery. This is mainly due to the heterogeneity of urban areas, where continuous and discrete elements occur side by side (Aplin, 2003). Another reason is the problem of a mixed pixel, especially in an urban environment where the land cover is very heterogeneous at the local scale (Lo and Choi, 2004). A commonly used approach to image analysis is image classification. The purpose of classification is to tag meaningful information to pixels in an image. Through classification of digital remote sensing imagery, thematic maps having the information such as the land cover types and their extent can be obtained (Tso and Mather, 2001; Matinfar et al., 2007).

One popular and commonly used approach to image analysis is digital image classification. The purpose of image classification is to label the pixels in the image with meaningful information representing the real world (Jensen and Gorte, 2001). Through classification of digital remote sensing image, thematic maps bearing the information such as the land cover type; vegetation type etc. can be obtained (Tso and Mather, 2001).

2.1.1 Objectives:

In this study three classification approaches are selected and compared and contrasted. Two involve traditional pixel based image analysis approaches and the other one is the object oriented image analysis approach commonly known as Geographic Object Based Image Analysis (GeOBIA). Typical methods of classification of remote sensing imagery have used Pixel Based

Analysis (PBA). Normally, multispectral data are used to perform the classification and, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Price, 1994; Lillesand et al., 2004). The PBA approach is based on conventional statistical techniques utilized in supervised and unsupervised classification. GeOBIA approaches image analysis by combining spectral information as well as spatial information such as texture and contextual information in the image (Flanders et al., 2003).

Earlier methods employed to do land use land cover classification using remotely sensed imagery were predominantly by PBA methods, where land cover classes are assigned to individual pixels. Although PBA method of classification is widely used, working at the pixel scale can have major drawbacks. Main among these is the problem of mixed pixels, whereby a pixel represents more than a single type of land cover (Fisher, 1997), which often times lead to misclassification. By removing the possibility of misclassifying individual pixels, object-based classification can improve pixel-based classification (Aplin et al., 1999; Platt and Rapoza, 2008). The object-oriented processing technique segments the images into homogenous regions based on neighboring pixels' spectral and spatial properties (Carleer et al., 2005; Alpin and Smith, 2008). One of the segmentation processes in eCognition is known as a "multi-resolution segmentation" and is based on "region growing approach" (Im et al., 2008).

GeOBIA uses the spatial scale of the object instead of the pixel. For example, the maximum likelihood classification algorithm has been used for object based classification either for classifying objects directly (Kiema, 2002; Dean and Smith, 2003; Walter, 2004) or by first classifying pixels individually and then grouping these to populate each object (Aplin et al., 1999; Geneletti and Gorte, 2003). Benz et al. (2004) reported use of fuzzy classification for object-based analysis. Aplin and Atkinson (2001) located fuzzy (sub-pixel) land cover class proportions spatially by segmenting pixels according to polygon boundaries, while Shackleford and Davis (2003) used combination of pixel based and object based approach using sub-pixel class proportions to derive new land cover classes at the object based scale.

Since the objective of the present study was to use remotely sensed image analysis to produce reasonably accurate (85% and above) land use classification of the imagery, as suggested by Fitzpatrick-Lins (1981), two methods of classifications namely; pixel based and object based were used. The traditional PBA method often exhibit salt and pepper effect to the classification. In unsupervised classification it is common for multiple classes to represent a single land cover type. After an initial classification is complete, multiple classes are recoded to the same land cover type. In PBA it is not uncommon for multiple land cover types to exist within one class which represent error. To correct these errors cluster busting is often done (Jensen, 2000). Thus, three methods of classification namely, unsupervised PBA, unsupervised PBA with cluster busting, and GeOBIA are compared in the present study. The results of the classification were statistically tested to determine which method will produce more accurate LULC classification than other methods. In GeOBIA the automated segmentation process of imagery has the advantage of being less time consuming. The whole classification process can be saved as a rule set. The advantage of creating a rule set is that it is much more flexible and can be modified to rectify any mistakes in the classification process. Further, the rule set developed on a data set can be applied to other similar data sets. For the present study the most accurate classification is used in land use projections using logistic regression as described in Chapter 3. The Soil Water Analysis Tool (SWAT) model is then used to make a decision on the suitable land use projection based on the effect of land use projections on the water quality within the Saugahatchee watershed as described in Chapter 4.

2.2 Data and Methods

2.2.1 Spatial data processing:

In various environmental studies (Aplin et al., 1999; Harold et al., 2002; Yang and Lo, 2002; Dean and Smith, 2003; Lo and Choi, 2004; Fan et al., 2007; Lathrop et al., 2007; Dappen et al., 2008), such as mapping and land use change detection, image analysis is based on the analysis of satellite data. While conducting image analysis for multi-temporal data, consideration must be given to the season of image acquisition, as well as cloud cover and impacts of the sun's inclination as these factors would affect the quantitative analysis of the changes. To overcome the impact of these factors anniversary images with similar characteristics such as sun angle and percent cloud cover are to be used (Singh, 1989). In this study, multi-temporal datasets of historical satellite imagery, aerial photographs and other vector datasets were used to determine LULC changes over the study period from 1991 to 2009. The Landsat 5 Thematic Mapper (TM) imagery for the study area was searched for using the USGS Global Visualization Viewer (GloVis) for the years 1991, 2001, and 2009 and downloaded from the EROS data center using the Earth Explorer interface. The acquisition dates of the three imageries were Sept. 27, 1991; Oct. 25, 2001; and Sept. 29, 2009 with 0% cloud cover. The images downloaded from USGS GloVis were georeferenced and radiometrically corrected.

The Landsat 5 platform operates from a Sun-synchronous, near-polar orbit, imaging the 115 miles ground swath every 16 days. The Landsat 5TM sensor has a spatial resolution of 30 meters for bands 1 through 5, and band 7, and a spatial resolution of 120 meters for band 6. Each TM band has a characteristic to maximize detecting and monitoring different types of earth surfaces. For example, TM band 1 penetrates water for bathymetric mapping along coastal areas and is useful for soil-vegetation differentiation and for distinguishing forest types. TM band 2 detects green reflectance from healthy vegetation, and TM band 3 is useful for detecting chlorophyll absorption in vegetation. TM Band 4 data is good for detecting near-IR reflectance peaks in healthy green vegetation and for detecting water-land interfaces. The two mid-IR red bands on TM (bands 5 and 7) are useful for vegetation and soil moisture studies and for discriminating between rock and mineral types. The thermal-IR band on TM (band 6) is designed to assist in thermal mapping, and is used for soil moisture and vegetation studies (USGS, 2011; Jensen, 2000).

For the present study TM Bands 1-7 are used in classification for both PBA and GeOBIA methods. For image interpretation bands 4, 3, and 2 are combined to make false-color composite images where band 4 represents the red, band 3 represents the green, and band 2 represents the blue portions of the electromagnetic spectrum. This 4-3-2 band combination makes vegetation appear as shades of red, with brighter reds indicating more abundant and productive vegetation. For soils with no or sparse vegetation color range from white to greens or browns depending on moisture and organic matter content. Water bodies appear blue in color. Deep and clear water appears dark blue to black in color, while shallow waters or water with sediments appear lighter in color. Urban areas appear blue-gray in color. This color information is then used to help classify imagery into five land use land cover categories for the present study.

Historical analysis of LULC change is done from year 1991, 2001, and 2009 with Landsat 5 Thematic Mapper (TM) imagery, 30 meter resolution, using a variety of traditional (unsupervised classification and cluster busting) and newer techniques including segmentation, classification, and change detection procedures to understand the trends of the LULC change.

The spatial extent of the study area was extracted by overlaying a boundary file (HUC 11 – 03150110030) of the Saugahatchee watershed with the Landsat 5 TM imagery and cropping imagery to the extent of the Saugahatchee watershed boundary. In order to view and distinguish the surface features clearly, all the input images were composed using the RGB false color composition in 4-3-2 bands. Although, the 4-3-2 false color composite is good for interpreting imagery it is important to realize both traditional PBA and GeOBIA (in generating a segmented image) considers all 7 bands. Since the present study is concerned mainly with the change in the urban/built up area and its impact on the water quality within the Saugahatchee watershed, only the major categories of LULC are considered for classification. The urban/ built-up areas have spatially heterogeneous features and such surface features have similar spectral response thus making it difficult to discriminate some of the features. In the present study the urban class includes all forms of built structure including residential, commercial, industrial, road and other impervious surfaces. A modified Anderson land use land cover classification system (Anderson et al., 1976) at Level I was used to classify land cover into 5 major land cover categories namely; water, forest, open/transition, urban, and ag/pasture. Ancillary data such as existing land cover maps, Digital Orhto Quad Quadrangles (DOQQs), obtained from Alabama Cooperative Extension System GIS portal, and Google maps were integrated in the classification study. These classified land use maps are used to carry out the analysis of LULC changes in a Geographic Information System (GIS).

2.2.2 Data Processing Utilizing Unsupervised classification for Pixel based Multispectral Remote Sensing:

Registration and rectification of anniversary Landsat 5 TM images from 1991, 2001, and 2009 was done to align the imagery properly. For classification of the imagery first unsupervised classification followed by cluster busting was implemented in ERDAS IMAGINE 9.3. In unsupervised classification method, the ISODATA clustering algorithm (Jensen, 2005) is used to classify the image into 100 classes. The 100 classes were derived in the unsupervised classification with maximum number of iterations set to 10 and convergence threshold set to 0.95. The pixels were identified for each of the categories, by referring to the 4-3-2 FCC and reference DOQQ aerial photos from corresponding time periods (obtained from alabamaview.org and City of Aburn), and were grouped into land cover categories: Water, Forest, Open/ Transition, Urban, and Ag/Pasture. The classified land cover map was produced as shown in Figure 2.1.

2.2.3 Data Processing Utilizing Unsupervised with Cluster Busting for Pixel based Multispectral Remote Sensing:

To separate the mixed up classes, especially in the urban areas, cluster busting is done to improve the classification. While doing pixel based classification of urban areas, often times open areas such as large bare soil areas, worn playgrounds and cemeteries are mixed up with urban features like large parking lots. A cluster busting technique to reclassify mixed pixels (Jensen, 2005) was employed to break out smaller clusters from larger ones that represented more than one distinct land cover type. Cluster busting is a procedure designed to separate pixels that are spectrally similar to one another by progressively decreasing the spectral variance between classes. First, candidate pixels were identified and masked from the raw TM data. The candidate pixels were then reclassified using an unsupervised classification approach. The resulting output clusters were reassigned to the output land-cover classes they most closely resembled. This method is useful in clearing up much of the mixed pixels in the urban areas. Using aerial photos to guide the classification process, final cluster assignments were made to the five land-cover classes to produce the land cover map. The results of the classification maps are shown in Figure 2.1.

The PBA is done in two ways; the first with only unsupervised and, the second with unsupervised combined with cluster busting. This is done to compare these two methods with GeOBIA method for time required for classification and accuracy of the classification. Using the unsupervised classification, the classification of imagery into specified classes is done relatively quickly using ISODATA clustering algorithm. Most time is spent in analyzing the 100 classes and comparing individual classes to the 4-3-2 false color composites and the DOQQs in order to assign each class to one of the 5 classes in the selected scheme. This takes less time than cluster busting because the user does not take the time to correct errors from mixed classes but the resultant classification has a salt and pepper effect and often times multiple land cover types exist within one class. Although cluster busting helps improve the unsupervised classification it is a time consuming process.

2.2.4 Data Processing Utilizing GeOBIA :

The GeOBIA approach considers groups of pixels and the geometric properties of image objects. It segments the imagery into homogenous regions based on neighboring pixels' spectral and spatial properties. In this analysis the image objects are classified based on a supervised maximum likelihood classification. The object-based image analysis approach to a certain extent avoids the mixed pixel problems commonly observed in the traditional pixel based method (Mori et al., 2004).

In this study eCognition Version 8.0 is used to classify Landsat imagery. Landsat 5 TM imagery with the 7 bands was loaded into eCognition as image layers. In Object-oriented image analysis the first step is to segment the image into vector polygons. Multiresolution Segmentation was done followed by the creation of a class hierarchy and then, classification rule sets were developed. During the image segmentation process image segments are defined and calculated. Parameters for segmentation are defined for the scale, shape and compactness properties. These image segments have to be calculated on different scale in a "trial and error" process to result in final image segments to represent single objects of interest having least mixing of classes (Benz et al., 2004; Laliberte et al., 2004).

In the process of segmentation spatial dimensions in image analysis are included by identifying relatively homogenous regions and treating them as objects. One of the segmentation processes in eCognition is known as a "multi-resolution segmentation" where the smallest objects containing single pixels are merged into larger objects based on the defined segmentation parameters. The multiresolution segmentation process requires users to set scale parameters ranging from 1 to 100. In this case, all the image layers were given equal importance 1 and different scale parameters were attempted based on visual analysis of the segmentation results. The segmentation parameters, which yielded the least mixing of classes with the Landsat TM datasets analyzed in the study area, were set as; image layer weight as 1, Scale to 3, Shape to 0.1, and Compactness to 0.5.

After creating 5 major categories of land cover at the modified Anderson Level I scheme, classification samples were selected for each category. Based on the samples collected, a nearest neighbor algorithm was applied. The ruleset created for classification is depicted in the Figure 2.1. Finally, the classified image objects were merged into respective classes and then the merged classes were exported in a vector format as an output to produce the land cover maps as shown in Figure 2.2.

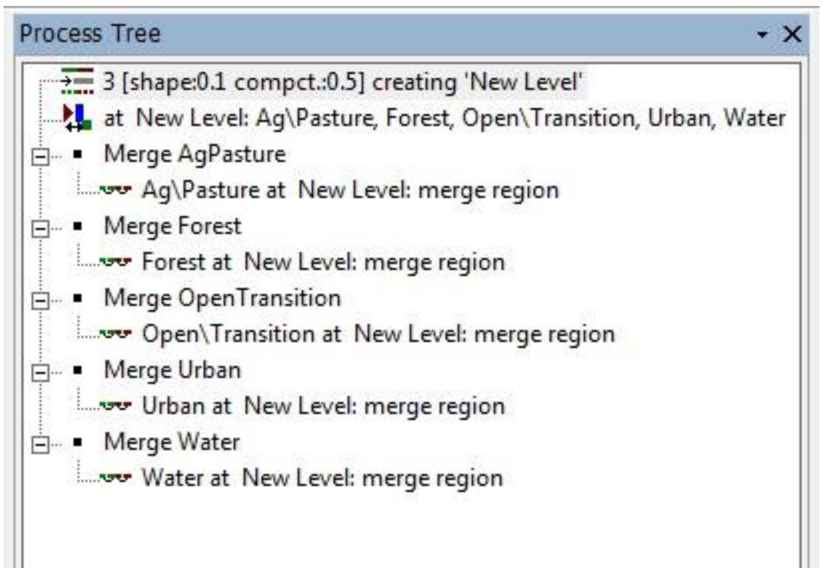
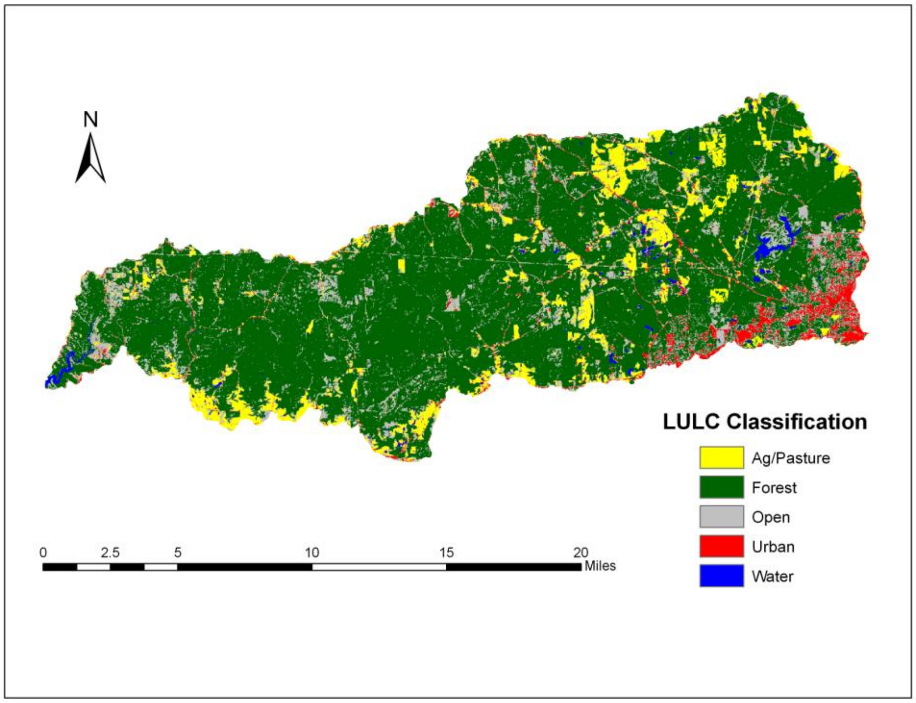


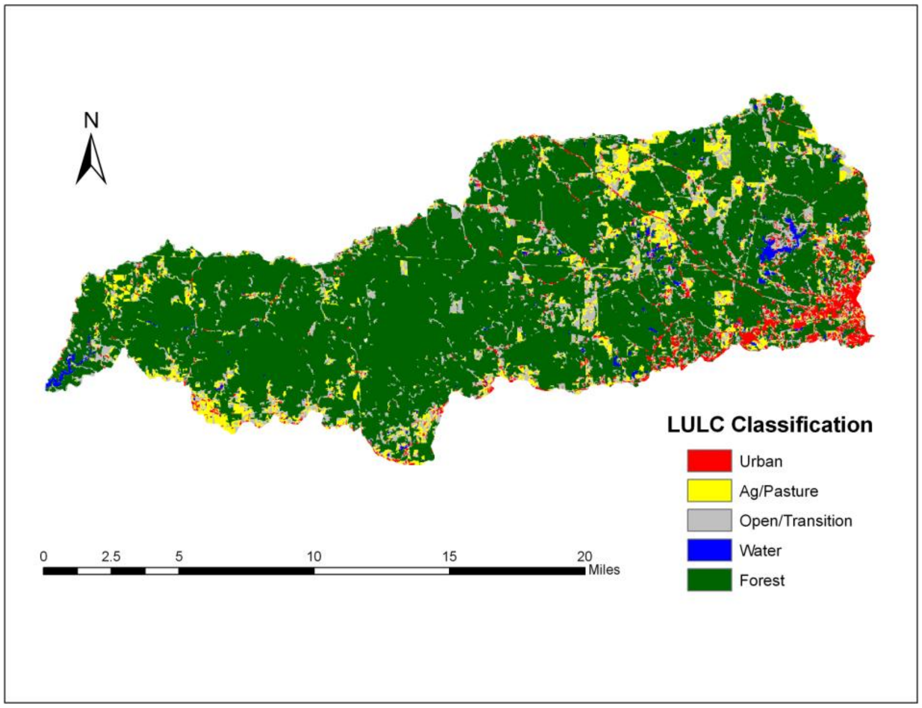
Figure 2.1 Ruleset for classification of the LandSat5-TM imagery

From the classified land cover maps shown in Figure 2.2 it can be deduced that the forest area has remained relatively stable over last 20 years. There is a distinct increased in urbanization within the Saugahatchee watershed, indicated by red color, over the last decade. Also the Ag/ Pasture area has reduced over the period from 2001 to 2009 which, indicate conversion of Ag/ Pasture land partly to urbanization and to regeneration of forest. The area in acres under each land use land cover category is presented in Tables 2.1, 2.2, and 2.3 for Unsupervised, Unsupervised with cluster busting and GeOBIA classification respectively. The accuracy of classification results are evaluated below in section 2.3.1.

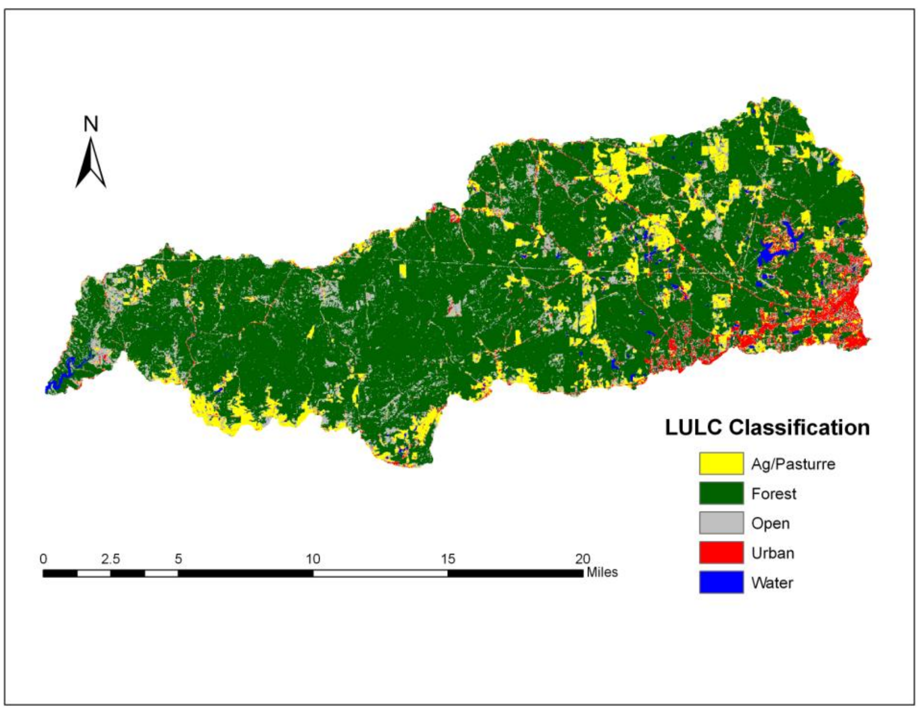
Figure 2.2 Land use land cover classifications maps



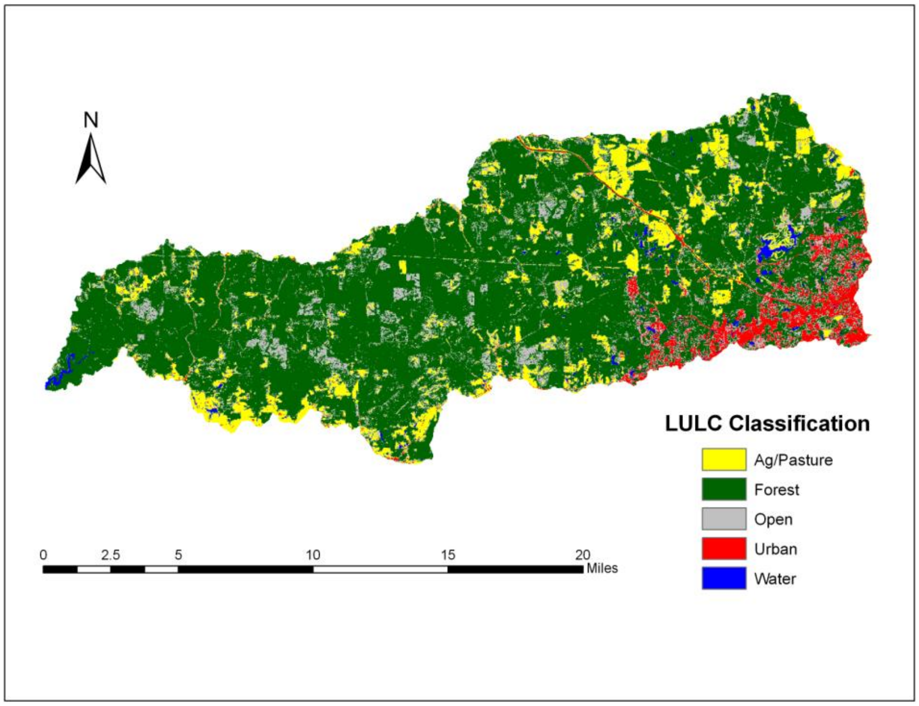
(a) Unsupervised with cluster busting, 1991



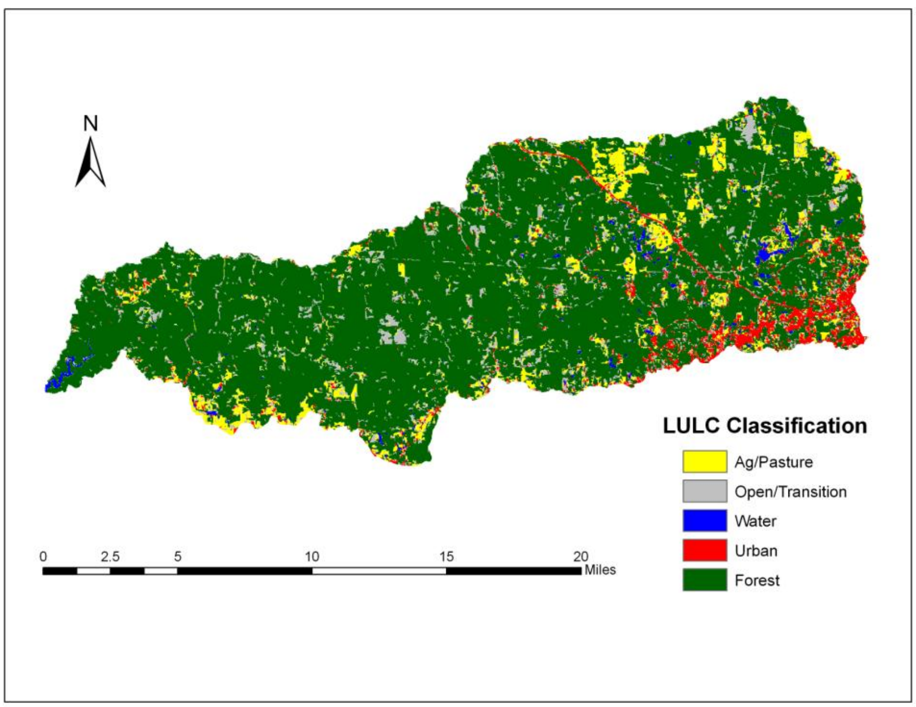
(b) Object based, 1991



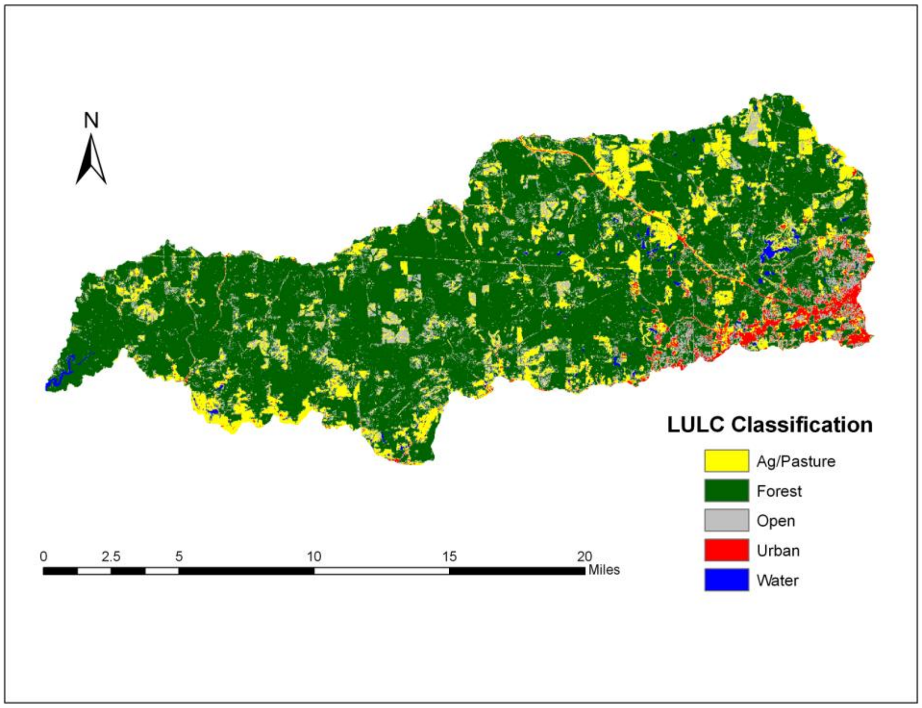
(c) Unsupervised, 1991



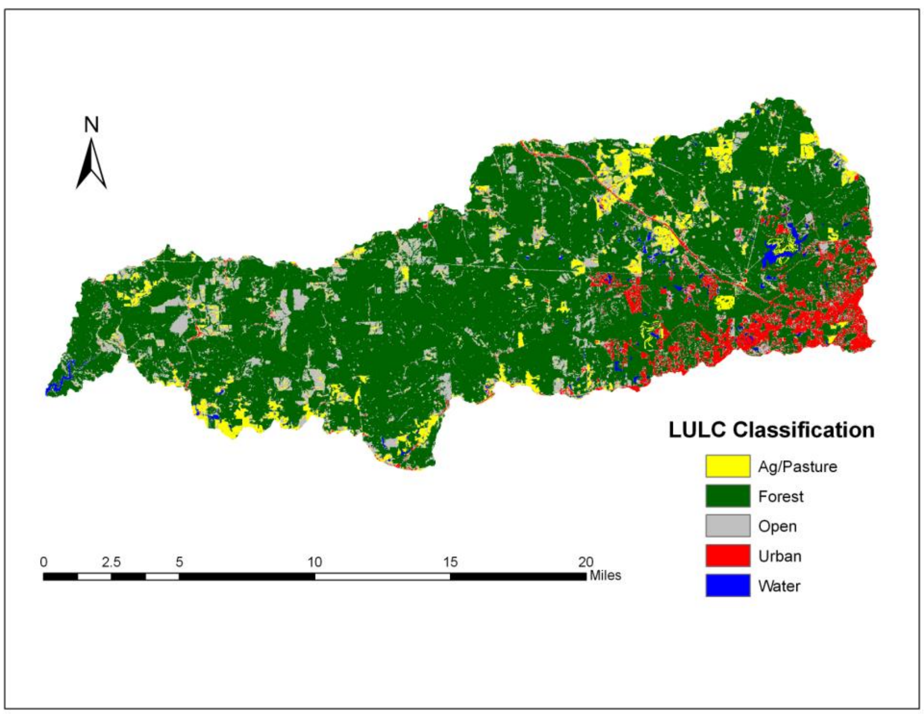
(d) Unsupervised with cluster busting, 2001



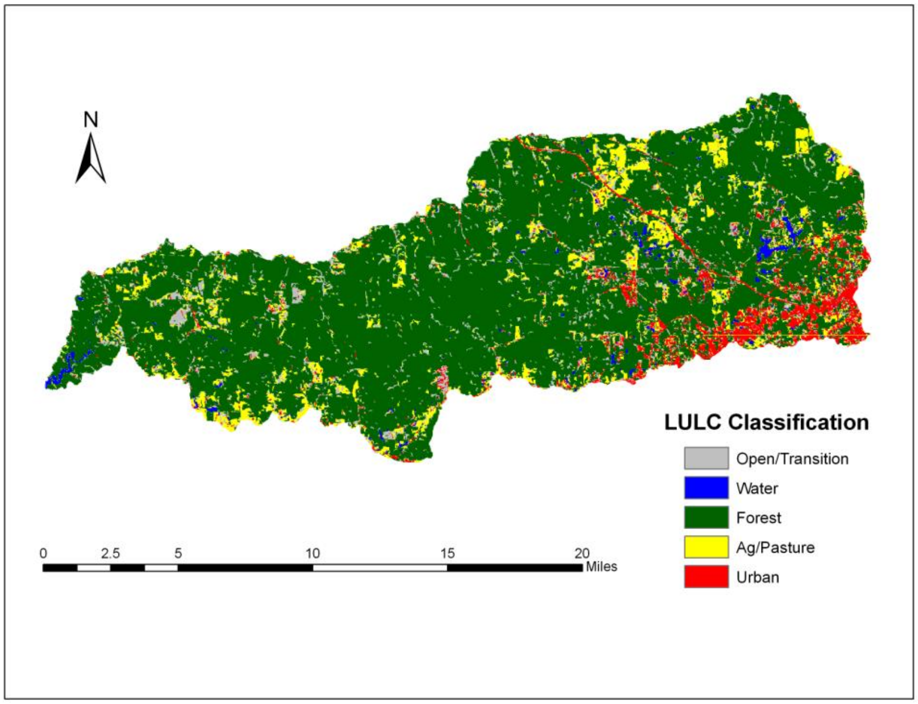
(e) Object based, 2001



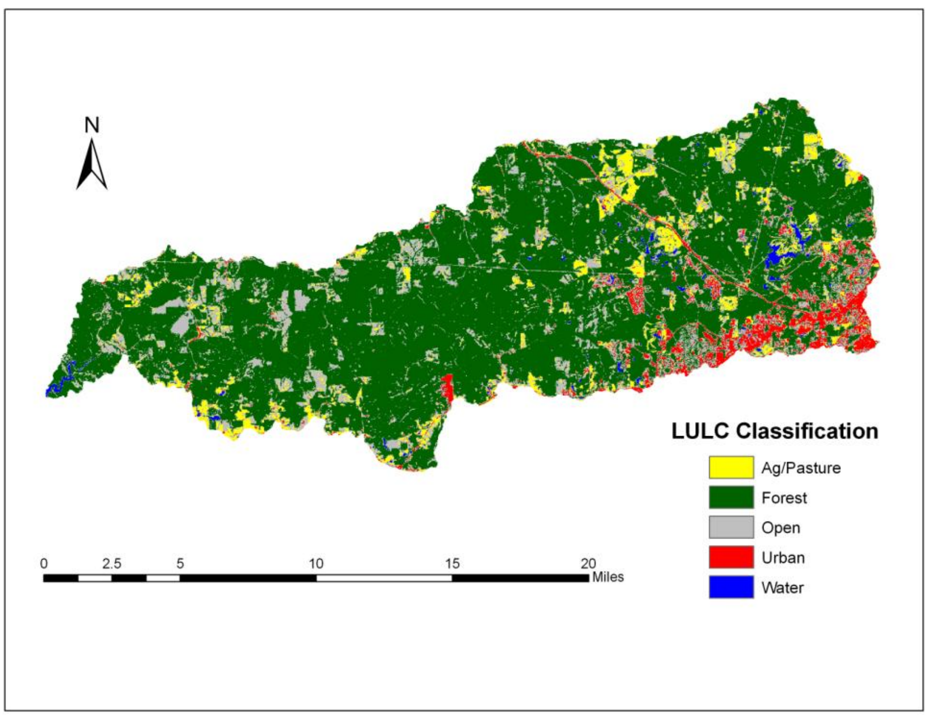
(f) Unsupervised, 2001



(g) Unsupervised with cluster busting, 2009



(h) Object based, 2009



(i) Unsupervised, 2009

Table: 2.1: Area in acres computed for unsupervised classification

	Year 1991	Year 2001	Year 2009
Water	1,360	904	1,079
Forest	101,989	99,299	101,023
Open	18,612	19,765	24,666
Urban	5,717	3,659	5,541
Ag/Pasture	12,069	16,119	7,437

Table: 2.2: Area in acres computed for unsupervised classification with cluster busting.

	Year 1991	Year 2001	Year 2009
Water	1,293	1,151	1,267
Forest	102,386	99,680	103,448
Open	19,980	20,419	20,386
Urban	5,154	6,038	7,035
Ag/Pasture	10,933	12,458	7,611

Table: 2.3: Area in acres computed for GeOBIA classification

	Year 1991	Year 2001	Year 2009
Water	1,408	1,307	1,649
Forest	105,612	110,970	108,987
Open	15,080	9,506	7,856
Urban	5,637	6,070	7,086
Ag/Pasture	9,361	9,329	11,454

2.3 Classification Accuracy Assessment:

Accuracy assessment is a process used to estimate the accuracy of image classification by comparing the classified map with a reference map (Congalton and Green, 1999). With the advancement of digital satellite remote sensing analysis the need for the advanced accuracy assessment received new interest (Congalton and Green, 1999). At present accuracy assessment is considered as an integral part of any image classification. This is because image classification using different classification algorithms may classify pixels or group of pixels to wrong classes. The most noticeable types of error that occurs in image classifications are errors of exclusion or inclusion. The classification accuracy is represented in the form of an error matrix. An error matrix is a square array of rows and columns and presents the relationship between the classes in the classified and reference maps. Using error matrix to represent accuracy is recommended and adopted as the standard reporting convention (Congalton and Green, 1999).

Error matrix is a simple cross-tabulation of the mapped class label against that observed in the ground or reference data for a sample of cases at specified locations (Qian et al., 2005). The overall accuracy is calculated by dividing the number of correctly classified pixels (presented as entries in the major diagonal of the confusion matrix) by the total number of reference pixels. Though simple, the overall accuracy has been the most conventional approach accuracy assessment (Woodcock, 2002; Qian et al., 2005). An improvement to this overall accuracy assessment metric is the Kappa coefficient of agreement, which expresses the proportionate reduction in error generated by a classifier compared with the error of a completely random classification. Beyond the compensation for chance agreement, the Kappa coefficient can be used in the z-test of the significance of the difference between two coefficients, thus enabling a comparison between different classifications in terms of accuracy. (Congalton and Green, 1999; Qian et al., 2005).

In this paper, Overall Accuracy, Producer's Accuracy and User's Accuracy were calculated. The Kappa coefficient, which is a statistical measure of the difference between the actual agreement and chance agreement, was also calculated. The Kappa statistics is a discrete multivariate technique used in accuracy assessment for statistically determining if one error matrix is significantly different than the other error matrix (Congalton and Green, 1999; Fan et al., 2007).

The reference data used for accuracy assessment included a combination of high resolution (1m) aerial imagery, land cover maps, and Landsat imagery used for the initial classification. Based on guidelines set by Congalton and Green (1999) for accuracy assessment a sample unit of a cluster of pixels (3X3 size) was used. Based on many empirical studies, Congalton and Green (1999) have suggested collecting minimum of 50 samples for each land cover category in the error matrix which provides a statistically sound and practically attainable sample collection. The number of referenced sample points (n) required for the accuracy classification was determined by the following equation, suggested by Fitzpatrick-Lins (1981);

$$N = \frac{4(p)(q)}{E^2}$$

where, p is the expected percent accuracy, q= 100 – p, and E is the allowable error, and Z=2 from the standard normal deviation of 1.96 for the 95% 2-sided confidence level. Fitzpatrick-Lins (1981) has also suggested an accuracy of at least 85% for each category. In the study an allowable error of 2% was taken since the study involved some field work. For the present study allowable error of 5% was considered to be reasonable as no field work was involved.

Substituting these values in the equation (1) result in:

$$N = \frac{4(85)(100 - 85)}{5^2}$$

The total number of sample points was estimated to be 204. A minimum of 50 samples for each land cover category were randomly generated. Thus, for five land cover categories a total of 250 random reference points were generated using the Accuracy Assessment tools in ERDAS IMAGINE 9.3. The classified map and reference aerial photo for the corresponding year were geolinked and then samples points on the classified map were labeled for accuracy by referring to the aerial photo.

Error matrices were then designed to assess the quality of the classification accuracy of all the maps. These error matrices were used for descriptive and analytical statistical techniques to examine accuracy of classification (Congalton, 1991). The Overall Accuracy, User's and Producer's Accuracies, as well as the Kappa statistic were then derived from the error matrices. The error matrix designed in object based image classification was compared with error matrix designed in initial unsupervised classification for pairwise comparison of z statistics to determine if they are significantly different. The object based image classification was also compared with the unsupervised classification improved by cluster busting method for pairwise comparison of error matrices. The results of statistical evaluation of classification accuracy are presented in the following section.

2.3.1 Evaluation of Classification Results:

As stated above the accuracy assessment was carried out and results of error matrix are presented in TABLE 2.4 to 2.12. The procedure outlined by Congalton and Green (1999) was followed to determine Overall Accuracy, Producer's Accuracy, User's Accuracy, and Kappa statistics from the error matrix.

Overall Accuracy:

This is computed by dividing the total correct number of pixels (i.e. summation of the diagonal) to the total number of pixels in the matrix (grand total). The overall accuracies for the pixel based unsupervised classification with cluster busting for year 1991, 2001, and 2009 were 90.00%, 90.00%, and 90.40%, respectively. The overall accuracy of the object based classification for 1991, 2001, and 2009 were 82.00%, 82.00%, and 84.40%, respectively. Similarly the overall accuracy of the pixel based unsupervised classification for 1991, 2001, and 2009 were 84.00%, 82.40%, and 84.00%, respectively. Anderson et al., (1976) noted that a minimum accuracy value of 85% is required for effective and reliable land cover change analysis and modeling. The pixel based classification with cluster busting carried out in this study produces an overall accuracy of 90.00%, which fulfils the minimum accuracy threshold defined by Anderson (1976).

Producer's Accuracy:

This refers to the likelihood of a reference pixel being classified correctly. It is also known as exclusion error because it only gives the proportion of the correctly classified pixels. It is obtained by dividing the number of correctly classified pixels in the category by the total number of pixels of the category (Column total) in the reference data. The overall result of the producer's accuracy for pixel based unsupervised classification with cluster busting ranges from 77% to 100%. For the object based classification the producer's accuracy ranges from 65% to 100%. Similarly, the producer's accuracy for the pixel based unsupervised classification ranges from 55% to 100%. The lowest producer's accuracy exists in the land cover classes open/transition. This is probably attributed to the similar spectral properties of some of the land cover classes (e.g. bare land in urban areas, bare land within the Ag/pasture, open areas within forest land etc).

User's Accuracy:

This evaluates the likelihood that the pixels in the classified map represent that class on the ground (Congalton, 1991). It is obtained by dividing the total number of correctly classified pixels in the category by the total number of pixels on the classified map. User's accuracy of individual land cover classes for pixel based unsupervised classification with cluster busting ranges from 86% to 96%. For the object based classification the producer's accuracy ranges from 78% to 94%. Similarly, the producer's accuracy for the pixel based unsupervised classification ranges from 76% to 96%. From user's point of view the lowest producer's accuracy exists in the land cover classes, ag/pasture, urban areas, and open/transition land. The Ag/pasture and urban were, to some extent, misclassified as open/transition and ag/pasture, respectively. This is probably caused by the spectral signature of the features.

Kappa Statistics:

The Kappa coefficient, which is a measure of agreement, can also be used to determine the classification accuracy. It expresses how well the classified map agrees with the reference data (Congalton and Green, 1999). The Kappa statistic incorporates the off-diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. To determine if the overall accuracies were statistically significant, Kappa coefficients were calculated for all the three methods of classification and a pair-wise Z test was calculated using the information in Tables 2.4, to 2.10 and the following formula given by Congalton and Green (1997):

$$\widehat{K} = \frac{P_o - P_c}{1 - P_c}$$

$$Z = \frac{\left|\widehat{K}_1 - \widehat{K}_2\right|}{\sqrt{\widehat{Var}\left(\widehat{K}_1\right) + \widehat{Var}\left(\widehat{K}_2\right)}}$$

where, P_o represents actual agreement, P_c represents chance agreement, and $\widehat{K}_1$ and $\widehat{K}_2$ represents the Kappa coefficients for the pixel-based classification, and object-based classifications, respectively. The Kappa coefficient is a measure of the agreement between observed and predicted values and whether that agreement is by chance. A Kappa value ranges from 0 to 1, with values closer to zero indicating higher chance agreement. The Kappa coefficients for the pixel-based unsupervised with cluster busting classifications were 0.87, 0.87 and 0.88 for the classified maps of 1991, 2001, and 2009 respectively. These Kappa results are considered to be a good result. The Kappa coefficients for the object-based classifications were 0.77, 0.77 and 0.80 for the classified maps of 1991, 2001, and 2009 respectively. Similarly, the Kappa coefficients for the initial pixel-based unsupervised classifications were 0.80, 0.78 and 0.80 for the classified maps of 1991, 2001, and 2009 respectively (Table 2.13).

Pairwise Comparison:

The Kappa values and a pair-wise Z test were calculated. The Z-scores and P-values are given in the table 2.14 and 2.15 for pair-wise comparison of Pixel-based unsupervised with cluster busting Vs. Object-based and pair-wise Comparison of initial Pixel-based unsupervised Vs. Object-based, respectively. The Z statistic is used for determining if the classification is significantly better than a random result. At 95% confidence level, the critical value would be 1.96. Therefore, an absolute value of pair-wise Z test greater than 1.96 indicates that the two error matrices are significantly different. The Z score and P-value in Table 2.14 indicates a statistically significant difference between pixel-based unsupervised with cluster busting classification and the object-based classification. The result of the pairwise test for significance (Table 2.15) between initial pixel-based unsupervised classification and object-based classification shows that the two matrices are not significantly different.

Table 2.4 Pixel-Based Unsupervised Classification after cluster busting, Year 1991

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	44	2	3	0	1	50	88.00
	Forest	0	48	1	0	1	50	96.00
	Open/Transition	0	4	44	0	2	50	88.00
	Urban	0	1	4	44	1	50	88.00
	Ag/Pasture	0	0	5	0	45	50	90.00
	Column Total	44	55	57	44	50	250	
	Producer's Accuracy	100.00	87.27	77.19	100.00	90.00		

Table 2.5 Object-Based Classification, Year 1991

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	43	3	4	0	0	50	86.00
	Forest	0	44	5	0	1	50	88.00
	Open/Transition	0	4	39	2	5	50	78.00
	Urban	0	1	6	39	4	50	78.00
	Ag/Pasture	0	5	4	1	40	50	80.00
	Column Total	43	57	58	42	50	250	
	Producer's Accuracy	100.00	77.19	67.24	92.86	80.00		

Table 2.6 Initial Pixel-Based Unsupervised Classification, Year 1991

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	44	4	0	2	0	50	88.00
	Forest	0	48	2	0	0	50	96.00
	Open/Transition	0	6	40	0	4	50	80.00
	Urban	0	2	6	40	2	50	80.00
	Ag/Pasture	0	2	8	2	38	50	76.00
	Column Total	44	62	56	44	44	250	
	Producer's Accuracy	100.00	77.42	71.43	90.91	86.36		

Table 2.7 Pixel-Based Unsupervised Classification after cluster busting, Year 2001

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	43	1	2	4	0	50	86.00
	Forest	0	48	2	0	0	50	96.00
	Open/Transition	0	2	44	0	4	50	88.00
	Urban	0	1	3	45	1	50	90.00
	Ag/Pasture	0	1	4	0	45	50	90.00
	Column Total	43	53	55	49	50	250	
	Producer's Accuracy	100.00	90.57	80.00	91.84	90.00		

Table 2.8 Object-Based Classification, Year 2001

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	39	8	3	0	0	50	78.00
	Forest	0	44	5	0	1	50	88.00
	Open/Transition	0	5	40	1	4	50	80.00
	Urban	0	0	7	41	2	50	82.00
	Ag/Pasture	0	2	6	1	41	50	82.00
	Column Total	39	59	61	43	48	250	
	Producer's Accuracy	100.00	74.58	65.57	95.35	85.42		

Table 2.9 Initial Pixel-Based Unsupervised Classification, Year 2001

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	42	2	6	0	0	50	84.00
	Forest	0	44	6	0	0	50	88.00
	Open/Transition	0	2	40	2	6	50	80.00
	Urban	0	0	8	42	0	50	84.00
	Ag/Pasture	0	0	12	0	38	50	76.00
	Column Total	42	48	72	44	44	250	
	Producer's Accuracy	100.00	91.67	55.56	95.45	86.36		

Table 2.10 Pixel-Based Unsupervised Classification after cluster busting, Year 2009

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	45	4	0	1	0	50	90.00
	Forest	0	47	3	0	0	50	94.00
	Open/Transition	0	2	45	1	2	50	90.00
	Urban	0	1	5	44	0	50	88.00
	Ag/Pasture	0	0	4	1	45	50	90.00
	Column Total	45	54	57	47	47	250	
	Producer's Accuracy	100.00	87.04	78.95	93.62	95.74		

Table 2.11 Object-Based Classification, Year 2009

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	40	6	3	1	0	50	80.00
	Forest	1	47	2	0	0	50	94.00
	Open/Transition	0	1	43	3	3	50	86.00
	Urban	0	1	6	41	2	50	82.00
	Ag/Pasture	0	1	8	1	40	50	80.00
	Column Total	41	56	62	46	45	250	
	Producer's Accuracy	97.56	83.93	69.35	89.13	88.89		

Table 2.12 Initial Pixel-Based Unsupervised Classification, Year 2009

		Reference Map						
		Water	Forest	Open/ Transition	Urban	Ag/ Pasture	Row Total	User's Accuracy
Classified Map	Water	46	2	1	0	1	50	92.00
	Forest	0	44	6	0	0	50	88.00
	Open/Transition	0	2	42	2	4	50	84.00
	Urban	0	0	12	38	0	50	76.00
	Ag/Pasture	0	0	10	0	40	50	80.00
	Column Total	46	48	71	40	45	250	
	Producer's Accuracy	100.00	91.67	59.15	95.00	88.89		

Table 2.13 Error Matrix Kappa Analysis

	Pixel-Based Unsupervised/ cluster busting		Object-Based		Pixel-Based Unsupervised	
Year	Overall Accuracy	Kappa Statistics	Overall Accuracy	Kappa Statistics	Overall Accuracy	Kappa Statistics
1991	90%	0.8750	82%	0.7750	84%	0.8000
2001	90%	0.8750	82%	0.7750	82.40%	0.7800
2009	90.40%	0.8800	84.40%	0.8050	84%	0.8000

Table 2.14 Pairwise Comparison: Pixel-based unsupervised with clusterbusting Vs. Object-based

Year	Z Statistics	P-value
1991	2.5945	0.0096
2001	2.5951	0.0096
2009	2.0311	0.0424

Table 2.15 Pairwise Comparison: Initial Pixel-based unsupervised Vs. Object-based

Year	Z Statistics	P-value
1991	0.5957	0.5552
2001	0.1168	0.9124
2009	0.1226	0.9044

2.4 Urban Land Use Change:

Since, the accuracy assessment results indicate unsupervised classification with cluster busting is more accurate over other classification methods used in this study; the maps derived from unsupervised classification with cluster busting were used for urban change analysis in the Saugahatchee watershed. Change detection is the process used in remote sensing to determine changes in the land use land cover between different time periods. To examine the urban land use changes, a "post-classification" change analysis was employed in ERDAS Imagine for the study area. The "post-classificaiton" is common and suitable method for land cover change detection. This method compares two independently classified images to produce a change map of matrix of changes (Singh, 1989; Araya and Cabral, 2010)

The land cover maps for the years 1991, 2001 and 2009 were first reclassified into two classes: Urban and Other areas. The post-classification comparison was then applied by overlaying the reclassified maps of 1991 with 2001 and 2001 with 2009 in ERDAS Imagine. Image interpretation was done by performing matrix function to generate change maps.

The matrix function creates an output file that contains classes that indicate how class values of two input images overlap. The accuracy of change map of two images depends on the accuracies of each individual classification. Image classification and post-classification techniques are, therefore, iterative and require further refinement to produce more reliable and accurate change detection results (Fan et al., 2007).The results from change detection for period from 1991 to 2001 and from 2001 to 2009 indicate significant changes in urban land use in the saugahatchee watershed. Most of the urban changes occurred around the peripheries of the existing urban land use areas. The changes in the urban areas shows spread of urban land use in the surrounding areas and also infill growth of the urban area within the study area as shown in the Figure 2.3 (a) and (b).

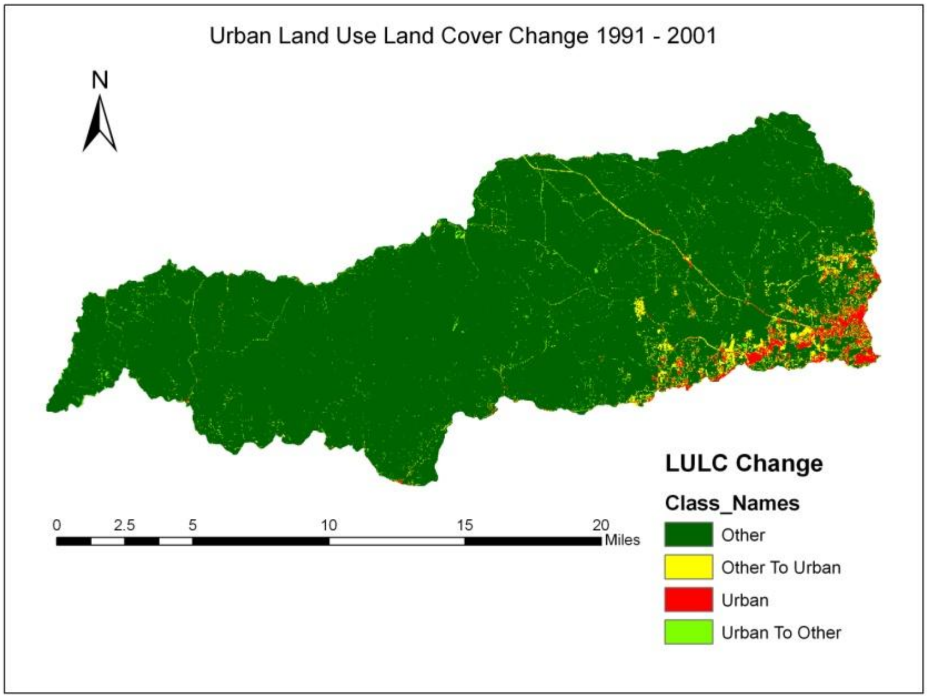


Figure 2.3 (a) Change from 1991 To 2001

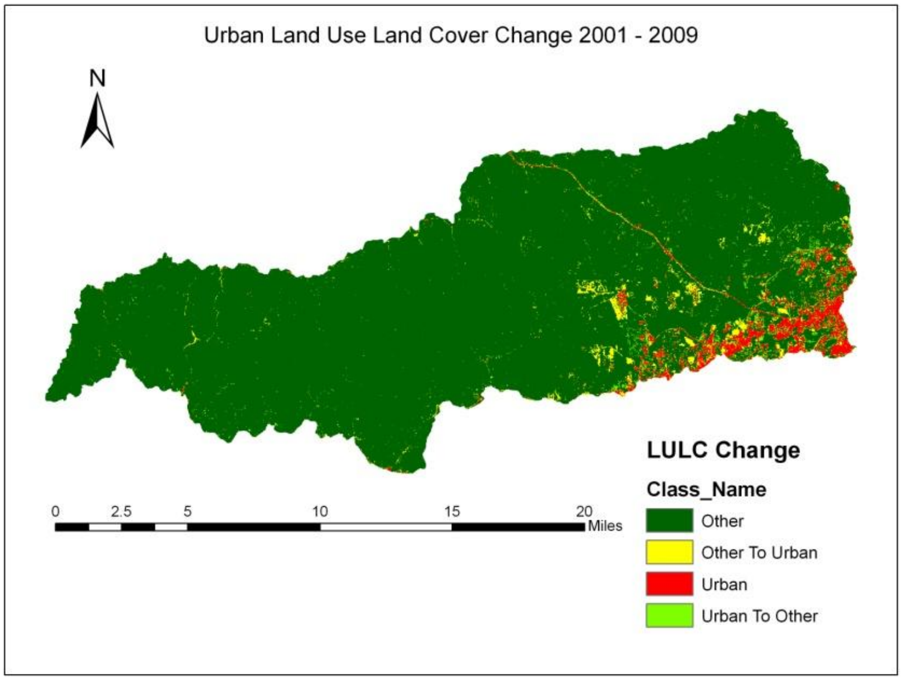


Figure 2.3 (b) Change from 2001 To 2009

Similarly the classified land cover maps for the years 1991, 2001 and 2009 were overlaid and matrix output for all five classes for the period from 1991 to 2001 and from 2001 to 2009 is generated. The Figure 2.3 (a) and (b) show the resultant map interpreting land use change from forest, open and pasture areas to urban over the study period. In the Figure 2.4 (a) and (b) the green color indicate conversions from forest to urban, yellow is conversion from Ag/Pasture to urban and black is conversion from Open/Transition to urban. The results of the change detection indicate that for both the study periods there were conversions of forested areas to urban. The open areas, which were within and immediate vicinity of the urban areas, were converted to urban. The land conversions of pasture to urban were relatively less and were observed mainly for the period from 2001 to 2009.

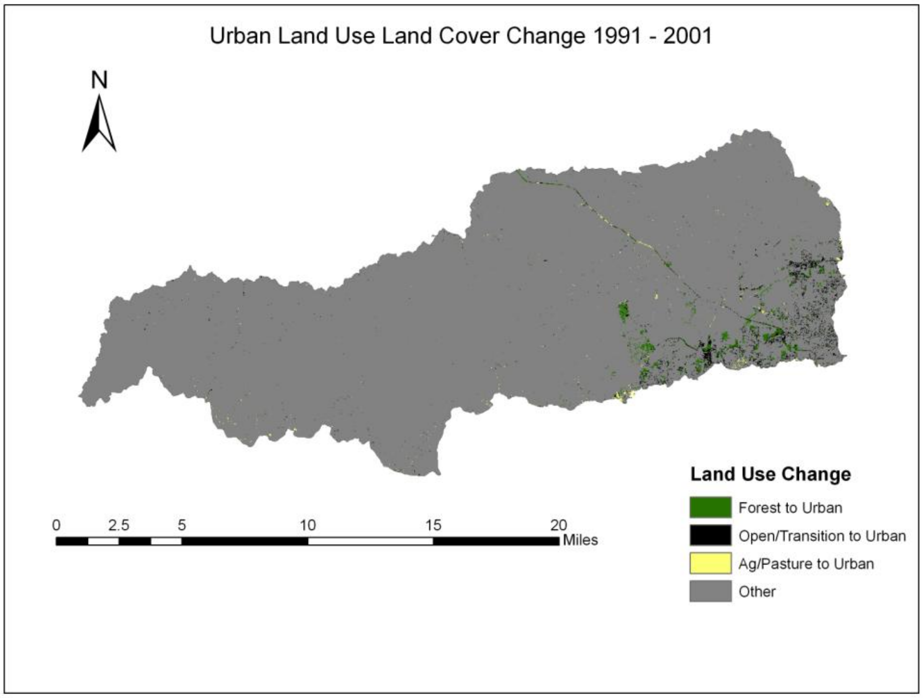


Figure 2.4 (a) Change from 1991 To 2001

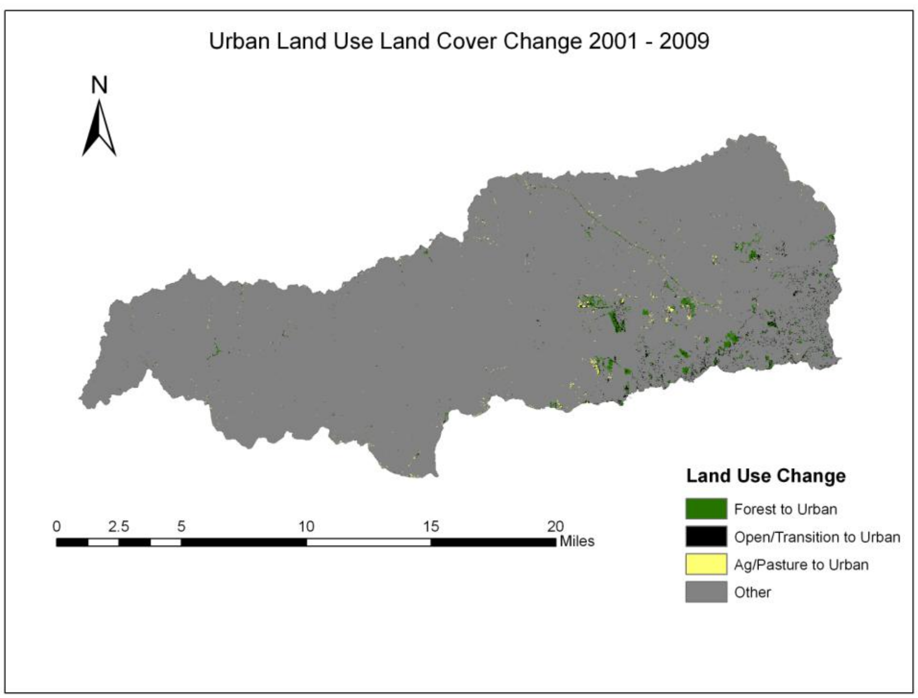


Figure 2.4 (a) Change from 2001 To 2009

2.5 Results and Discussion:

Pixel-based unsupervised classification with cluster busting and object-based image classification methods have been performed by classifying the remote sensing image of LandSat-5TM imagery. Accuracy of the classification results were assessed for unsupervised classification with cluster busting, object-based image classification and initial pixel-based unsupervised classification by creating the error matrix. Comparison of the result of the accuracy assessment shows that unsupervised classification with cluster busting has higher overall accuracy and higher individual producer's and user's accuracy for each classified land cover category. Tables 2.1 to 2.9 show the accuracy assessment results of the classification with pixel-based and object-based image analysis. The pair-wise comparison of Z test indicates unsupervised classification with cluster busting is significantly better than the pixel-based classification scheme followed in this work. But, the pixel-based and initial pixel-based unsupervised classification is not significantly different. If two different techniques are shown to be not significantly different, then it would be prudent to use the quicker and more efficient method, which in this case is the object-based classification.

Assessing the accuracy of image classification is fundamental in land use studies. Maps developed from remote sensing data contain errors due to inefficient number of training sites or lack of reference data. Accuracy levels that are acceptable for certain tasks may not be suitable for other tasks. Hence, classification accuracy of 85% is defined as minimum classification accuracy for effective LULC change analysis and modeling. The results obtained from pixel-based unsupervised with cluster busting classification and the validation of statistical results were higher than the minimum validation threshold defined. Therefore, it was reasonable to employ the maps derived from pixel-based unsupervised with cluster busting for further studies. However, it is noted that the GeOBIA methods could utilize contextual information to improve classifications and this will be explored in future given the overall speed of applying rule sets to multiple images in change detection.

A study area analysis was carried out on spatio-temporal changes in the Saugahatchee watershed with the most common change detection method. Results of the analysis indicate that there have been a remarkable urban land use changes during the study period. The post-classification overlay method used in the present study presents only the spatial extent of urban land use changes.

TABLE 2.16 Percent change in land use land cover

	Year 1991	Year 2009	Percent Change
Water	1,293	1,267	-2.01
Forest	102,386	103,448	1.04
Open	19,980	20,386	2.03
Urban	5,154	7,035	36.50
Ag/Pasture	10,933	7,611	-30.39

From the analysis of land use land cover changes in the Saugahatchee watershed as shown in TABLE 2.13 it can be deduced that from the year 1991 footprint of urban area within the Saugahatchee watershed has increased by 36.50% to 7,035 acres in year 2009. Although the area of urbanization is only about 5.04% of the total area of Saugahatchee watershed, the urbanization has likely played a role in impairment of the Pepperell branch of the Saugahatchee creek. Like the urban land use the Ag/ Pasture land also has significant impact on the water quality and quantity in the watershed. Impervious surfaces contribute to increases in surface runoff and pollutants, in runoff water. To evaluate impact of future land uses on water quality a logistic regression model is used to forecast future growth and a biophysical model called SWAT is used to assess sediment and nutrient loadings reaching the water bodies. The results of the logistic regression modeling and SWAT model are discussed in the Chapter 4.

CHAPTER 3

MULTIPLE LOGISTIC REGRESSION AND GIS TO MODEL THE LAND USE CHANGE IN SAUGAHATCHEE WATERSHED

3.1 Introduction:

Changes in landscape development patterns occur in time and space due to complex interactions of physical, biological and social factors. Landscapes are influenced by human land use and the resultant landscape is a mosaic of landscape patches which vary in size, shape and spatial arrangement (Turner, 1987). Geospatial technologies such as Geographic Information System (GIS) and Remote Sensing (RS) have made it possible to develop spatially-explicit models of the social and environmental implications of land use land cover changes (LULCC). These models can define and test relationships between environmental and social variables using a combination of existing data (census data, land use land cover (LULC) maps, and RS data), and field observations (ecological measurements, and surveys). These spatial models of LULC change drivers and their associated impacts can be used to evaluate cause and effects in LULC change observed in the past and are also extremely useful tools for offering forecasts of future land use changes and their effects on the environment and in the case of this proposed study; effects on water quality and quantity (Heistermann et al., 2006).

This study models and interprets urbanization patterns in Saugahatchee watershed, encompassing City of Auburn and Opelika in the state of Alabama, using RS imagery and GIS coupled with a logistic regression model. Locally, the Auburn-Opelika metropolitan area is one of the fastest growing Metropolitan Statistical Area (MSA) in Alabama (U.S. Census Bureau, 2009) and therefore has experienced rapid land cover change. Analysis of future land use change within the Saugahatchee sub-watershed is important in view of water quality and its supply for the community. Land use models are useful to better our understanding of drivers of change, consequences of changes and feedbacks. Land use models provide tools to predict and project changes in the land and the resultant consequences of such changes (Heistermann et al., 2006).

To understand past land use patterns and for forecasting future land use patterns reviewing the driving forces behind LULC change is necessary (Ellis, 2007). Changes in LULC in Saugahatchee Watershed are impacting water quality. Population growth, increase in impervious surfaces, sediments, and quarries and mining are some of the factors that are impacting water quality and quantity in the Saugahatchee Watershed (SWaMP, 2005). The change detection analysis done in chapter2 shows conversion of forest to municipal land use in the Saugahatchee watershed has been the most dominant LULC change in the past two decades. It is essential to understand how land use patterns evolve and what drives those changes in land use patterns. Land use models are useful to improve our understanding of drivers of change, consequences of changes and feedbacks. They are used to project how much and where land will be used and for what purpose it will be used. Land use models support the analysis of underlying forces of land use change and the consequence of such processes. A land use model serves as a tool used to analyze changes in land and the resultant consequences of such changes (Heistermann et al., 2006).

This chapter provides an overview of the statistical and GIS techniques used in the spatial analysis of LULCC. The overall objective is to use the developed models to help forecast future LULC. The first section of this paper reviews literature on land use and modeling. The second section explains the logistic regression characteristics and the underlying assumptions. The third section details the data collection procedure and delineates the processes involved in building an efficient spatial database. Details of regression analysis are provided in the fourth part followed by a section detailing the validation technique. Section five describes the land use projection for 2030 using logistic regression model. The last section is the conclusion of logistic regression modeling for the land use land cover change study.

Patterns of LULCC are formed by the interaction of economic, environmental, social, political, and technological forces. These drivers may have considerable effects on future land use and cover (CCSP, 2003). The majority of land use change in general is due to human use (Turner et. al., 1993). With the changes in the land use the climate, biodiversity, agriculture, and hydrology of the region also change (Turner et. al., 1993; Schneider and Pontius, 2001; Vitousek et. al., 1997; Theobald and Hobbs, 1998). This also affects the functioning of ecosystems (Vitousek et al., 1997). Examination of historic land use change can inform us about the drivers of changes as well as the individual impacts of population growth, and demographics on land use change (Turner et al., 1993).

Logistic regression is a frequently used methodology in LULCC research. Serneels and Lambin (2001) used logistic regression to identify how much of an understanding of the driving forces of land use changes can be gained through a spatial statistical analysis for the Mara ecosystem in Kenya. All predictive variables suggested by the conceptual model for the study area were introduced in the statistical model. The analysis was carried out, based on the full model information, for identifying which variables contributed significantly to the land use changes. Schneider and Pontius (2001) used logistic regression for modeling deforestation in the Ipswich watershed of Massachusetts. Geoghegan et al. (2001) used logistic regression to model tropical deforestation and land use intensification in the southern Yucatán peninsular region, in combination with household survey data on agricultural practices.

Xie et al. (2005) developed a spatial logistic regression model to obtain the development patterns in the New Castle County, Delaware and to assess the predictive capacity of the model. The study also used GIS to develop the spatial, predictor drivers and performed spatial analysis on the results. The model is built using land use changes between1984-1992 and 1992-1997. Seven predictive variables based on three classes of variables namely; site specific characteristics; proximity; and neighborhoods were employed.

Allen and Lu (2003) in their research developed a GIS-based integrated approach to modeling and prediction of urban growth in terms of land use change in the Charleston region of South Carolina. The model was built upon a binomial logistic framework, coupled with a rule-based suitability module and focus group involvement. It was modeled to predict land transition probabilities and simulate urban growth, through the year 2030, under different scenarios. The model was calibrated through a GIS-facilitated participatory process involving both statistical assessment and human evaluation. Although the model's predictive power varied spatially and temporally with different types of land use, it achieved reasonably high overall success rates.

Theobald and Hobbs (1998) examined two ways to model land use change at a landscape scale. The first model assumed the location factor such as proximity to towns and highways and assumed that likelihood of development decreases with increasing distance from urban areas. The second model assumed that future development patterns respond to development patterns of existing development and that the likelihood of development is higher in areas of higher neighboring density. The forecasted development patterns of these two models were compared with the observed historical development patterns. The second model, which is a spatial transition model, produced better observed land use patterns compared to the other aspatial model.

The overall objective of this chapter is to develop a land transformation model of urban growth to forecast land use changes in the saugahatchee sub-watershed surrounding Auburn-Opelika metropolitan area in the state of Alabama.

3.2 Logistic Regression:

Logistic regression is useful for situations where the dependent variable has a binary output, e.g. the presence or absence of outcome. In the present study dependent variable (y) has two outcomes namely, parcel land use either urban or not urban. The independent variables of logistic regression could be a mixture of continuous and categorical variables. Normality assumption is not needed for logistic regression. Hence, logistic regression is advantageous compared to linear regression and log-linear regression. It is an approach to extract the coefficients of explanatory factors from the observation of land use conversion, since urbanization does not usually follow normal assumption and its influential factors are usually a mixture of continuous and categorical variables (Menard, 2001).

The equation for the relationship between the dependent variable and the independent variables becomes:

$y = a + b1x1 + b2x2 + \ldots + bmxm$

$y = \log_e (P/1\text{-}P) = logit(P)$

$P = e^y/1 + e^y$

where *x*1, *x*2,…, *x*m are independent variables, y is a linear combination function of the independent variables representing a linear relationship. The parameters *b*1, *b*2,…, *b*m are the regression coefficients to be estimated. If y is denoted as a binary response variable (0 or 1), value 1 (y = 1) means the occurrence of new unit such as transition from other type of land use to urban, and value 0 (y = 0) indicates no change. *P* refers to the probability of occurrence of a new unit, i.e. 1. Function y is represented as logit(*P*), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable is 1 (Xie et al., 2005). Probability P increases when y value increases. Regression coefficients, *b1-bm*, imply the contribution of each predictive variable on probability value *P*. A positive sign means that the predictive variable helps to increase the probability of change and a negative sign implies the opposite effect.

In spatial land use analysis the linear and logistic regression methods assume the observations to be statistically independent and identically distributed (Cliff and Ord, 1981; Lesschen et al., 2005). However, spatial land use data have the tendency to be dependent, a phenomenon known as spatial autocorrelation. Spatial autocorrelation may be defined as the property of random variables to take values over distance that are more similar or less similar than expected for randomly associated pairs of observations, due to geographic proximity (Legendre and Legendre, 1998; Lesschen et al., 2005).

To overcome spatial dependence a spatial sampling scheme was adopted to expand spatial distance interval between sampled sites. First systematic sampling was done by selecting parcels every 0.5 miles in x and y direction within a study area. Ideally the points would be 3000 feet apart, at which distance spatial autocorrelation would have been absent (Rutherford et al., 2007). This may result into even less sample size (Rutherford et al., 2007). For the present study total 656 samples were systematically selected. After this the stratified sampling was done as the population density varied over the study area. In order to represent the true population in the sampling the data was stratified into four classes based on the population density (See Figure 3.1). The random sampling was then done for each stratum to select candidate parcels to represent the true population. Total of 164 samples were selected for the analysis (Xie et al., 2005).

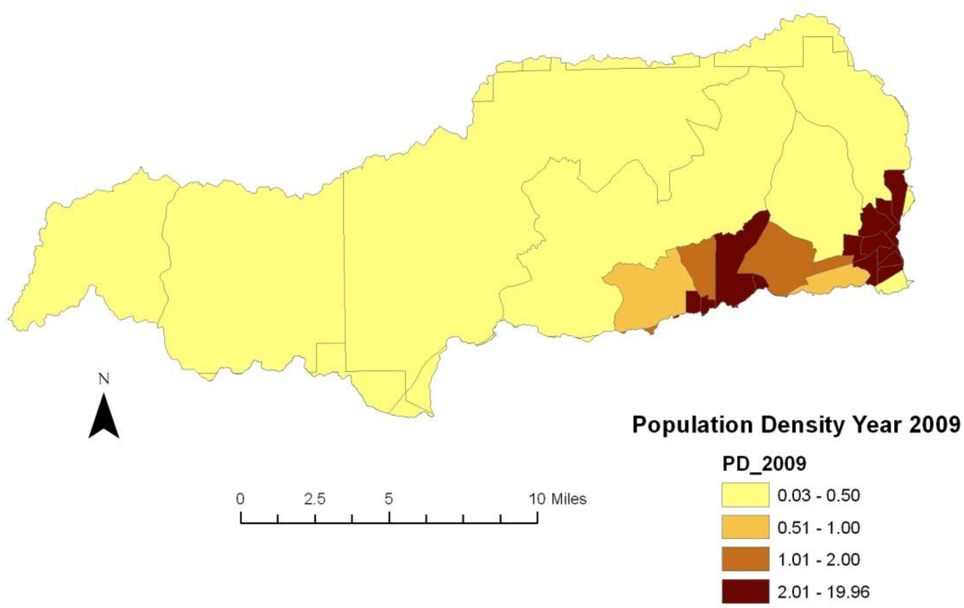


Figure 3.1 Population density map for the year 2009.

3.3 Data and Methods:

3.3.1 LULC Data:

The methods using remote sensing techniques for LULCC analysis have evolved from the basic visual interpretation into a computer based analysis. Commonly used approach to image analysis is multispectral image classification. The extraction of urban areas and differentiation of various land cover types is still a challenge (Erbek et al., 2004; Lo and Choi, 2004; Qian et al., 2005). At present, the extraction accuracy of built-up area is still unsatisfactory, which usually varies around 70%-80%. This is mainly due to the heterogeneous character of urban areas, where continuous and discrete elements occur side by side (Aplin, 2003). Another reason is the problem of mixed pixels, especially in an urban environment (Lo and Choi, 2004). The purpose of classification is to assign meaningful information to pixels in an image. Through classification of digital remote sensing images, thematic maps can be produced that have information such as the land cover types and their extent can be obtained (Tso and Mather, 2001; Matinfar et al., 2007).

For the purpose of present study LULC datasets derived from LandSat-5TM Thematic Mapper (TM) were obtained from USGS Global Visualization Viewer (GLOVIS) for the anniversary images for year 1991, 2001 and 2009 (as described in detail in Chapter 2). Five types of land use classification were employed: Water, Forest, Open/Transition, Urban and Ag/Pasture. For classification two approaches are used including unsupervised classification followed by cluster busting of urban areas. The LULC classification of LandSat-5TM was done using algorithms utilized in ERDAS Imagine 9.3. For modeling purposes the spatial unit utilized is the Lee County tax parcels. The raster dataset for the three time periods was then transferred from the image pixels to vector dataset of Lee County parcels using a 'Majority' algorithm in

ERDAS Imagine. The resultant parcel land cover maps in vector dataset are given the Figure 3.2, 3.3 and 3.4.

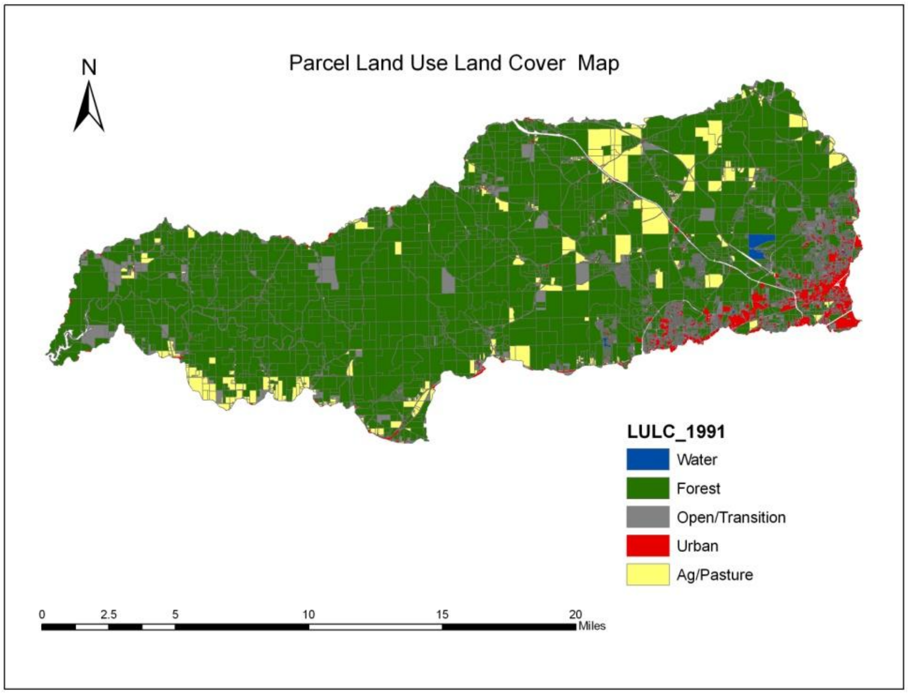


Figure 3.2 Parcel land use land cover map for the year 1991.

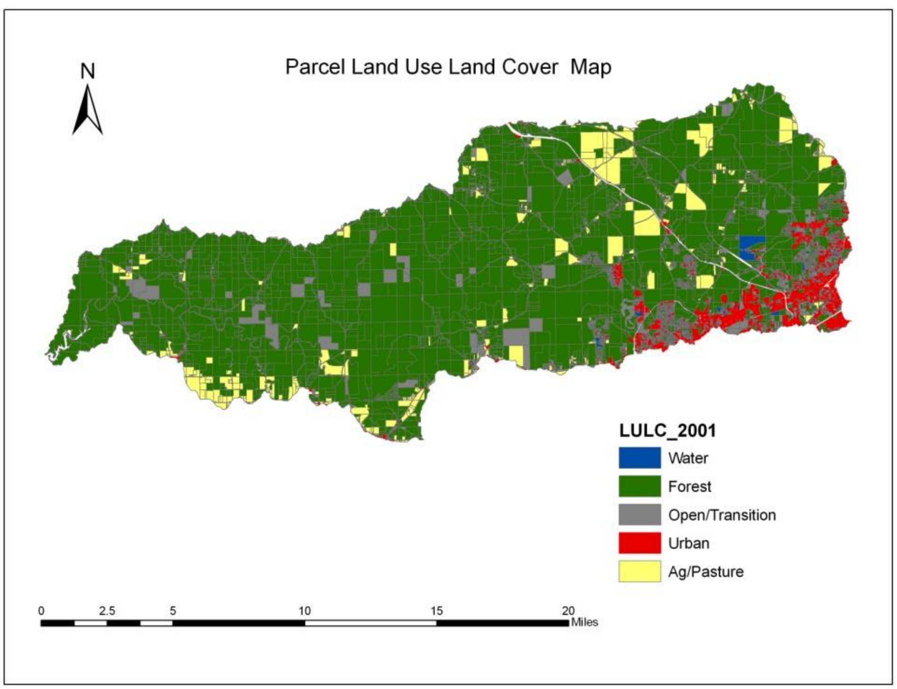


Figure 3.3 Parcel land use land cover map for the year 2001.

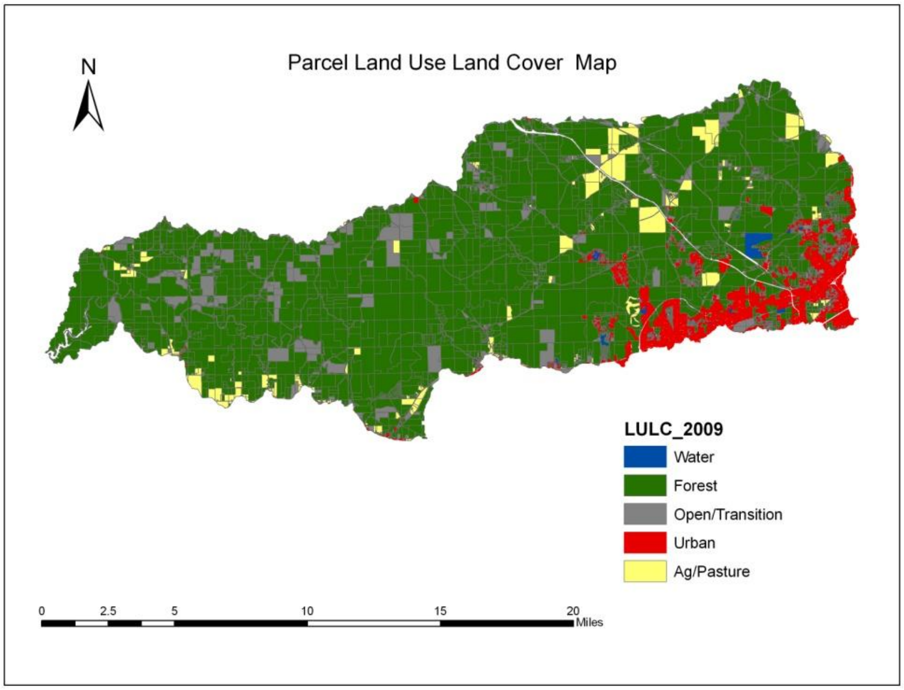


Figure 3.4 Parcel land use land cover map for the year 2009.

3.3.2 Census Data:

The County parcel data were obtained from Lee County revenue commissioner for the Saugahatchee Watershed. The demographic data were obtained from the US Census Bureau's 1990 and 2000 corresponding census block group GIS layers. Since the population data for 2009 were not available, they were then obtained by interpolation. Census track and block group population data exist for 1990 and 2000, but at the time of this research, only census track population data were available for 2010. Therefore we applied the census track population change trend from 2000 to 2010 to all census blocks in 2009 (Deichnann et al., 2001). To estimate census track population for 2009 we used census track data for 2000 and 2010 to compute average annual population growth rate, as given below:

$$\text{Pop}_{\textit{Future}} = \text{Pop}_{\textit{Present}} \times (1 + i)^{\mathbf{n}} \qquad \textbf{.........I}$$

Where,

Pop $_{Future}$ = Future Population

Pop $_{Present}$ = Present Population

i = Growth Rate (Unkown)

n = 10

Therefore, solving equation I for i calculates the annual growth rate for the period 2000 to 2010. This census track growth rate was then applied to compute census block population for 2009. After this, the population densities of 1990, 2000 and 2009 were calculated and then transferred to the attributes of County parcel data. The road vector data were obtained from the City of Auburn. Using 2009 road network to serve as 1990 and 2001 road network will definitely reduce the accuracy of land transformation model. Since only major road network is used for the analysis the effect is minimal. The nearest distance analysis for parcels was carried out in a GIS for distance from the major road and also from the commercial areas of the city of Auburn and Opelika.

3.3.3. Drivers of LULC Variables:

The land use change is influenced by number of factors. In various land use studies (Turner et al., 1995; Verburg et al., 2001; Landis and Zhang, 2000) different drivers of land use change have been used. The proximity factors appear to drive land use conversions in these studies. In the present study proximity to road, school, commercial and industrial areas have considered as predictor variables as people tend to live close to such facilities. Further, provision of utilities is assumed to be an important factor for urban growth. Since the previous studies on land use indicates growth occur within and around the areas having high population density, the conversion of a parcel into urban use is assumed for the parcels located within the high population density areas. The datasets for the predictor variables used in the present study were obtained from the planning departments of City of Auburn and City of Opelika were in ESRI shape file format. The dataset layers were further processed in ArcGIS ArcView to extract desirable features of the predictor variables. For example, for the major road network in the study area only the major roads were selected from the road layer and clipped to the Saugahatchee watershed boundary layer. For utility, only areas served with the utility in the year 1991, 2001 and 2009 for the study area were selected from the utility layer. Similarly for other predictor variables school, commercial and industrial areas the location of these variables in the year 1991, 2001 and 2009 were extracted from the parcel layer dataset. The predictor variables which were found to have significant effect on parcel land use change to urban in the year 2009, for the present study, are shown in the Figure 3.5, 3.6, and 3.7. The summary of predictor variables is given in the TABLE 3.1

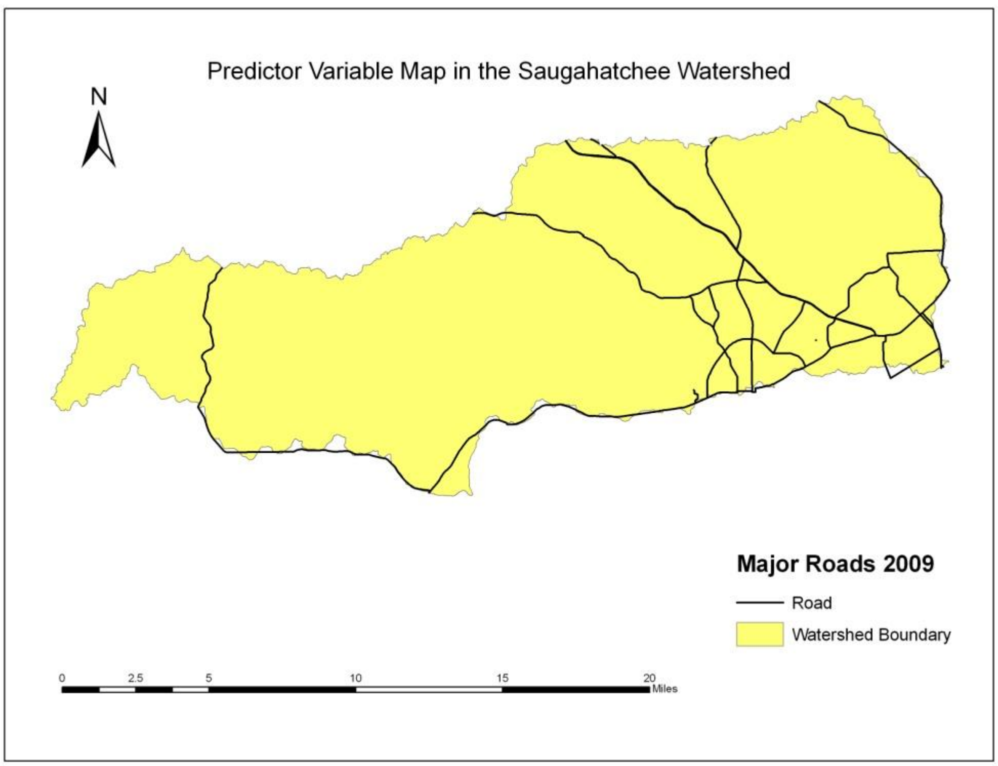


Figure 3.5 Major road network in year 2009

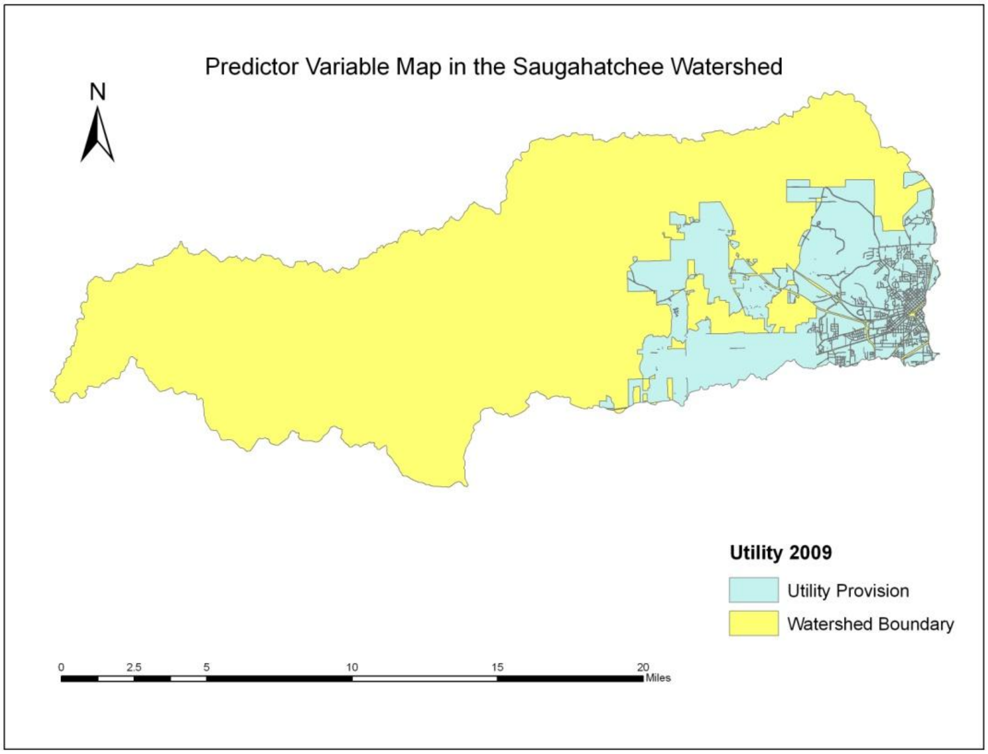


Figure 3.6 Utility served area in year 2009

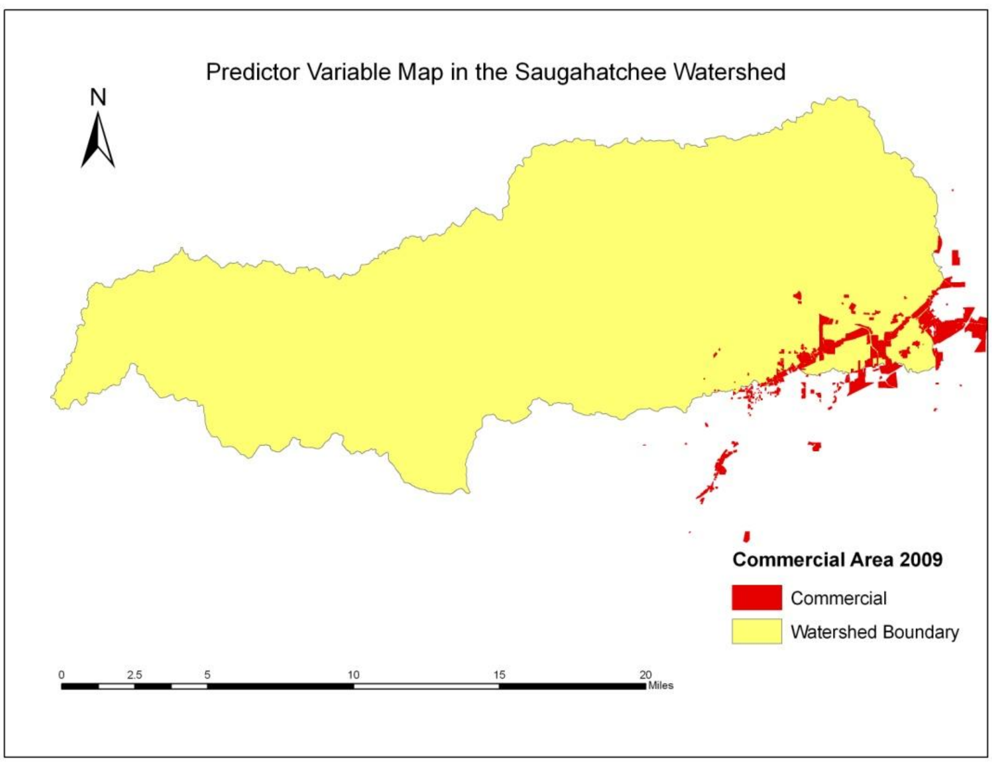


Figure 3.7 Commercial area in year 2009

Table 3.1 Predictor variables

Predictor Variable	Description
Dist_Road	Distance from the parcel centroid to the nearest major road
Dist_Utly	Distance from the parcel centroid to the nearest Utility
Dist_Sch	Distance from the parcel centroid to the nearest school
Pop_Den	Population Density of a Parcel
Dist_Comm	Distance from the parcel centroid to the nearest commercial area
Dist_Ind	Distance from the parcel centroid to the nearest Industrial area

Two classes of predictors were used: site specific and proximity. The site specific factor, was population density. The population density was scaled into three levels ranging from 1 to 3 with 3 as the highest density of more than 2 persons per acres. A total of five proximity variables were used for parcel distance from major road, utility, school, commercial area and distance from the industrial parcel. Weightage is given to scale the distance of five predictors from a parcel. For example, the proximity predictor for distance from road was scaled into five levels 1 to 5 with 5 as the nearest and proximity predictor for distance from commercial was scaled into three levels 1 to 3 with 3 as the nearest. The weightage given to different predictors is given below in the Table 3.2 A and B.

The major urban uses are confined to south-east corner of the Saugahatchee watershed. The north-west and west part of the study area is mainly a forested landscape. Most of the conversion of the land into urban area occurred, in subsequent years, was along the boundary of the original urban land uses.

Table 3.2 A Proximity predictors

Predictor Variable	Distance (miles)	Weightage
Dist_Road	0 to 0.25	5
	0.25 to 0.5	4
	0.5 to 1.0	3
	1.0 to 2.0	2
	> 2.0	1
Dist_Utly	0	3
	0 to 0.5	2
	> 0.5	1
Dist_Sch	0 to 2.0	3
	2.0 to 4.0	2
	> 4.0	1
Dist_Comm	0 to 2.0	3
	2.0 to 4.0	2
	> 4.0	1
Dist_Ind	0 to 2.0	3
	2.0 to 6.0	2
	> 6.0	1

Table 3.2 B Site Specific Predictor

Predictor Variable	Population Density (per Acre)	Weightage
Pop_Den	> 2	3
	1 to 2	2
	0 to 1	1

3.4 Results and Discussion:

3.4.1 Logistic regression modeling:

The land conversion models of 1991- 2001 and 2001- 2009 were analyzed using SAS/STAT software and the regression results are presented in TABLE 3.3 A & B. When all the five predictors were used together to formulate the regression equation for the period 1991 to 2001 and 2001 to 2009, the SAS results indicate that the p-values (Pr >ChiSq) of predictor variables Road, Utility and Commercial are less than 0.05 and therefore, they are significant for both periods as shown in the Table 3.3 A & B. The Chi-Square test indicates that the coefficients of above three predictors are not equal to zero and are needed in the model to explain the variation in the response variable.

Table 3.3 A. Analysis of Maximum Likelihood Estimates Year 1991 to 2001

Parameter	**DF**	**Parameter Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > Chi Sq**
Intercept	1	-7.2229	1.2475	33.5232	<.0001
Road	**1**	**0.9633**	**0.2415**	**15.9164**	**<.0001**
Utility	**1**	**1.1561**	**0.4926**	**5.5071**	**0.0189**
School	1	0.2561	0.4716	0.2948	0.5872
Population Density	1	0.6216	0.4116	2.2815	0.1309
Commercial	**1**	**1.2061**	**0.4806**	**6.2979**	**0.0121**
Industrial	1	-1.2549	0.6692	3.5167	0.0608

Table 3.3 B. Analysis of Maximum Likelihood Estimates Year 2001 to 2009

Parameter	**DF**	**Parameter Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > Chi Sq**
Intercept	1	-17.6412	127.5	0.0191	0.8900
Road	**1**	**1.2674**	**0.3382**	**14.0448**	**0.0002**
Utility	**1**	**1.4461**	**0.7084**	**4.1675**	**0.0412**
School	1	1.3661	0.8811	2.4039	0.1210
Population Density	1	6.8867	127.5	0.0029	0.9569
Commercial	**1**	**1.7697**	**0.8559**	**4.2754**	**0.0425**
Industrial	1	0.4984	1.0148	0.2412	0.6233

Therefore, in order to predict conversion to urban only significant variables were considered for these data to fit the model. Predictive variable, population density, was not found to be a significant predictor (alpha = 0.05) of urban land use for both models. This may be attributed to wider spread of the medium and low density residential population in the study area resulting into less effect of high population density on the dependent variable. The distance to the major road and distance to utility were found to be significant predictors of urban land use along with the distance to commercial area. Similarly, when backward selection was done, the predicators Dist_Road, Dist_Utly and Dist_Sch together were found significant. When Dist_Road, Dist_Utly, Dist_Sch and Dist_Comm were taken together then both Dist_Sch and Dist_Comm were found redundant. Therefore, the model with three predictors namely, Dist_Road, Dist_Utly, Dist_Comm were considered for determining urban conversion in the study area. Multiple Logistic Regression results of land conversion models of 1991-2001 and 2001- 2009 are given in the Table 3.4 A & B).

Table 3.4 A. Analysis of Parameter Estimates (1991- 2001)

Parameter	DF	Parameter Estimate	Standard Error	Wald Chi-Square	Pr > Chi Sq
Intercept	1	-7.4469	1.2750	34.1131	<.0001
Road	1	0.8912	0.2235	15.8962	<.0001
Utility	1	0.6248	0.3086	4.0982	0.0429
Commercial	1	1.2437	0.2970	17.5313	<.0001

TABLE- 3.4 B Analysis of Parameter Estimates (2001- 2009)

Parameter	DF	Parameter Estimate	Standard Error	Wald Chi-Square	Pr > Chi Sq
Intercept	1	-10.3352	2.0882	24.4951	<.0001
Road	1	1.3340	0.3362	15.7438	<.0001
Utility	1	1.8851	0.4985	14.2980	0.0002
Commercial	1	1.6526	0.6367	6.7369	0.0094

Land conversion model for year 1991- 2001:

$$\mathrm{Logit}(P) = -7.4469 + 0.8912X1 + 0.6248X2 + 1.2437X3$$

Land conversion model for year 2001- 2009

$$\mathrm{Logit}(P) = -10.3352 + 1.3340X1 + 1.8851X2 + 1.6526X3$$

To check the adequacy of the models for the two periods, 1991- 2001 and 2001-2009, a likelihood ratio test was carried out. The results of the test given below in the Table 3.5 A & B. From the test results it can be deduced that these two models adequately fit the data.

TABLE 3.5 A. Likelihood ratio test period: 1991- 2001

Test	**Chi-Square**	**DF**	**Pr > Chi Sq**
Likelihood Ratio	109.4444	3	<.0001

Testing Null Hypothesis: BETA = 0 against alternative hypothesis BETA≠0 The likelihood ratio test statistic is G2 = 109.4444 with 3 degrees of freedom and the p-value is <0.0001. Hence, we reject the Null Hypothesis. This model adequately models the variability in data.

TABLE 3.5 B. Likelihood ratio test period: 2001- 2009

Test	**Chi-Square**	**DF**	**Pr > Chi Sq**
Likelihood Ratio	147.6705	3	<.0001

Testing Null Hypothesis: BETA = 0. The likelihood ratio test statistic is G2 = 147.6705 with 3 degrees of freedom and the p-value is <0.0001. Hence, we reject the Null Hypothesis. This model adequately models the variability in data.

From the result obtained from the two models in different periods, it can be deduced that the pattern of land use conversion to urban land varies with location and also with time. Therefore, the land conversion model developed for a specific period for one area may not fit well for the same area in another time period. A simple averaging of coefficients cannot model the non-linear relationship between response variable and predictor variables. However, for obtaining coefficients for a whole period i.e. from 1991 to 2009, weighted average operation can be used for the two sub periods 1991-2001 and 2001-2009. Thus, the model for period 1991-2009 was obtained as follows:

Logit(P) = -9.3543 + 1.3201X1 + 1.5760X2 + 1.6174X3

Table 3.6 Analysis of Parameter Estimates

Parameter	**DF**	**Parameter Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > Chi Sq**
Intercept	1	-9.3543	1.8016	26.9600	<.0001
Road	1	1.3201	0.3000	19.3610	<.0001
Utility	1	1.5760	0.4892	10.3763	0.0013
Commercial	1	1.6174	0.6127	6.9689	0.0083

The logistic procedure of Analysis of Maximum Likelihood Estimates was done for the model to determine the significance of the three predictor variables (Table 3.6)

Further, testing Global Null Hypothesis: BETA = 0 is carried out for the model to assess the fitness of model for the data (Table 3.7)

Table 3.7 Goodness of fit

Test	**Chi-Square**	**DF**	**Pr > Chi Sq**
Likelihood Ratio	142.5320	3	<.0001

The likelihood ratio test statistic is G2 = 142.5320 with 3 degrees of freedom and the p-value is <0.0001. This model adequately model the variability in data.

3.4.2 Model Validation:

The model validation for accuracy is performed for the period of 1991- 2009. For this the study area parcels and their development status of 1991- 2009 is first determined. For each parcel probability of change is computed with the fitted model. The probability of conversion is compared with the critical probability. A critical probability is selected, which makes the area of urban land use calculated with model is almost equal to the area of urban land use observed. If the probability of conversion of parcel is greater than critical probability, which is 0.9850 for the present model, then the parcel is treated as urban, otherwise the land use of parcel remains unchanged.

Figure 3.8 and 3.9 illustrates visual comparison of the urban area indicated by model prediction with the observed urban area for the year 2009. From the TABLE 3.8 the overall accuracy of the model determined as 70.39%, with accuracy of correct prediction of urban area is 74.96%.

Table 3.8 Results of model prediction with the observed land conversion for year 2009

Observed	**Predicated**		**Percent Correct**
	Urban	**Non-urban**	
Urban	7,519	2,512	74.96
Non-urban	2,519	4,424	63.78
Overall	10,031	6,936	70.39

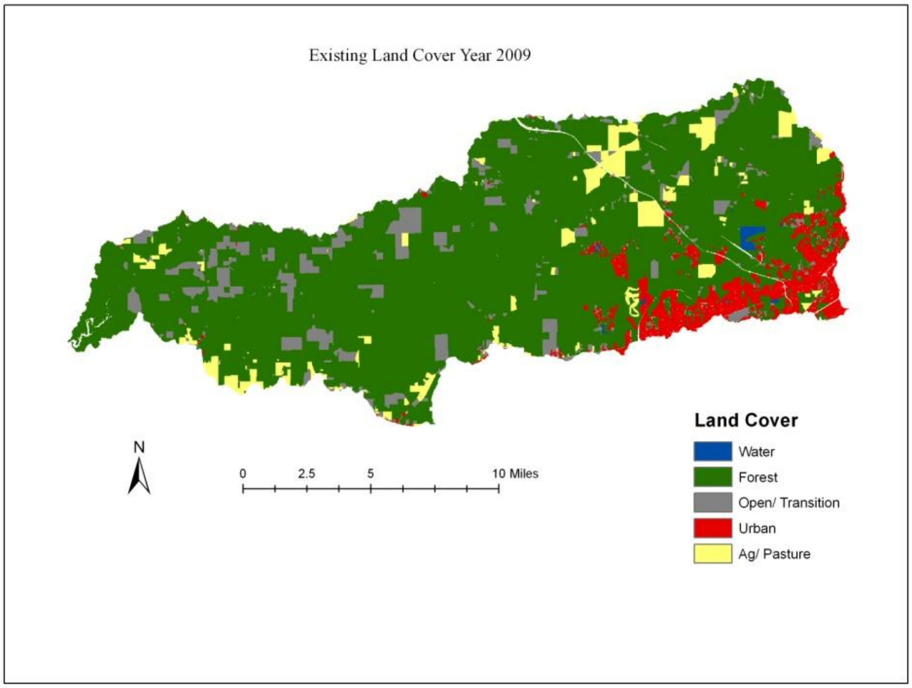


Figure 3.8 Existing land cover in year 2009

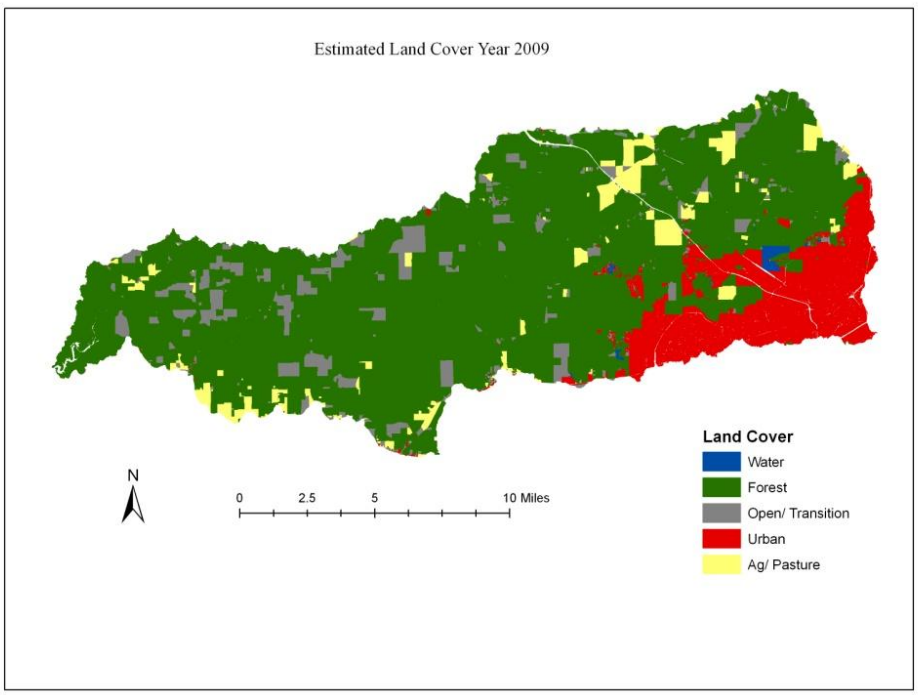


Figure 3.9 Estimated land cover in year 2009

3.5 Land Use Land Cover Projection:

The logistic model is then utilized to predict development for the year 2030. To determine the major road network, utility provision and commercial development in the year 2030, guidelines of Comprehensive plan for City of Auburn and zoning regulation for Opelika was used (CoA; CoO). Discussion with the city officials helped determine the future development areas for the study areas. The areas that will be served with utility by 2030 in the study area are determined Thus a future road network, utility provision and commercial areas are marked for 2030 scenario generation as shown in the Figure 3.10.

For each parcel probability of change is computed with the fitted model for the 2030 scenario. The projection of the development pattern for the year 2030 is given in the Figure 3.11.

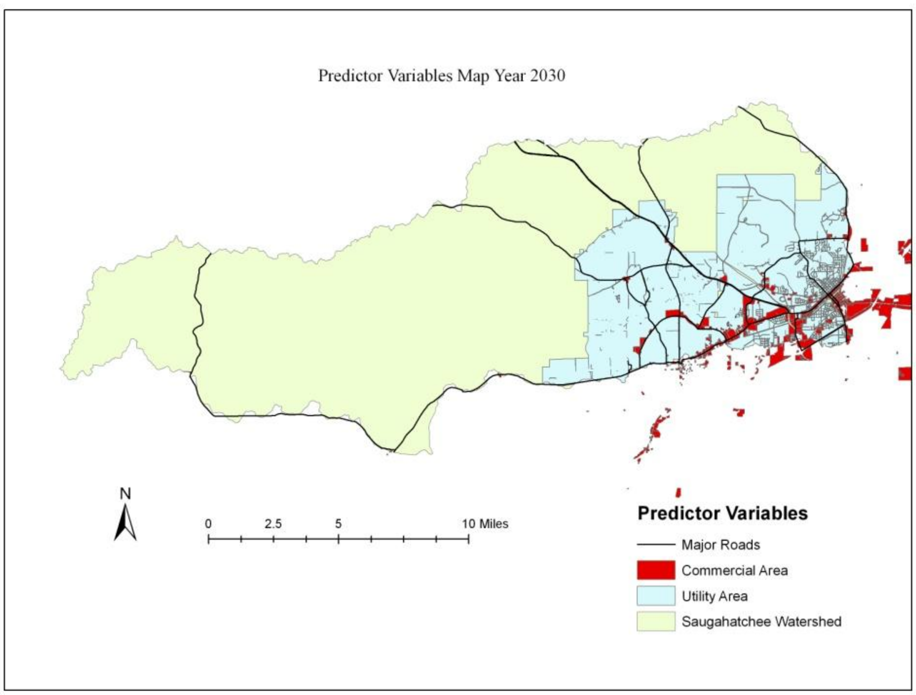


Figure 3.10 Predictor Variables for year 2030.

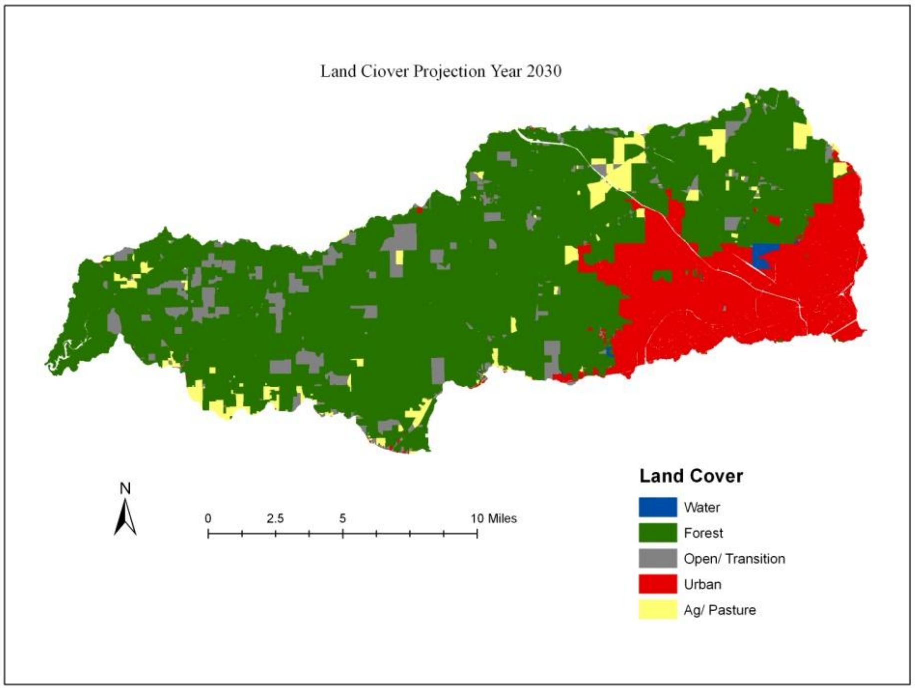


Figure 3.11 Land Cover projection for year 2030

3.6 Conclusion:

This study used the road network, utility provision, commercial area, and land cover data to develop a predicting model of land conversion to urban in the Saugahatchee sub-watershed. The model based on multiple logistic regression analysis is found to be partially significant in revealing land use conversion pattern. However, the model is not efficient due to lack of relevant land use change factors such as parcel neighborhood analysis. The model also needs to incorporate other important factors like socio-economic factors of near neighborhoods, policy decisions about growth. Results of model validations over the period 1991 to 2009 indicate that the logistic model is statistically reliable for short-term prediction, but becomes less reliable once the time-span becomes longer. The logistic model was found useful for identifying three significant predictors of land use conversion and has achieved moderate prediction success rate for the land use categories as a whole. The model has moderate success rate for the urban use projection for a 20-year time period. The year 2030 projection of land use using logistic regression is later used in analyzing effect of urban growth on the water quality and quantity within the Saugahatchee watershed. In the Chapter 4 the base line LULC data developed for 1991, 2001 and 2009 was evaluated in the SWAT model. The year 2030 projection of land use using logistic regression are also used in the SWAT model to analyze effects of urban growth on the water quality and quantity within the Saugahatchee watershed.

CHAPTER 4

USE OF SWAT FOR ASSESSING WATER QUALITY AND QUANTITY IMPACT OF LAND USE CHANGE IN THE SAUGAHATCHEE WATERSHED

4.1 Introduction:

Soil erosion, sedimentation, and contamination of water bodies through nonpoint sources are major environmental, social and economical problems in many states of the US (Borah et al., 2003, 2004). Nonpoint source pollution (NPP) is caused by the movement of water, over and through the ground, generally after a precipitation event. The runoff water picks up and carries away with it natural and manmade pollutants. These pollutants eventually get deposited in lakes, rivers and coastal waters. The U.S. Environmental Protection Agency (USEPA) found that over one-third of streams, lakes, rivers, and estuaries surveyed nationally in 1996 did not fully support their designated uses such as for drinking water or recreation (USEPA, 1998), citing NPP as the major cause of water quality degradation. According to USEPA (1998) the agricultural sector is the largest contributor to NPP through runoff of nutrients, sediment, pesticides, and other contaminants to water bodies. Besides agricultural lands, land in residential and developed areas have lawns and gardens which are managed more intensively resulting in the generation of more pollutants. Urban areas tend to have higher percentages of impervious surface that results in lower soil infiltration and higher runoff amounts. Runoff generated due to precipitation carries nutrients and sediment from agricultural and residential land, to receiving water bodies. Thus, increasing urbanization coupled with increasing use of nutrients and chemicals in agricultural lands creates significant challenges for water quality protection and enhancement. (Bhattarai et al., 2008)

There are many watershed models available today for studying NPP (Borah and Bera, 2004). One such model is the Soil Water Assessment Tool (SWAT), developed by the U.S. Department of Agriculture-Agricultural Research Service's (USDA-ARS) Grassland, Soil and Water Research Laboratory in Temple, TX, is used in the present study to evaluate impact of land use changes from 1991 to 2009 on the water quality and quantity in the Saugahatchee watershed. SWAT is also used to assess the impact of the future development projection on water quality for the year 2030 in the Saugahatchee watershed. SWAT is a basin scale, continuous time model that operates on a daily time step. It is useful for long–term continuous storm event simulation and is designed to predict the impact of Best Management Practices (BMPs) on water, sediment, and agricultural chemical yields in large watersheds and river basins. Major model components include weather data, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management (Borah and Bera, 2004; Gassman et al., 2007). The model predicts the average impact of land use and management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land uses, and management conditions over long periods of time (DiLuzio et al., 2002; Winchell et al., 2007). In comparative studies using hydrologic and NPP models, SWAT has been shown to be among the most promising for simulating long-term NPP in agricultural watersheds (Borah et al., 2003).

In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the subwatershed area and are not identified spatially within a SWAT simulation. Alternatively, a watershed can be subdivided into only subwatersheds that are characterized by dominant land use, soil type, and management (Borah et al., 2003; Gassman et al., 2007; Bhattarai et al., 2008).

4.2 Data and Methods:

The study site, Saugahatchee sub-watershed (HUC # 03150110030), covering an area of 220 square miles, is located in the Lower Tallapoosa River Basin in east-central Alabama, primarily in Lee and Tallapoosa counties. Saugahatchee Creek has been identified as a high priority watershed by the Lower Tallapoosa Clean Water Partnership, the Alabama Soil and Water Conservation Committee, US Environmental Protection Agency and the Alabama Department of Environmental Management (SWaMP, 2005). Based on present study the area under forest cover is around 72% of watershed area and urban development, mainly observed in southeastern part of the watershed occupies 7.9% of watershed area. Other predominant activity observed in the watershed is pasture land covering 10.5% of the area. Urban land use and pasture land has substantial impact on the water quality and quantity in the watershed. Impervious surfaces contribute to increases in surface runoff and pollutants, such as oil, sediments, and nutrients in runoff water. Conversion of forest to pasturelands also increases sediments and nutrient loads in the Saugahatchee creek as pasture lands are more intensively cultivated with application of fertilizers and tillage operations (SWaMP, 2005).

The SWAT model used in this study was developed in collaboration with partners in the Biosystems Engineering Department at Auburn University for the Saugahatchee watershed as a part of the Auburn University Water Resources Center funding of the interdisciplinary project titled "Bridging the Gap Between Science, People and Policy for Sustainable Watershed Management in theTallapoosa River Basin and Beyond." The calibrated SWAT model was used in the present study utilizing the land use land cover (LULC) datasets developed for the 1991, 2001, 2009 and projected land use land cover for 2030 (Chapter 2). Other input variables included he precipitation data used in the model for a twelve year period from January 1997 to December 2008. Daily streamflow data were collected from USGS station (ID# 02418230) located at the Loachapoka near Auburn for the same twelve year period. The 30m digital elevation model was used to help model flow and the Soil Survey Geographic (SSURGO) database provided by the Natural Resources Conservation Service as an estimator of infiltration.

The SWAT model was run on monthly steps for the baseline years 1991, 2001 and 2009 followed by the land cover projected for the 2030 to assess the annual changes in variables for the average stream flow, sediment, total nitrogen and phosphorous load for the twelve year period. The watershed was divided into 84 hydraulic response units (HRU). Out of the 84 HRU the HRU#61 which covers the Auburn Opelika drainage area and flows to Loachapoka USGS station (See figure 4.1) was assessed for studying the impact of land use land cover change based on the four variables mentioned above. The HRUs created in SWAT were with dominant land use observed within them. Figure 4.1 shows a relative location of HRU #61 within the watershed. In Figure 4.2, 4.3, 4.4, and 4.5 HRUs having dominant urban land cover in year 1991. 2001, 2009, and 2030 are illustrated. These HRUs are the major sources of non point source pollution contributing to streams in the Saugahatchee watershed.

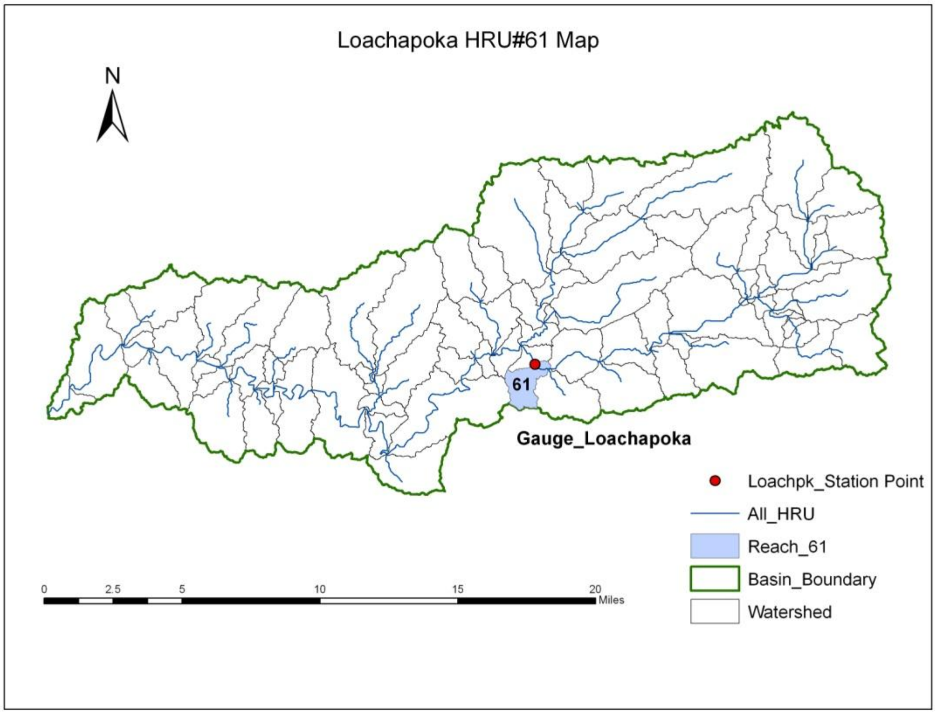


Figure 4.1 Location map of HRU#61 and Gauge station at Loachapoka

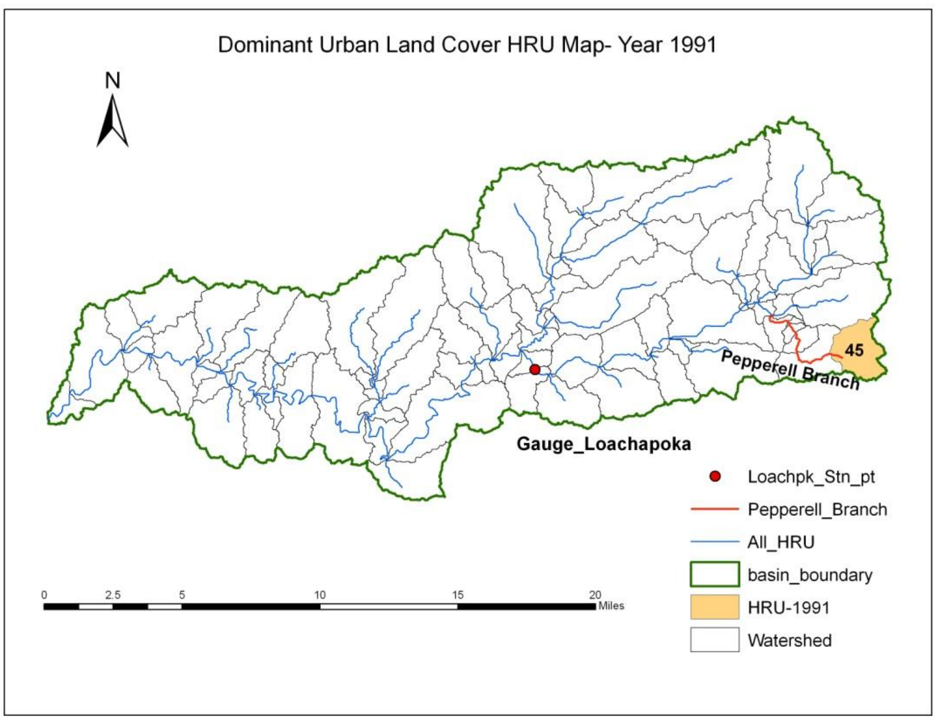


Figure 4.2 HRU having dominant urban land cover in year 1991

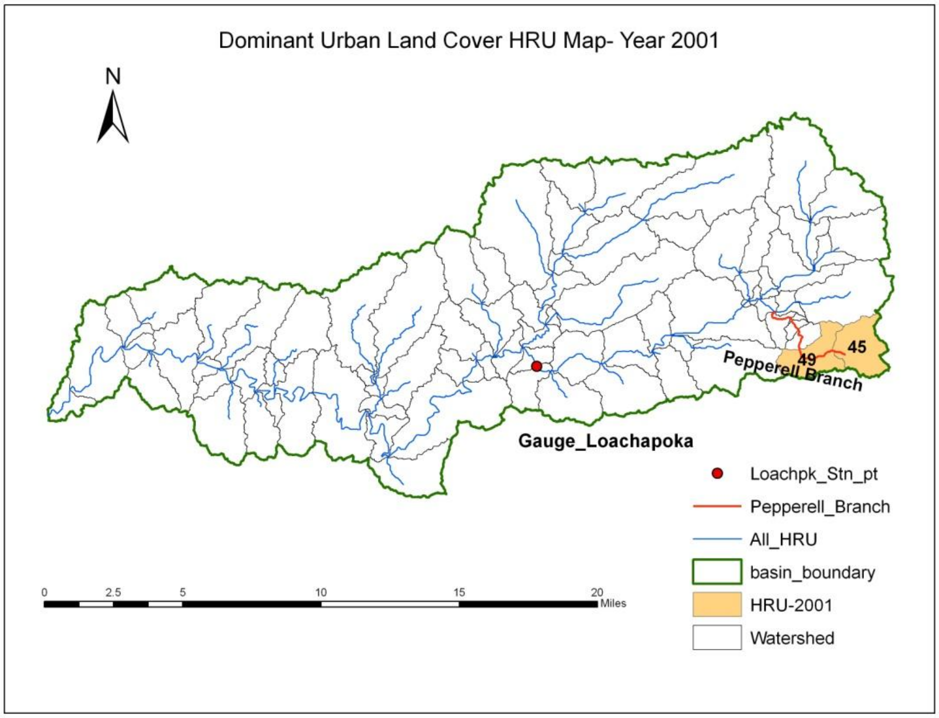


Figure 4.3 HRUs having dominant urban land cover in year 2001

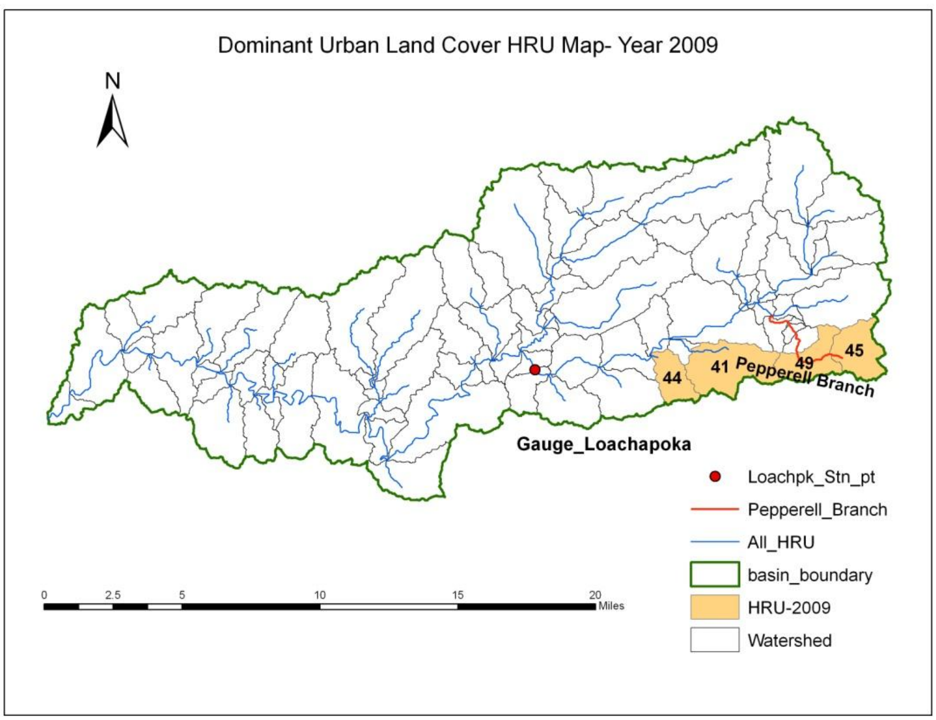


Figure 4.4: HRUs having dominant urban land cover in year 2009

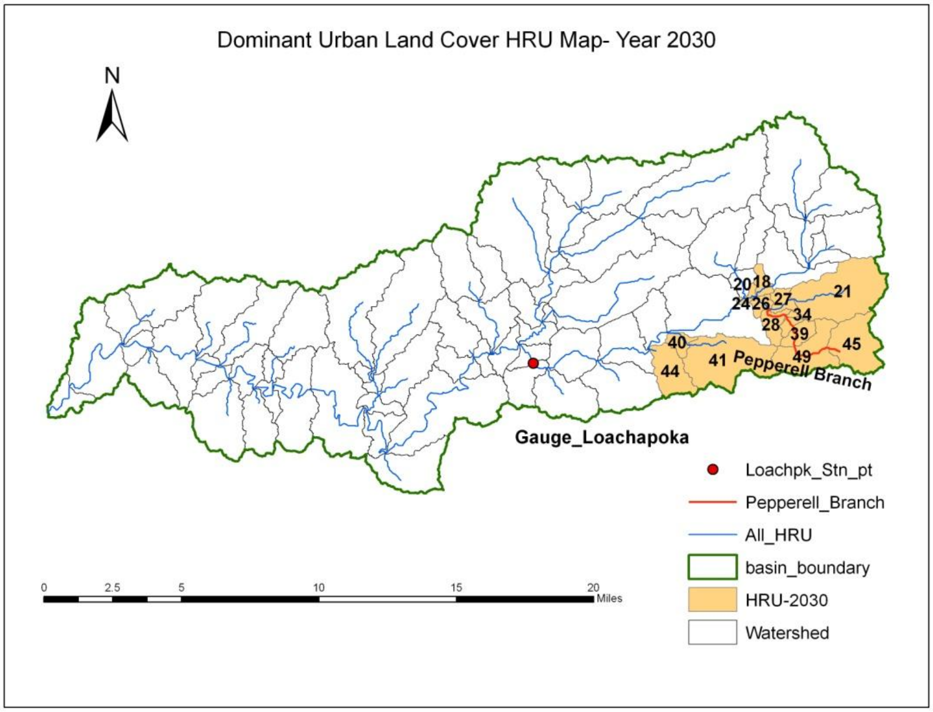


Figure 4.5: HRUs having dominant urban land cover in year 2030

4.3 Results and Discussion:

In Table 4.1 LULC distribution in the Saugahatchee watershed is compared for the study period. Over the study period from 1991 to 2009 the area under urban land use has increased by 1,881 acres. If we assume this trend of urbanization to continue in the Saugahatchee watershed with the resultant urban growth as predicted by the regression model (Chapter 3) for the year 2030 will be 2.6 times the area in 2009. Impact of projected future development, in 2030, on the water quality and quantity was evaluated by using the SWAT model. The SWAT model generated sub-basin areas, also known as HRU with a dominant land cover. Table 4.2 shows the relative number and area coverage of dominant HRUs under four land use scenarios namely; 1991, 2001, 2009 and 2030. There was only one dominant urban land cover HRU in 1991, which increased to 4 urbanized HRUs in 2009. The urbanized HRUs for a projected future development are 15 and only 69 HRUs have forested HRUs.

Table 4.1 Land use land cover distribution in the Saugahatchee watershed

	Year 1991	**Year 2001**	**Year 2009**	**Year 2030**
Water	1,293	1,151	1,267	423
Forest	102,386	99,680	103,448	101,737
Open/Transition	19,980	20,419	20,386	11,160
Urban	5,154	6,038	7,035	18,417
Ag/Pasture	10,933	12,458	7,611	7,024

Table 4.2 Area coverage of dominant HRUs

Major land use	**Number of HURs**			
	Year 1991	**Year 2001**	**Year 2009**	**Year 2030**
Forest	83	82	80	69
Urban	1	2	4	15
Open/Transition	0	0	0	0
Ag/Pasture	0	0	0	0
Water	0	0	0	0

The land use and land cover for the study areas was evaluated for four time periods for stream flow generating estimates of sediments loads, total nitrogen and total phosphorus for each time period. The output of SWAT for the four variables is given in the TABLE 4.3 below. The average annual stream outflow from the HRU# 61 for the land use land cover analysis from year 1991 to 2030 indicates a slightly decreasing trend. This may be attributed to the suitability of the SWAT model to predict monthly stream flow than annual or daily flows (Borah and Bera, 2004). The stream flow data were further evaluated for the winter season period in the month of March to see any changes in streamflow due to changes in the land use land cover. The average flow in the month of March, for changes in the land use land cover, indicates increase in the stream flow with increase in urbanization of the watershed (See TABLE 4.4). The streamflow output by the SWAT model underscores the impact of impervious surface increases on the water quantity in the Saugahatchee watershed.

The other attributes such as sediments load and total nitrogen (N) and total phosphorus (P) also show increase in the load of pollutants over the study period with the increase in the urbanization (See TABLE 4.3).

Table 4.3 Annual estimates of pollutant loads

Variables	**Annual total flowing out of HRU#61**			
	Year 1991	**Year 2001**	**Year 2009**	**Year 2030**
Stream Flow (M^3/S)	4.70	4.69	4.66	4.63
Sediments (Tons)	206.07	229.56	492.74	641.
Total N (Tons)	199.82	203.99	218.27	236.43
Total P (Tons)	12.96	14.16	17.74	22.46

Table 4.4 Estimates of pollutant loads for the month of March

Variables	**Land use land cover Average for the month of March**			
	Year 1991	**Year 2001**	**Year 2009**	**Year 2030**
Stream Flow (M^3/S)	7.16	8.35	8.60	9.18

4.4 Conclusion:

Biophysical models such as SWAT used in the present study are found to be useful in assessing the impacts of urbanization on quantity and quality of water bodies in a given watershed. They are useful tools for policy planners to assess water quality and plan for intervention through Best Management Practices. The SWAT model has been found to show increase in pollution load in the streams with increase in urban land cover for the study period. The impervious surface generates more runoff which carries with it sediments and other pollutants and moves quickly over the surface thus contributing increase in the stream flow during a storm event. The model has responded to variables as expected with the changes in the land cover to impact the water quality and quantity.

CHAPTER 5

SUMMARY

The Auburn-Opelika metropolitan area is the fastest growing Metropolitan Statistical Area (MSA) in Alabama (U.S. Census Bureau, 2009) and therefore has experienced rapid land cover change. The metropolitan area encompasses the Saugahatchee sub-watershed which was identified to include two stream segments that the Alabama Department of Environmental Management (ADEM) has classified as impaired. The two impaired stream segments namely, Pepperell Branch and Saugahatchee Creek (Yates reservoir embayment) listed under 303d list of ADEM (see figure 1) are polluted due to nutrient and organic enrichment flowing from non point source pollution from construction activities, non-irrigated crop production and pasture grazing uses, home gardens, and runoff from parking lots and roads. Land use changes associated with urbanization and forestry/agricultural land conversions within the Saugahatchee watershed has also been shown to impact the water quality substantially (ADEM, 2010).

This study interprets and models urbanization patterns in Saugahatchee watershed, using a GIS and RS imagery coupled with a logistic regression model. Analysis of future land use change within the Saugahatchee sub-watershed is important in view of water quality and its supply for the community. Land use models are useful to better our understanding of drivers of change, consequences of changes and feedbacks. These models also provide tools to predict and project changes in the land and the resultant consequences of such changes (Heistermann et al., 2006).

The aim of this study was to analyze historical land use trends and evaluate various methods to detect, quantify, analyze, and forecast land use changes in the Saugahatchee Watershed. The present study has evaluated future land use scenario and its impact on water quality and quantity.

The following are the research questions posed in the study and summary of the findings:

- Can we improve traditional multi-spectral pixel based land use land cover classification through Object Based Image Analysis?

In the present study to improve unsupervised classification method, Pixel Based Analysis unsupervised classification with cluster busting and object-based image classification methods have been performed by classifying the remote sensing image of LandSat-5TM imagery. The accuracy assessment shows that unsupervised classification with cluster busting has higher overall accuracy of 90 percent and higher individual producer's and user's accuracy for each classified land cover category. The overall accuracy of 82 percent was achieved for both PBA unsupervised classification and GeOBIA classification without cluster busting. Cluster busting methods could also be performed on the GeOBIA classification to improve the accuracy. It is noted that the GeOBIA methods could utilize contextual information to improve classifications as well. The major advantage of using object based image analysis is that after the rule sets are created they can then be readily applied for to other dates for multi-temporal change detection image analysis.

- What are the changes in land use and land cover in the study areas that are having the most substantial impact on water quality?

The analysis of land use land cover changes in the Saugahatchee watershed shows that from the year 1991 footprint of urban area within the Saugahatchee watershed has increased by

36.50% to 7,035 acres in year 2009. Although the area of urbanization is only about 5.04% of the total area of Saugahatchee watershed, the urbanization has likely played a role in impairment of the Pepperell branch of the Saugahatchee creek. The results of the change detection indicate that for both the study periods, from 1991 to 2001 and from 2001 to 2009, there were conversions of forested areas to urban. The open areas, which were within and immediate vicinity of the urban areas, were converted to urban. The land conversions of pasture to urban were relatively less and were observed mainly for the period from 2001 to 2009.

- What is the spatial and temporal extent of the land use and land cover change and where have the highest rates of changes have occurred?

The results from change detection for both the study periods indicate significant changes in urban land use in the Saugahatchee watershed. Most of the urban changes occurred around the peripheries of the existing urban land use areas. The changes in the urban areas shows spread of urban land use in the surrounding areas, where utility has been provided along with the proximity of the development site to major roads and commercial areas. An infill development was also observed within the existing urban area.

- What are the major driving forces for the land use and land cover changes?

The logistic model analysis done for the present study has identified three significant predictors of land use conversion to urban namely; major roads, provision of utility and commercial area for the Saugahatchee watershed. The model has achieved moderate prediction success rate for the land use categories as a whole. It also has a moderate success rate for the urban use projection for a 20-year time period. The land conversion model based on multiple logistic regression analysis is found to be partially significant in revealing land use conversion pattern. The accuracy level of 70 percent for the land use prediction model developed in the present study is found to be satisfactory for a statistical based model. The urban land conversions predicted by the model are mainly confined to south-east corner of the Saugahatchee watershed. The north-west and west part of the study area is mainly a forested landscape. Most of the conversion of the land into urban area that occurred in subsequent years was along the boundary of the original urban land uses and also the infill development.

- What will be the extent of the land use and land cover changes in the future?

The three significant predictors of land use conversion to urban, as identified through regression analysis of the predictor variables, namely; major roads, provision of utility and commercial area are assumed to dictate future land use land cover changes in the Saugahatchee watershed. After discussion with the city officials and analysis of the 2030 plan of the City of Auburn, the locations of these driving forces of LULC were determined in the Saugahatchee watershed to project future development for the year 2030. The logistic regression model then used to project extent of land use land cover change in the future, based on provision of driving forces of LULCC.

- What is the impact of future development scenarios on the water quality and quantity?

It was assumed that the increasing urban area in the watershed shall have an impact on the water quality and quantity within the watershed. The Soil and Water Assessment Tool (SWAT) model used in the present study to assess the impact of urbanization on the water quality and quantity showed increases in sediment load and total nitrogen and phosphorus in the streams with increases in the urbanization in the Saugahatchee watershed. The effect of stream flow increase with increasing urban areas was distinct when the analysis of monthly flows was done for the study period. The stream flow increased with an increase in impervious area in the watershed along with associated sediments and nutrients. SWAT model may be useful for planners to evaluate the impact of Best Management Practices and policy decisions such as conservation of open spaces and forest preservation and the kind of future development anticipated on the water quality and quantity. For the future study alternate scenarios of development looking at policy decisions integrating a planning support systems such as “WhatIf” with SWAT can be a useful tool to assess our precious water resources and how future development decisions may impact them. The change detection remotely sensed imagery analysis will also be useful to planners to study the historical land use patterns and make decisions about the future developments.

Bibliography

ADEM. 2010. Alabama Department of Environment Management. 303(d) list of Clean Water Act. http://www.adem.state.al.us/programs/water/303d.cnt. Accessed on April 7, 2010.

Allen, J., and K. Lu. 2003. Modeling and prediction of future urban growth in the Charleston region of South Carolina: a GIS-based integrated approach. *Conservation Ecology* 8(2): 2 Available at http://www.consecol.org/vol8/iss2/art2. Accessed on April 7, 2010.

Aplin, P. 2003. Comparison of simulated IKONOS and SPOT HRV imagery for classifying urban areas. In *Remotely Sensed Cities*, edited by Victor Mesev. London and New York: Taylor & Francis. pp. 23-45.

Aplin, P., P. M. Atkinson, and P. J C.urran, 1999. Fine spatial resolution simulated satellite imagery for land cover mapping in the UK. *Remote Sensing of Environment*, 68: 206-216.

Alpin, P., and G. M. Smith, 2008. Advances in Object-Based Image Analysis. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.* XXXVII (B7): 725 – 728.

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer. 1976. *A land use and land cover classification system for use with remote sensor data.* US Geological Survey Professional Paper 964, Washington, DC.

Araya, Y.H., and P. Cabral. 2010. Analysis and Modeling of Urban Land Cover Change in Setúbal and Sesimbra, Portugal. *Remote Sens.*, 2: 1549-1563.

Benz, U.C., P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58: 239-258.

Bhattarai, G., P. Srivastava, L. Marzen, D. Hite, and U. Hatch. 2008. Assessment of Economic and Water Quality Impacts of Land Use Change Using a Simple Bioeconomic Model. *Environmental Management*, 42:122–131

Borah, D. K., M. Bera, and S. Shaw. 2003. Water, sediment, nutrient, and pesticide measurements in an agricultural watershed in Illinois during storm events. *Trans. ASAE*, 46(3): 657−674.

Borah, D. K., and M. Bera. 2004 Watershed –scale hydrological and nonpoint source pollution models: review of applications. . *Trans. ASAE*, 47(3): 789−803

Carleer, A.P., O. Debeir, and E. Wolff. 2005. Assessment of very high spatial resolution satellite image segmentations. *Photogrammetric Engineering and Remote Sensing*, 71: 1285-1294.

Casals-Carrasco, P., S. Kubo, and B. Babu Madhavan. 2000. Application of spectral mixture analysis for terrain evaluation studies. *International Journal of Remote Sensing*, 21, (16): 3039-3055.

CCSP, 2003.Strategic Plan for the Climate Change Science Program. Final Report, A Report by the Climate Change Science Program and the Subcommittee on Global Change Research 2003. Available at http://www.climatescience.gov/Library/stratplan2003/final/

Cliff A.D., and J. K. Ord. 1981. *Spatial processes: Models and applications*. Pion, London, UK.

CoA, City of Auburn Comprehensive Plan 2030. Available at http://www.auburnalabama.org/Compplan2030/Default.aspx?PageID=248. Accessed on August 16, 2011.

Congalton, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 37(1): 35-46.

Congalton R, and K. Green. 1999. Assessing the accuracy of remotely sensed data: Principles and practices. Lewis Press: Boca Raton

CoO, City of Opelika zoning maps. Available at http://www.opelika.org/Default.asp?ID=508& pg =Planning. Accessed on August 16, 2011.

Dappen, P. R., I. C. Ratcliff, C. R. Robbins, and J. W. Merchant. 2008. Mapping Agricultural Land Cover for Hydrologic Modeling in the Platter River Watershed of Nebraska. *Great Plains Research*, 18:39-52

Dean, A.M., and G.M. Smith. 2003. An evaluation of per-parcel land cover mapping using maximum likelihood class probabilities. *International Journal of Remote Sensing*, 24: 2905-2920.

Deichnann, U., D. Balk, and G. Yetman. 2001. Transforming Population Data for Interdisciplinary Usages: From census to grid. NASA Socioeconomic Data and Applications Center (SEDAC), Columbia University, Palisades, NY, USA. Working Paper available on-line at: http://sedac.ciesin.columbia.edu/plue/gpw/GPWdocumentation.pdf. Accessed on June 3, 2011.

Diluzio M, R. Srinivasan, J. Arnold, and S. Neitsch. 2002. ArcView Interface for SWAT2002: User's Guide. TWRI Report TR-193, Texas Water Resources Institute, Texas. 2002

Ellis, Erle (Lead Author); Robert Pontius (Topic Editor). 2007. "Land-use and land-cover change." In: Encyclopedia of Earth. Eds. Cutler J. Cleveland (Washington, D.C.: Environmental Information Coalition, National Council for Science and the Environment). [First published in the Encyclopedia of Earth July 17, 2006; Last revised August 10, 2007. http://www.eoearth.org/article/Land-use_and_land-cover_change. Accessed on November 25, 2010.

Erbek, Sunar F., C. Ozkan, and M. Taberner. 2004. Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing*, 25(9): 1733-1748.

Fan, F., Q. Weng, and Y. Wang. 2007. Land Use and Land cover Change in Guangzhou, China, from 1998 to 2003, Based on Landsat TM/ETM+ Imagery. *Sensors*, **7**: 1323-1342.

Fisher, P. 1997. The pixel: a snare and a delusion. *International Journal of Remote Sensing*, 18: 679-685.

Fitzpatrick-Lins, K. 1981. Comparison of sampling procedures and data analysis for a land use and land cover maps. *Photogrammetric Engineering and Remote Sensing*, 47(3): 343-351.

Flanders, D., H. Mryka, and P. Joan, 2003. Preliminary evaluation of eCognition object based software for cut block delineation and feature extraction, *Can. J. Remote Sensing*, 20: 441-452.

Gassman, P. W., M. R. Reyes, C. H. Green, and J. G. Arnold. 2007. The soil and water assessment tool: Historical development, applications and future research directions. *Trans. ASAE*, 50(4): 1211-1250

Gao, Y., J.-F. Mas, B.H.P. Maathuis, X. M. Zhang, and P. M.Van Dijk. 2006. Comparison of pixel-based and object-oriented image classification approaches - a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, 27: 4039-4055.

Geist, H., and E. Lambin. 2001. What drives tropical deforestation? LUCC report series no. 4. International Human Dimension Programme on Global Environmental Change (IHDP) and International Geosphere-Biosphere Programme (IGBP). Louvain-la-Neuve, Belgium

Geneletti, D., and B.G.H. Gorte. 2003. A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. *International Journal of Remote Sensing*, 24: 1273-1286.

Geoghegan J., V. S Cortina, P. Klepeis, M. P. Macario, Y. Ogneva-Himmelberger, R. R. Chowdhury, B. L. Turner II, and C. Vance. 2001. Modeling tropical deforestation in the southern Yucatán peninsular region: Comparing survey and satellite data. *Agriculture Ecosystems and Environment*, 85:25–46.

Giada, S., T. De Groeve, D. Ehrlich, and P. Soille. 2003. Information extraction from very high resolution satellite imagery over Lukole refugee camp, Tanzania. *International Journal of Remote Sensing*, 24, (22): 4251-4266.

Gong, P., D. Marceau, and P. J. Howarth. 1992. A comparison of spatial feature extraction algorithms for land use classification with SPOT HRV data. *Remote Sensing of Environment*, 40: 137–151.

Heistermann, M., C. Muller, and K. Ronneberger. 2006. Land in sight? Achievements, deficits and potentials of continental to global scale modeling. *Agriculture, Ecosystems and Environment*, 114: 141-158.

Herold, M., J. Scepan, and C. Clarke. 2002. The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. *Environment and Planning A*, 34(8): 1443-1458.

Herold, M., N. C. Goldstein, and K. C. Clarke. 2003. The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sensing of Environment* 86, (3) (August): 286-302.

Im, J., J. R. Jensen, and J. A. Tullis. 2008. Object-based change detection using correlation analysis and image segmentation. *International Journal of Remote Sensing*, 29: 399-423.

Jensen, J. R. 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice-Hall: Upper Saddle River, NJ.

Jensen, J. R. 2000. *Remote Sensing of the Environment: An Earth Resources Perspective*. Prentice Hall: Upper Saddle River, NJ.

Jensen, J. R. 2005. *Thematic Map Accuracy Assessment. In Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice Hall Inc., NJ.

Jensen, H. R. 2006. *Remote sensing of the environment: and earth resource perspective*. NJ: Prentice Hall.

Jensen, L. L. F. and B.G.H. Gorte, 2001. *Principle of remote sensing*, Chapter 12 Digital image classification, ITC, Enchede, 2nd Edn. The Netherlands.

Kiema, J.B.K. 2002. Texture analysis and data fusion in the extraction of topographic objects from satellite imagery. *International Journal of Remote Sensing*, 23: 767-776.

Laliberte, A. S., A. Rango, K. M. Havstad, J. F. Paris, R. F. Beck, R. McNelly, and A. L. Gonzales. 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment*, 93: 198-210

Lambin, E. F., B.L. Turner, H. J. Geist, S. B. Agbola, A. Angelsen, J. W. Bruce, O. T. Coomes, R. Dirzo, G. Fischer, C. Folke, P.S. George, K. Homewood, J. Imbernon, R. Leemans, X. Li, E. F. Moran, M. Mortimore, P.S. Ramakrishnan, J. F. Richards, H. Skanes, W. Steffen, G. D. Stone, U. Svedin, T. A. Veldkamp, C. Vogel, and J. Xu. 2001. The cause of land use and land cover change: moving beyond the myths. *Global Environmental Change*, 11: 261–269.

Landis, J. H., and M. Zhang. 2000. Using GIS to Improve Urban Activity and Forecasting Models: Three Examples, chapter five in: Fotheringham, A. S., and M. Wegener. Spatial Models and GIS – New Potential and New Models, Taylor & Francis, London.

Lathrop, R. G., D. L., Tulloch, C., Hatfield. 2007. Consequences of land use change in the New York–New Jersey Highlands, USA: Landscape indicators of forest and watershed integrity. *Landscape and Urban Planning*, 79: 150–159

Legendre P., and L. Legendre. 1998. *Numerical ecology: Developments in environmental modelling 20*. Elsevier, Amsterdam, the Netherlands.

Lesschen, J. P., P. H. Verburg, and S. J. Staal. 2005. Statistical methods for analyzing the spatial dimension of changes in land use and farming systems. Land-Use and Land-Cover Change (LUCC) Project. IV. International Human Dimensions Programme on Global Environmental Change (IHDP) V. International Geosphere-Biosphere Programme (IGBP). *LUCC Report Series*: 7.

Lillesand, T.M., R.W. Kiefer, and J.W. Chipman, 2004. Remote sensing and image interpretation. 5th Edn. John Wiley and Sons, Inc. USA.

Lo, C. P., and J. Choi. 2004. A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM +) images. *International Journal of Remote Sensing*, 25, (14): 2687–2700.

Lu, D., P. Mausel, E. Brondízio, and E. Moran. 2004. Change detection techniques. *International Journal of Remote Sensing*, 25, (12): 2365-2407.

Matinfar, H.R., F. Sarmadian, S.K. Alavi Panah, and R.J. Heck. 2007. Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Lansadsat7, Etm+ Spectral Bands (Case Study: Arid Region of Iran). American-Eurasian J. Agric. & Environ. Sci., 2, (4): 448-456

Menard S. 2001. *Applied logistic regression analysis*. Sage University Papers, series on quantitative applications in the social sciences, 07-106. Sage, Thousand Oaks, USA.

Meyer, W. B., B. L. Turner, eds. 1994. *Changes in land use and land cover: a global perspective*. New York: Cambridge Univ. Press.

Meyer, W. B., 1996. *Human impact on the earth*. New York: Cambridge Univ. Press.

Moran, E.F., 1993.Deforestation and land use in the Brazilian Amazon. *Human Ecology,* 21:1–21.

Platt, R.V. and L. Rapoza, 2008. An evaluation of an object-oriented paradigm for land use/land cover classification. *Professional Geographer*, 60: 87-100.

Price, J.C., 1994. How unique are spectral signatures. Remote Sensing of Environment, 49: 181-186.

Qian Jing, Q. Zhou, and Q. Hou. 2005. Comparison of pixel based and object oriented classification methods for extracting built-up areas in arid zone. ISPRS Workshop on Updating Geo-spatial Databases with Imagery & The 5th ISPRS Workshop on DMGISs.

Reutebuch, E., L. Marzen, and M. Martin. 2008. Impact of Urbanization on Water Quality in the Saugahatchee Watershed. Alabama Water Resources Conference. Orange Beach, AL, September.

Rutherford, G. N., A. Guisan, and N. E. Zimmermann. 2007. Evaluating sampling strategies and logistic regression methods for modeling complex land cover changes. *Journal of Applied Ecology* 44: 414- 424.

Schneider L.C., and R. G. Pontius Jr. 2001. Modeling land use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems and Environment*, 85:83–94.

Serneels, S., and E. F. Lambin. 2001. Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. *Agriculture, Ecosystems and Environment*, 85:65–81.

Shackelford, A. K. and C. H. Davis. 2003. A combined fuzzy pixel-based and object-based approach for classification of high-resolution multispectral data over urban areas. *IEEE Transactions on Geoscience and Remote Sensing*, 41, (10): 2354-2364.

Singh, A. 1989. Review Article Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, 10, (6): 989-1003.

Stehman, S. V., and R. L. Czaplewski. 1998. Design and analysis for thematic map accuracy assessment: Fundamental principles. *Remote Sensing of Environment*, 64, (3): 331-344.

SWaMP Stakeholder Group and Auburn University, 2005. *Saugahatchee Creek Watershed Past, Present, and Future*. Alabama Water Watch, Auburn, AL.

Theobald, D. M., and N. T. Hobbs. 1998. Forecasting rural land use change: A comparison of regression-and spatial-transition based models. *Geographical and Environmental Modeling*, 2, (1): 65-82.

Turner, M. G. 1987. Spatial simulation of landscape changes in Georgia: A comparison of 3 transitional models. *Landscape Ecology*, 1, (1): 29 – 36.

Turner II B.L., R. H. Ross, and D. L. Skole. 1993. *Relating land use and global land cover change*. IGBP Report No. 24; HDP Report No. 5.

Turner II, B. L., W. B. Meyer, and D. L. Skole. 1994. Global land-use/land-cover change: Towards an integrated study. *Ambio*, 23, (1): 91–95.

Turner II, B.L., Skole, D.L., Sanderson, S., Fischer, G., Fresco, L.O., Leemans, R., 1995. Land-use and land-cover change. Science/Research Plan. Stockholm and Geneva: IGBP Report No. 35 and HDP Report No. 7, 132 pp.

Tso, B., and P.M. Mather, 2001. *Classification methods for remotely sensed data*. Taylor and Francis, Inc.

U.S. Census Bureau 2009. Metropolitan and Micropolitan Statistical Area Estimates. http://www.census.gov/popest/metro/CBSA-est2009-pop-chg.html. Accessed on April 7, 2010.

U.S. Environmental Protection Agency (USEPA), Office of Water. 1998. “National Water Quality Inventory: 1996 Report to Congress. ” Washington, DC

USGS. http://landsat.usgs.gov/Satellite_and_Sensor_Information.php Accessed on September 22, 2011.

Verburg, P. H., G. H. J. Koning, K. Kok, A. Veldkamp, and J. Priess. The CLUE Modelling Framework: An Integrated Model for the Analysis of Land Use Change, chapter 2 in: Singh R. B., Jefferson F. and Himiyama Y. (editors) Land Use and Cover Change. Science Publishers, Inc., Enfield (NH), USA, 2001

Vitousek, P. M., L. J. Mooney, and J. M. Melillo. 1997. Human domination of earth ecosystems. *Science*, 277: 494–499.

Walter, V. 2004. Object-based classification of remote sensing data for change detection. ISPRS *Journal of Photogrammetry and Remote Sensing*, 58: 225-238.

Winchell, M., R. Srinivasan, M. DiLuzio, and J. Arnold. 2007. ArcSWAT interface for 2005 User’s Guide.

Woodcock, C. E. 2002. Uncertainty in remote sensing. In Uncertainty in remote sensing and GIS., eds. G. M. Foody, P. M. Atkinson, 19-24. New York: John Wiley & Sons.

Wu, S., J. Silvan-Cardenas, and L. Wang. 2007. Per-field urban land use classification based on tax parcel boundaries. *International Journal of Remote Sensing*, 28: 2777-2800.

Xie C, B. Huang, C. Claramunt. 2005, ``Spatial logistic regression and GIS to model rural – urban land conversion", in Second International Colloquium on the Behavioral Foundations of Integrated Land-use and TransportationModels: Frameworks,Models and applications Toronto, July, http://www.civ.utoronto.ca/sect/traeng/ilute/processus2005/ PaperSession/Paper10 Xie-etal SpatialLogisticRegression CD.pdf. Accessed on June 25, 2011.

Yang, X., and C. P. Lo. 2002. Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia, metropolitan area. *Int. J. Remote Sens.*, 23**,** 1775–1798.

Yeh, A. and Li, X., 2001. Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. *Photogrammetric engineering and remote sensing*, 67(1): 83-90.

Zhou, Q., and M. Robson. 2001. Automated rangeland vegetation cover and density estimation using ground digital images and a spectral–contextual classifier. *International Journal of Remote Sensing*, 22, (17): 3457–3470.

Zhou, Q., B. Li, and C. Zhou. 2004. *Detecting and modeling dynamic landuse change using multitemporal and multi-sensor imagery*. Paper presented at 20th ISPRS Congress, 12-23 July 2004, Istanbul, Turkey.