Growth of Alabama Urban Areas and Its Impact on Changing Environmental Dynamics

by

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Abstract

Urbanization plays a key role in modifying land cover and has widespread impact on the environment. Atlanta has always been the focus of urban studies in south-eastern United States. Little attention is given to urban areas smaller than Atlanta yet growing at an alarming rate. Keeping this in view -the focus of this study is on the eight cities of Alabama which have encountered greater than 15 percent population increase between 1982 and 2010 and two large ones which have lost population. The main objectives are 1) To determine the expansion of urban built-up areas of the ten cities over time (1982-2010); 2) To examine temporal trends in temperature, precipitation, and air pollution for the study areas (1980-2010) and understand the impact of urban built-up area on each; and 3) To project future urban growth scenario (2040) for selective five cities using Cellular Automata (CA) Markov model. Results revealed that there has been immense expansion of urban built-up areas from1982 to 2010 due to population increase. Every study area chosen there is an increasing trend in temperature and precipitation pattern. Air quality has improvement in each city though expected otherwise. Regression results revealed that variation in temperature, precipitation and $PM_{2.5}$ can be explained by urban built-up expansion. The future growth model exposed that urban growth will take place along the transportation routes mainly. The outcome of this research will help scientific planning of cities in Alabama as well as implementing on other mid-sized cities globally.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

US	United States
UN	United Nations
LULCC	Land Use Land Cover Change
LULC	Land Use Land Cover
MK	Mann-Kendall
MSA	Metropolitan Statistical Area
CA	Cellular Automata
GIS	Geographic Information System
TM	Thematic Mapper
IR	Infra-Red
USGS	United States Geological Survey
GLOVIS	Global Visualization Viewer
AOI	Area of Interest
AL	Alabama
O_3	Ozone
$PM_{2.5}$	Particulate Matter 2.5
NWS	National Weather Service
NCDC	National Climatic Data Center
EPA	Environmental Protection Agency

MCE	Multi Criteria Evolution
AHP	Analytic hierarchy process
IPCC	Intergovernmental Panel on Climate Change
SIP	State Implementation Plan
H_0	Null Hypothesis
H_1	Alternative Hypothesis
Rst	Raster
Img	Image

Chapter 1: Introduction

1.1 Introduction

The coming decades will see a steady increase in urban population globally. A United Nations report mentions that the world population is expected to be on the order of 70 percent urban by 2050 (UN 2007). In case of United States (US) urbanization developed over the last two centuries from being a major rural, agricultural nation into an industrial one. In US the urbanization process was slow with the nation becoming an urban-majority between 1910 and 1920 (US Census 2010 a). At present, just over four fifths of the US citizens live in urban areas, and the number is still on the rise (US census 2010 a).

Narrowing it down to Alabama, within the group of southeastern states of US, it is the only one where, between 2000 and 2009, more than half of the growth (53 percent) resulted from natural increase (number of births minus number of deaths) (Georgia Office of Planning and Budget, 2010). Also, Alabama is one of the slowest growing states in the US (30^{th} in rank) on the basis of overall population. During the 1990s, the population in Alabama grew by 10.1 percent whereas nationally, population increased by 13.1 percent. Particularly significant was in 2010 when the nation's population increased by 9.7 percent whereas in Alabama it increased by only 0.48 percent (US census 2010a).

Though the state of Alabama shows slow population growth, individual cities within Alabama tells a very different story. Over past few decades, the population of major cities in Alabama has shown huge increases with the exception of Birmingham and Mobile. Madison, Hoover and Auburn have shown significant growth over time in past 30 years too. Population increase creates pressure on the infrastructure and dynamics of the city and to accommodate the growing population there is naturally an increase in urban built-up area (Lambin *et al* 2001, Cohen 2006). And the rate at which urban areas are growing is of much concern to both social and natural scientists since urban area has an impact on human health (Jackson 2003) as well as on surrounding physical environment (Oke 1973). So in this study as a proxy to growing population and its impacts on landuse, urban built-up area increase over time will be considered and quantified.

Presently most of the urban studies focus on large sized cities across the world like Atlanta, New York, Tokyo, Kolkata and Dhaka (Yang 2002,Islam and Ahmed 2011, and Mitra *et al* 2012) thus ignoring the medium sized cities, which have the most growth potential with significant ecological footprint on the face of the earth. For the same reason this research mainly focuses on medium sized and small sized cities which have the potential of both horizontal and vertical growth. Based on population, the US Census categorized all medium sized cities ranking them between 101 and 200 compared to all sizes (US Census 2010a). The populations of these medium-sized cities ranged from 98,000 to 210,000 in 2010. Based on these statistics, there are one large sized (Birmingham: rank 100) and three mid-sized cities in the State of Alabama (Montgomery: rank 105, Mobile: rank 120, and Huntsville: rank 126). Rest of them fall in small-sized categories above 200. A study revealed that medium-sized cities grew faster in population than the largest ones (Detroit, Cleveland, Pittsburg, Saint Louis, New Orleans) which lost more than 20 percent of their population during the 1990s in the US (Vey and Forman 2002). The study also revealed fastest growing cities were in the south and western part of US (Vey and Forman 2002). Echoing the above findings the major Alabama cities are losing population whereas medium sized ones are gaining population rapidly in a short period of time (Table 1). Birmingham city and Mobile city have slower growth (25.4 percent and 2.7 percent population were lost respectively for each stated urban areas from 1980 to 2010) compared to other small cities like Hoover and Madison (more than 300 percent and 900 percent growth shown for respective cities from 1980 to 2010) (data calculated from US census 2010a).

Rapid urbanization in the form of population increase has led to an increase in built-up area and impervious surfaces, increased greenhouse gas emissions and more anthropogenic activities which are argued to be detrimental to the delicate yet complex environmental-climate system of the Earth (Yang *et al* 2003). The ability of an urban area to generate an effect on environment is now a well-accepted fact (Oke 1973, Han *et al* 2013). A relationship has been found between intensity of this effect and size of urban areas (in terms of population). It is revealed that larger the areas, the higher the impact on environment (Oke 1973). Han *et al* (2013) also mentioned that urban areas affect the spatial distribution and amount of precipitation in south-eastern Brazil.

Keeping this in mind, this research focuses on understanding the dynamics of urban built-up expansion in Alabama and changing urban environment. Here urban built-up area is defined as the area confined by the built-up impervious surface in a city as described in remote sensing literature (Yang *et al* 2003). The research has delved on urban built-up expansion and whether it has modified the various environmental parameters. In particular, the project would have sought to address the following objectives:

1. To determine the expansion of urban built-up areas over time (1982-2010), for ten cities using supervised classification.

2. To examine temporal trends in temperature, precipitation, and air pollution (concentration of ozone and particulate matter 2.5 in air) in the study region (using Mann-Kendall trend test) for 1980-2010 and to understand the impact of urban built-up expansion on environmental parameters (using multiple linear regression).

3. Project future urban growth scenario (2040) for selective five cities using cellular automata (CA) Markov model.

1.2 Urbanization and its Impact

The global population has become concentrated in cities (UN 2007). Over the last hundred years, depending on the region, the world has rapidly become an urban one, with detrimental consequences caused by changes in population distribution. The share of world population that lives in urban areas has increased from 5 percent in 1900 to over 50 percent today with the largest proportion of this urban population in developing countries (Maktav *et al* 2005). Urbanization is accompanied by artificial changes in land use land cover change (LULCC). Urban areas are composed of numerous man-made structures and urban surfaces covered with materials such as concrete and asphalt (Han *et al* 2013).

In the United States, there was a 34 percent increase in the amount of land devoted to urban and built-up uses between 1982 to 1997 (Alig *et al* 2003). Their main source of data was United States Department of Agriculture. According to the 2010 (c) census, 80.7 percent of US population lives in urban areas, a substantial increase from 73.7 percent in 1980 (US census, 1995d). Statistical projections (estimated regression model coefficients) suggest continued urban expansion over the next 25 years, with the magnitude of increase varying regionally (Alig *et al* 2003). The developed area within US is projected to increase by 79 percent, raising the proportion of the total land base in the US that is developed from 5.2 to 9.2 percent (Alig *et al* 2003). Here urban and built-up areas are defined as land uses consisting of residential, industrial, commercial, and institutional land as well as several public infrastructure land use categories such as railroads, landfills etc. (Alig *et al* 2003).

Many studies reveal that urbanization has several impacts on environmental parameters. Some studies have been done in India (precipitation), Turkey (relative humidity), Nigeria (temperature) and US (air quality). These studies indicate that increasing trend in urbanization has a positive relationship on environmental parameters (temperature and precipitation). (Tayanc and Toros 1997, Mitra *et al* 2011, Babatola 2013).

The benefits of urbanization are increasingly measured against ecosystem impacts, including degradation of air and water quality and others (Squires 2002; Yuan *et al* 2005). Large cities across the US have seen marked increases in urban growth and the associated impacts of environmental degradation (Yuan *et al* 2005). Research has highlighted urbanization effects on different environmental parameters, for instance, temperature, precipitation, and air quality (Oke 1973, Tayanc and Toros 1997, Superczynski and Christopher 2011).

1.3 Study Area

In this research, the study areas have been selected on the basis of city population from 2010 census data (US census 2010 b), the cities which have had a population growth greater than 15 percent from 1980 to 2010 (table 1, figure 2). This research did not consider the Metropolitan Statistical Area (MSA) population. The main reason behind this is to highlight how the small sized cities like Hoover and Madison have been growing in the recent past. If MSA would be considered then Madison and few other smaller cities which are not yet metro areas would not be considered under the scope of this research. The two exceptions showing negative population growth in recent past are Birmingham and Mobile cities. Their inclusion in the study will help in understanding whether population decline also influences urban built-up.

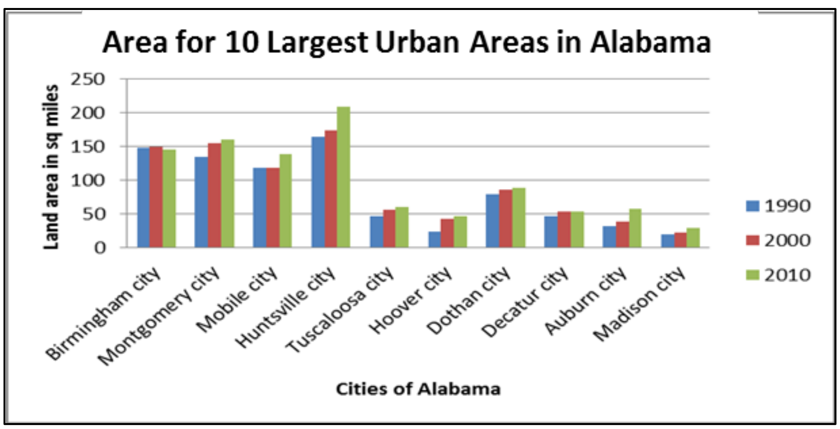
Figure 1 shows the areal extent of the ten study areas and figure 2 shows their spatial coverage spread over the whole Alabama state. Table 1 indicated that major cities like Birmingham and Mobile are growing slowly (25.4 percent and 2.7 percent population were lost respectively for each stated cities from 1980 to 2010) compared to other cities like Hoover and Madison (more than 300 percent and 900 percent growth shown for respective cities from 1980 to 2010) (data calculated from US census 2010a).

For classification purpose in this study, the study areas are consisted of 2010 urbanized areas reference map in the state of Alabama (US census 2010 b) for supervised classification.

Table 1.Growth (increase and decrease) in population for the ten cities in Alabama from 1980 to 2010.

Study Areas (Based on city population)	Population		Population Change, 1980 to 2010	
	1980	2010	Number	Percent
Birmingham	284413	212237	-72176	-25.4
Montgomery	177852	205764	27912	15.7
Mobile	200452	195111	-5341	-2.7
Huntsville	142513	180105	37592	26.4
Tuscaloosa	75211	90468	15257	20.3
Hoover	19792	81619	61827	312.4
Dothan	48750	65496	16746	34.3
Decatur	42002	55683	13681	32.6
Auburn	28471	53380	24911	87.5
Madison	4057	42938	38881	958.4

Source: United States Census Bureau, 2010 a.



Source: United States Census Bureau, 2010a.

Figure 1. Area of 10 Study Areas.

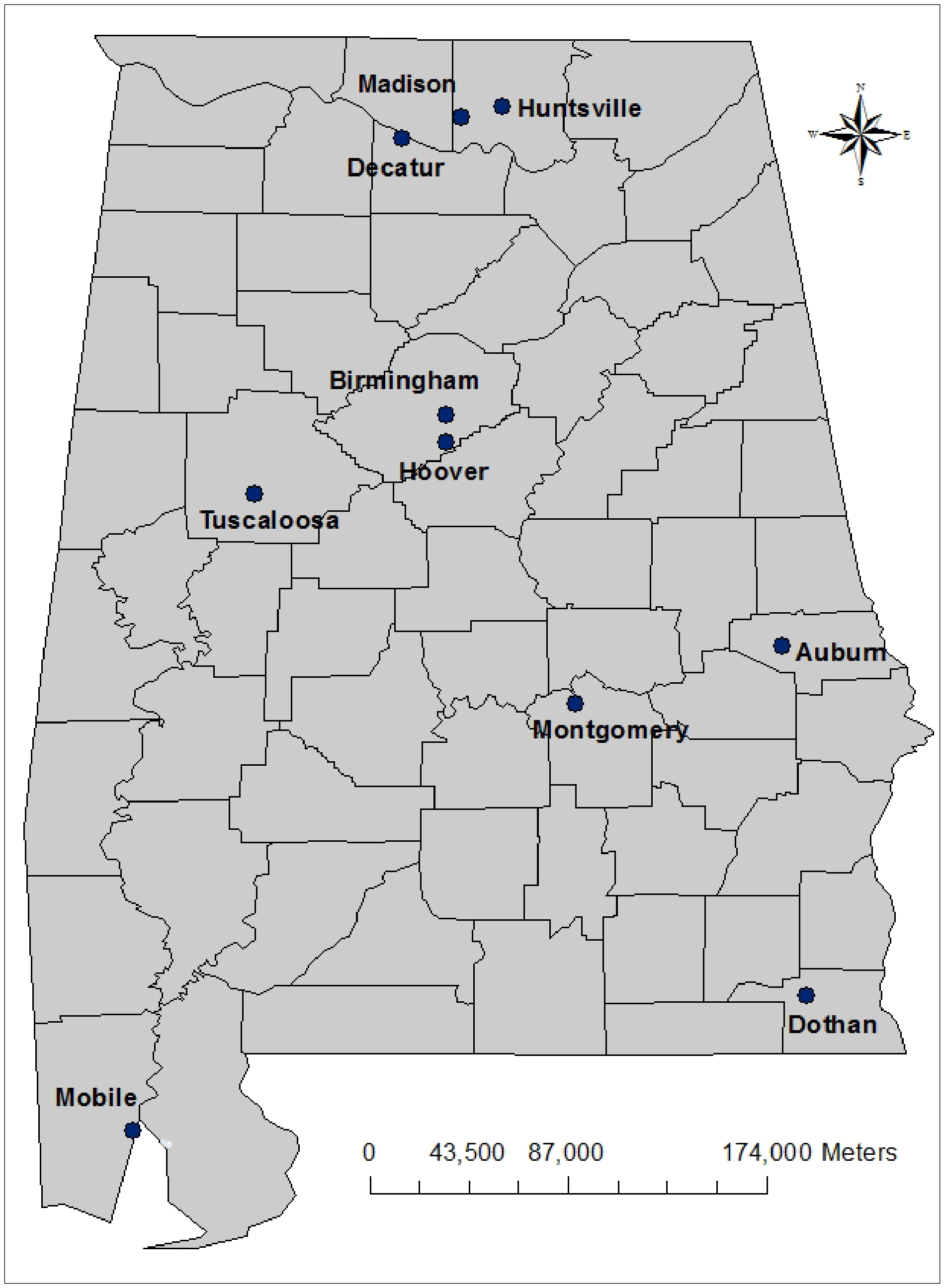


Figure 2. Location of Ten Study Areas (Map created by Mahjabin Rahman)

1.4 Methodology

Various geospatial methodologies have been used in different studies to quantify and analyze impacts of land use land cover change on the environment. In this study three different methods have been approached to fulfill the objectives.

Chapter 2 deals with determination of urban expansion. Remote sensing techniques to study urban expansion are discussed in this chapter. Image analysis of Landsat 5 Thematic Mapper (TM) imagery methods utilizing supervised classification using ERDAS Imagine 13 software has been conducted here. This technique is used to determine the urban expansion of all study areas over 28 years (1982-2010).

Chapter 3 looks at the change of environmental parameters over time (1980-2010).This research has been selected two weather parameters (temperature, precipitation) and two air quality parameters (PM $_{2.5}$ and Ozone). Man-Kendall statistical technique was used to test the non-parametric variables which require that data should be independent and can tolerate outliers in the dataset (Onoz and Bayazit 2003). To investigate the relationship between urban built-up and environmental parameters, multiple linear regression has also been demonstrated in this chapter. It is important to highlight that analysis of urban expansion has been done from 1982 to 2010, whereas trends of environmental parameters has been analyzed from 1980 to 2010 based on data availability.

In chapter 4 Cellular Automata (CA) Markov is used to forecast urban expansion for 2040 for five urban areas (Birmingham, Hoover, Madison, Mobile, and Auburn). These urban areas were chosen based on their significance. Birmingham and Mobile, though largest have been losing population and the others are gaining population. This model is developed in the Geographic Information System (GIS) environment and provides spatial outputs which may help to manage and evaluate urban areas in development scenarios.

Chapter five summarizes the findings of this research highlighting the significance of the study in the perspective of the dynamic nature of urban areas and their influence on environment and the people who live in them.

1.5 Significance

This study will be a unique synergy of urban land cover dynamics and environmental parameters. Future prediction and managing urban growth requires rigorous use of technologies and methods in order to produce accurate mapping of land use and land cover. Remote sensing imagery will provide geographic and temporal overview of urban development in Alabama. Various statistical techniques (Mann-Kendall test and multiple linear regression) will provide a quantitative analysis of the environmental parameters: how their temporal trends are changing with time and relationship between urban expansion and environmental parameters. The principal objective to use urban growth model is evaluating possible future paths of development on various urban sectors.

It is important to analyze not only the urban built-up expansion but also see how it influences precipitation, temperature, air quality, water availability, health etc. which could be compromised in the future with population pressure in the urban areas. Extreme events like heat waves, tropical cyclones, and rainfall events are predicted to be on the rise in recent decades (Peterson *et al* 2013) and thus it is very important to understand the dynamics of urban areas and be prepared for adapting and mitigating the impacts. As it is well known that more than half of the world’s population lives in urban areas (Population Reference Bureau 2012) so their resource intensive living patterns must be having a large impact on local environment and eventually on the global environment as well. Thus it is very important to manage urban areas in a sustainable way and be environmentally conscious and be conservative on energy usage.

The significance of this study also lies in shifting focus from large cities to smaller cities which have the maximum potential to grow in future. It is better to be prepared ahead of time to cope with the local and regional changes.

By using ten cities in the study, the findings will establish a possible link between urban built-up expansion and changing patterns of environmental parameters. The findings of this research will provide a better understanding of what we are expecting in our future and what we can do to adapt and mitigate the impacts.

Chapter 2: Urban Built-up Expansion

2.1 Introduction

It is important to understand what urbanization is and why it is important in present scenarios. Urbanization is a dynamic process which changes patterns with increasing number of people coming to live in urban areas. It predominantly results in the physical growth of urban areas, horizontal or vertical (UN 2007). It is also important to quantify this conversion from natural to built-up environments in urban areas as it can profoundly impact the land atmosphere dynamics locally as well as regionally.

Determination of urban expansion involves procedures of monitoring and mapping which require robust methods and techniques (Yang 2002). Traditional methods for gathering demographic data, censuses, and maps using samples are limited for urban management purposes because updating process is time and labor intensive (Maktav 2005). Also traditional survey and mapping methods cannot deliver the necessary information in timely and cost-effective manner. These methods are also time consuming, contain errors, and are not appropriate here. Given their technological challenges, remote sensing technologies are increasingly becoming popular in urban land use change research (Civco *et al* 2000; Yang 2002, Araya and Cabral 2010). The basic premise of using remote sensing is that it can identify change between two or more time periods (Roy 2000; Shalaby and Tateishi 2007). Roy (2000); Shalaby, and Tateishi (2007) also note that remote sensing and GIS provide opportunities for integrated analysis of spatial data.

Supervised and unsupervised classifications are two traditional pixel-based methods of analyzing remotely sensed data (Maktav *et al* 2005). In supervised classification, a user selects training sites for desired classes and then pulls them from the image using a statistical algorithm, while in unsupervised classification, the software statistically groups pixels into similar clusters then the user assigns the clusters to a class by referencing the imagery used for the classification (Campbell 2002). Pixel-based classification is easy to use and quite successful in classifying land cover of a homogenous nature like closed forest (Whiteside and Ahmad 2005).

A large body of research exists in the field of assessing urban extent using remote sensing and GIS techniques (Maktav *et al* 2005). According to Maktav *et al* (2005) remote sensing – as a technique for observing the surface of the Earth from different platforms – and Geographic Information Systems (GIS) can mitigate the problems of traditional field-based data collection methods by providing up-to-date spatial information over large expenses of territory. Moreover, remote sensing data can identify LULCC between two or more time periods effectively (Roy 2000; Shalaby and Tateishi 2007).

Many researchers also used remote sensing and GIS techniques to understand urban areas across the world. Lambin and Ehrilch (1997) used ten years of data to assess and analyze land cover changes in the African continent between 1982 and 1991. Another study was conducted in the lake regions of central Ethiopia using aerial photographs dated 1972 and 1994 from Landsat thematic mapper (TM) images (Ferrari 2000; Shalaby and Tateishi 2007). Ram and Kolakar (1993) also studied land use changes in India (Shalaby and Tateishi 2007). In addition a supervised classification was done for the Northwestern coast of Egypt by Shalaby and Tateishi (2007) to delineate LULCC.

Here in the US many studies were conducted to understand LULCC using remote sensing. Xiaojun Yang (2002) monitored the urban spatial growth in the Atlanta metropolitan area in 2002 using an unsupervised classification system from Landsat TM data between 1973 and 1999. According to Yang, remote sensing and GIS offer the best way to manage urbanization because these techniques provide accurate spatial information. Similarly Yuan *et al* (2005) studied land cover classification and change analysis of the twin cities in Minnesota. They used a supervised-unsupervised hybrid approach to classify images. The result has proven the potential of multi-temporal Landsat data to provide an accurate map of landscape changes and valuable statistics documenting change over time (Yuan *et al* 2005). In addition they also examined the relationship between population growth and growth in urban land area through Landsat-derived change maps.

In Alabama, Trousdale (2010) conducted a study of Birmingham and Hoover using supervised classification. He measured the expansion of urban sprawl over a 34 year period (1974-2008). The results reveal that over the study period there was a steady decline in forests, agricultural lands, and green space and an expansion of urban and residential land-use/land-cover in the metropolitan area in the form of built-up area.

2.2 Expansion of Urban Built-Up Areas

Remotely sensed image analysis is a challenging task. One popular and commonly used approach for image analysis is image classification. The purpose of image classification is to label the pixels in the image with meaningful information of the real world (Jensen *et al* 2001; Matinfar 2007). Through classification of digital remote sensing images, thematic maps bearing the information such as land cover types; vegetation types etc. can be obtained (Tso *et al* 2001; Matinfar 2007).

2.2.1 Data Acquisition and Image Processing

Landsat Thematic Mapper (TM) imagery has been used for this study. The Landsat TM is a technologically advanced sensor integrating multiple radiometric, spectral, and geometric enhancements from its predecessors. The imagery provides data in seven bands of the spectrum—visible spectrum (blue, green, red), near-IR, 2 mid-IR bands, and thermal. The wavelength location and range of the TM bands have been enhanced from its predecessors, improving the spectral differentiability of surface features of Earth (Lillesand *et al* 2004). It has a spatial resolution of 30x30 m, temporal resolution of 16 days and radiometric resolution of 8 bits.

For urban land cover classifications with Landsat TM, the most useful bands are visible, near infrared, and middle-infrared, because combination of these bands highlights LULC in a better way (Jensen 2007). TM images were obtained for four decades -1982s, 1990s, 2000s and 2010s from the United States Geological Survey (USGS) Global Visualization Viewer (GLOVIS) for ten different study areas of Alabama (http://glovis.usgs.gov/).

Raw remotely sensed image data are full of geometric, radiometric, and atmospheric flaws caused by the curved shape of the Earth, the imperfectly transparent atmosphere, daily and seasonal variations in the amount of solar radiation received at the surface. USGS offers correction of these flaws. Geometric flaws are corrected by process rubber sheeting (Lillesand and Kiefer 1994). It involves stretching and warping an image to georegister control points shown in the image to known control point locations on the ground. There are several numerous radiometric correction techniques, including Earth-sun distance corrections, and sun elevation corrections. Atmosphere errors are corrected by haze compensation (Lillesand and Kiefer 1994).

Temporal resolution became an issue while trying to find adequate satellite imagery for analysis. Acquiring anniversary images is the best option with corresponding season, month, and preferably week for each year. Many times this is not possible because of the times that the sensor system passes over the particular area. However, with classification methods a user can account for seasonal differences as images are classified independently. Another problem is weather; when there is a thunderstorm or just cloud cover it is impossible to produce an accurate urban land cover classification. Many times anniversary dates are impossible, and the logical alternative would be to find images of the area in the same month or season (Jensen 2007). For this study it was possible to acquire satellite data close to anniversary dates (Table 2).

Table 2. Information of the Satellite Image used in this Study.

Study Area	Path	Row	Date			
			1982	1990	2000	2010
Auburn	19	37	December	January	January	January
Dothan	19	38	December	January	January	January
Tuscaloosa	27	37	June	June	June	June
Mobile	21	39	January	February	March	February
Huntsville	20	36	April	April	April	April
Madison	20	36	April	April	April	April
Decatur	21	36	October	November	November	November
Birmingham	20	37	December	December	January	December
Hoover	20	37	December	December	January	December
Montgomery	20	38	March	March	March	March

The downloaded images covered a larger area than actual urban extent, so a subset of the required area was needed. The study area for each urban area is a chosen ‘area of interest’ (AOI) around the most recent boundary of census bureau defined urbanized area (figure 3) (US census 2010b).

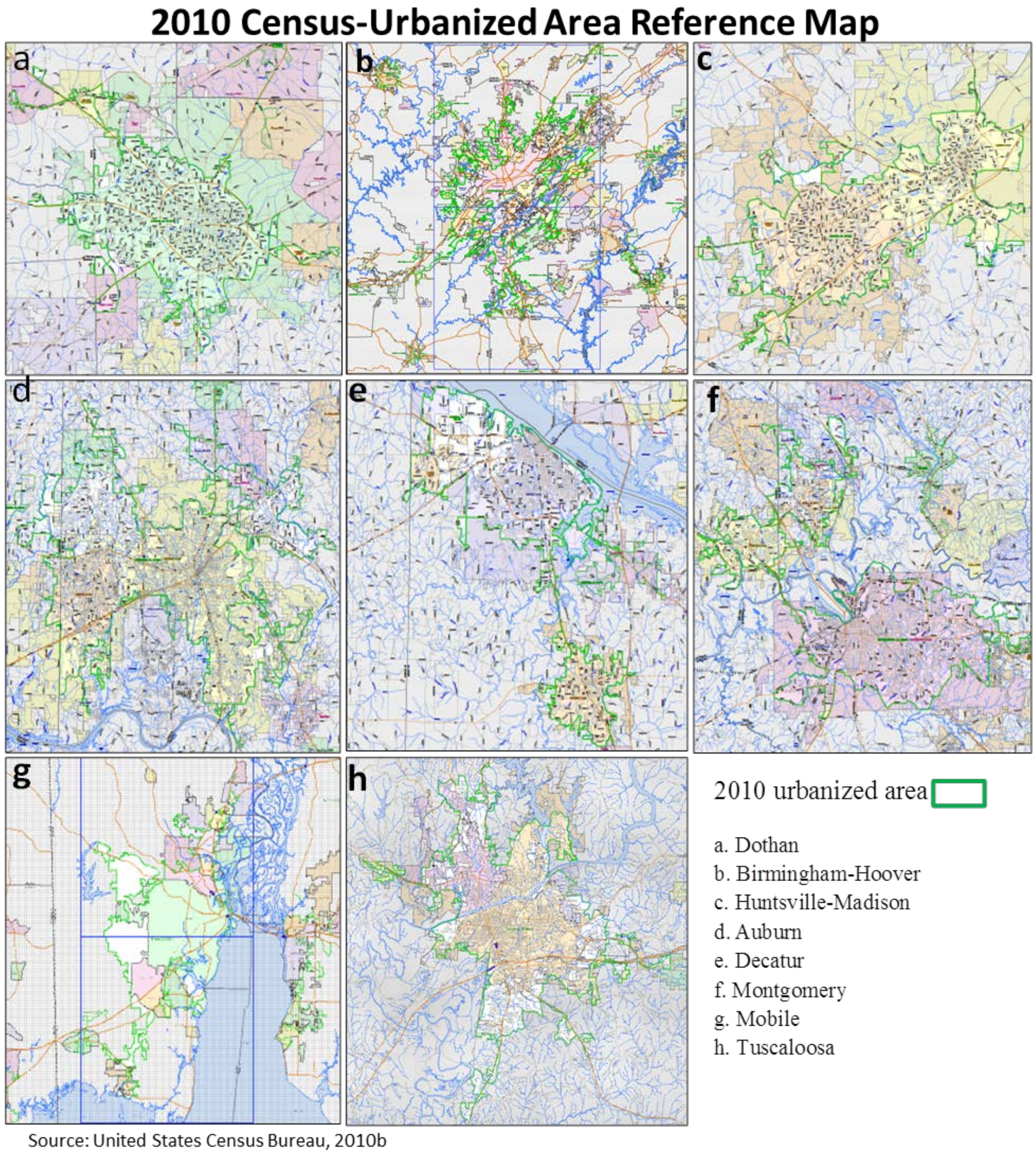


Figure 3. 2010 Census Urbanized Area Reference Map for 10 Study Areas.

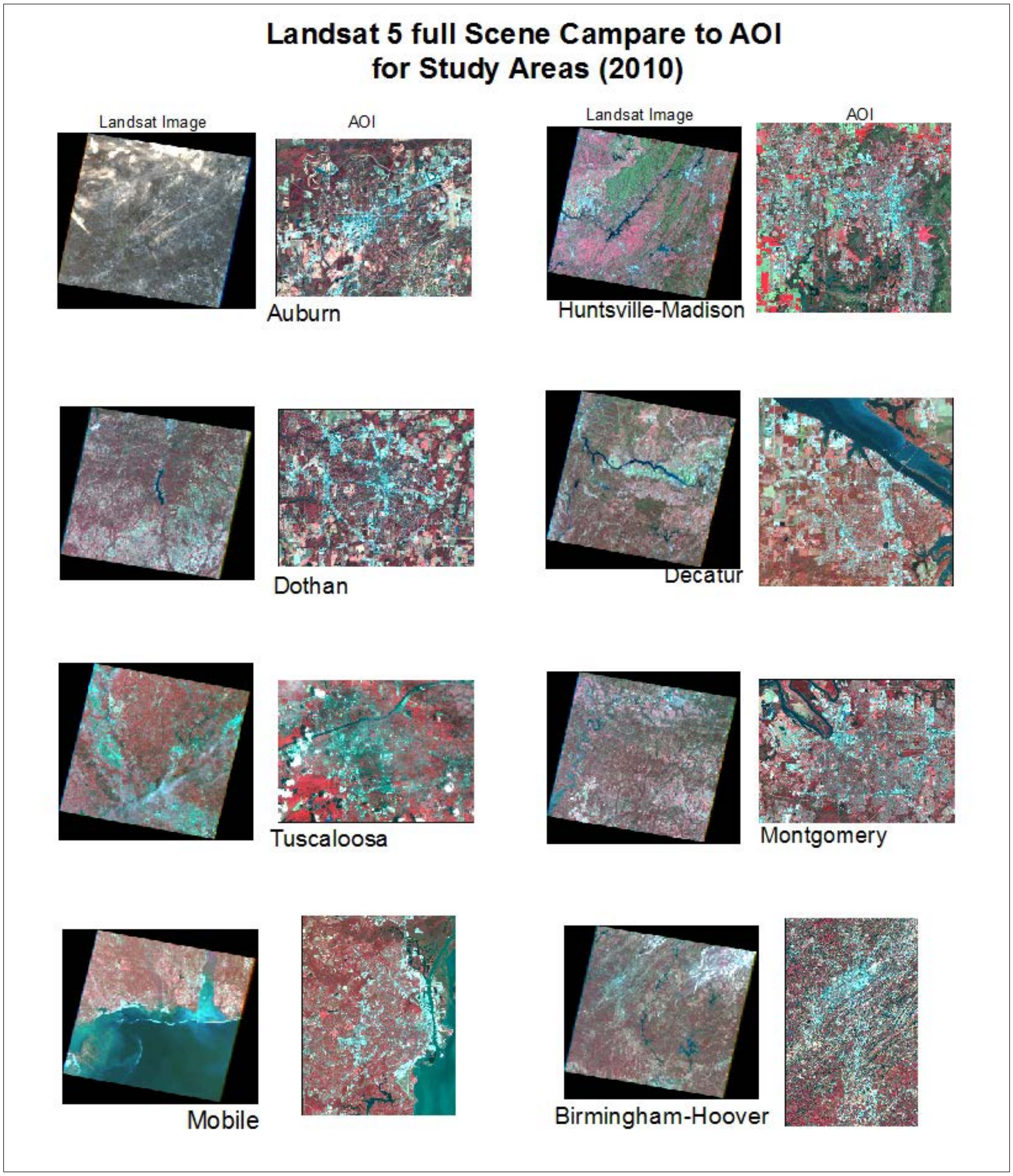


Figure 4. Landsat Full Scene (Left) Compare to AOI (Right) for 10 Study Areas (2010).

2.2.2 Supervised Classification System for Urban Expansion

The main objective of the image classification procedure is to automatically categorize all pixels in an image into land cover classes (Lillesand and Kiefer 1994; Shalaby and Tateishi 2007). As mentioned earlier there are two types of classifications, namely supervised and unsupervised.

The classification system that has been used for this research is the supervised classification. In supervised classification, spectral signatures are developed from specified locations in the image. These specified locations are given the generic name of 'training sites' and are defined by the user. The training sites will help further to develop spectral signatures for the outlined areas. This classification system is also very efficient to identify natural and manmade land use and land cover (Jensen 2007). The band combinations utilized were 4, 3, and 2 (Near-Infrared, Red, and Green).This combination is very useful in identifying urban areas (Yang 2002). Before image classification, a classification scheme must be established: that is how many classes will be in the image classification and what they consist of (Yang 2002).

Determination of urban built-up area is the key to this study. All of the objectives are mainly focused on urban built-up expansion. Environmental parameters have been studied on the basis of urban built-up area. For this reason, three classification classes were chosen namely, urban built-up area, water bodies, and other (Table 3).

First step of the classification was to delineate several training sites that are representative of each land cover class. To achieve the most reliable classification 30 training sites per class have been taken. Training sites were different for every study areas. Google Earth was used to visually confirm whether the chosen training sites were accurate or not.

Table 3. Image Classification Scheme.

LULC	Characteristics
Urban built-up	Consists of concrete and impervious surface, which is mainly- • Commercial, industrial, and residential buildings with large open roofs. • Large open transportation facilities and local roads.
Water bodies	Consists of open water bodies such as, streams, lakes, rivers, reservoirs and wetland.
Other	Consists of Vegetation (forest) cover, cultivated land (with crop and without crop), cropland/grassland, and exposed/barren land.

Once the image has been classified, the next step was to select the appropriate image classification logic. For this research the parametric rule selected was maximum likelihood. This method merges continuous spectral values and a set of prior probabilities (weights) into a single classification (e.g., each land use type). This decision rule computes the results for each class and assigns a pattern to that class having the final output. In this way a better classification can be performed than other parametric rules (Ahmed and Quegan 2012). When maximum likelihood calculations were performed, the prior probabilities appropriate to the particular pixel were used in classification (Strahler 1980). Next, every image must be recoded. The recoding process eliminates all of the classes that do not have any value. The recoding process puts all land use land cover classes in the same order as they classified for each image. After that classification was examined using visual analysis and classification accuracy (Ahmed and Quegan 2012).

To understand the results of the classification an accuracy assessment is required. It is vital that the thematic classification is accurate because important application decisions will be made using these data. It is an unavoidable fact that these data will contain errors but it should be minimized as much as possible. An accuracy assessment informs the user how much confidence they should have in the thematic information they are looking at. An accuracy assessment makes information derived from remotely sensed data credible (Jensen 2007).

The accuracy assessment sampling method chosen for this research was the stratified random sampling (Maktav *et al* 2005). This method is preferred because a set minimum number of samples are taken from each land-use/land-cover category after a supervised classification has been created. The main advantage of stratified random sampling is that all land use and land-cover classes, no matter their spatial size in proportion to the study area, will have a minimum number of samples allocated for accuracy and error evaluation. It is very difficult to locate adequate samples for classes that only take up a small amount of the study area without stratification (Jensen 2007).

2.3 Results of Classification for all Ten Study Areas

Urban expansion as a dynamic process of land use change is a complicated social and economic phenomenon. It is also related to topography, demography, transportation, land use, and presence of functions (e.g. school, industry) in an area (Li *et al* 2003. Mohammadi *et al* 2012).

Development of functions, form and pattern of an urban area are governed by two specific forces: centrifugal and centripetal (Colby 1933). The former one can explain by which functions and populations migrate from central part of an area to periphery and the later one hold certain functions in the central part and make that part the center of gravity for the entire urbanized area (Colby 1933).

Different urban forms (linear, grid, radial etc.) are outcome of several urban functions and forces (Furundzic and Furundzic 2012). Linear pattern runs parallel to a major urban transportation route (interstate, highway, and railway) or physical infrastructures (e.g. river) (Furundzic and Furundzic 2012). Grid pattern is the result of accessibility of transportation routes and availability of functions all over the areas which grow from a constrained location such as river or road junctions or islands (Rodrigue 2013). Radial pattern is mainly the result of centrifugal forces along several transportation routes (Rodrigue 2013).

In this following section, several factors and forces have discussed as a reason of urban built-up expansion as well as how much they grew from 1982 to 2010.

2.3.1 Birmingham-Hoover, Alabama

As mentioned earlier population of Alabama's largest city, Birmingham shrunk by 25.4 percent from 1980 to 2010 while the adjacent Hoover grew by over 300 percent (table 1 in chapter 1) according to census data. Although urban built-up expansion cannot be inferred using population as a variable, however for both Birmingham and Hoover their urban built-up increased over the same time period at a different rate. Birmingham grew slowly compared to Hoover.

It is obvious (figure 5 left) that there has been urban built-up growth in the Birmingham study area over the 1982-2010 twenty eight year period while water bodies and 'other' area has decreased. Based on table 4 an analysis of the 1982 data shows that urban built-up was 8.8 percent of the total study area. In 2010, the total urban built-up area was 11.4 percent. For Hoover, in 1982 there was 3.9 percent of built-up area and in 2010 urban built-up area was 11.6 percent. The net addition to urban built up area was 29.4 percent for Birmingham. On the other hand, it was 194 percent for Hoover (table 4).

For Birmingham, this addition was mainly concentrated in central parts following interstate 65 (north-east to south-west direction) such as downtown and university areas. Significant growth of Hoover took place from north to south directions. The linear pattern of urban expansion was along interstate 65 (I-65) which also goes from north to south direction.

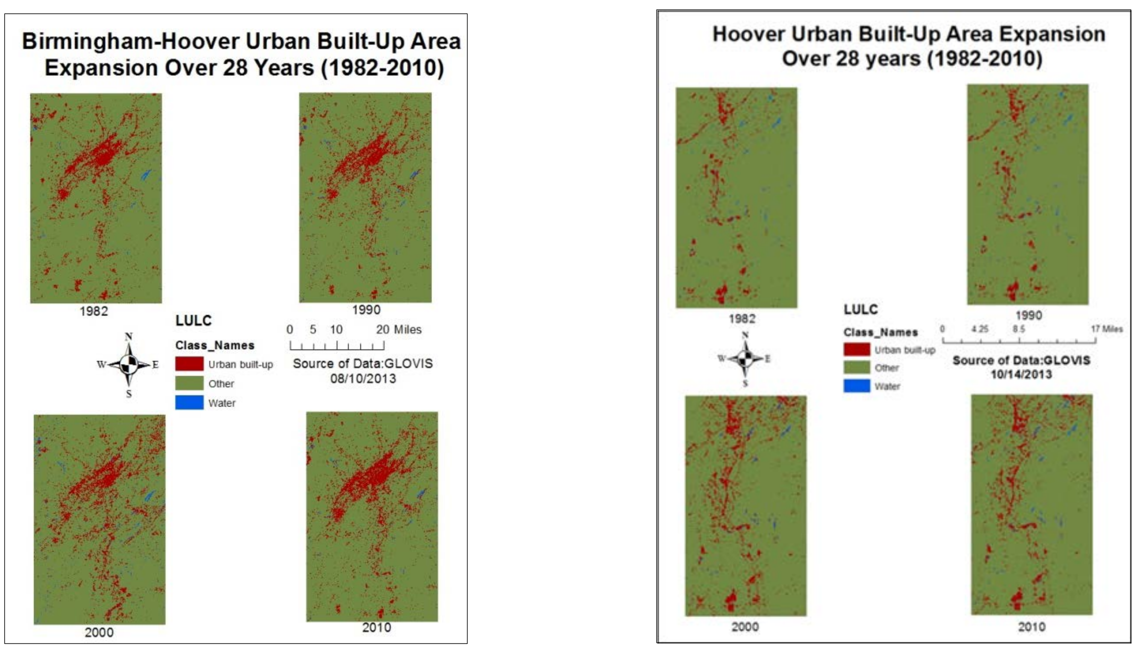


Figure 5. Urban Built-up Expansion for Birmingham (left) and Hoover (right).

Table 4. Land Use Land Cover Statistics for Birmingham- (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	28687.35	8.82	28916.4	8.89	35419.6	10.9	37136.1	11.42	+301.74
Water bodies	1422.15	0.43	1367.1	0.42	1169.91	0.40	1155.42	0.40	-9.5
Others	294832	90.73	294658	90.68	288352	88.73	286650	88.21	-292.21
Total	324941.5	100	324941.5	100	324941.5	100	324941.5	100	

Table 5. Land Use Land Cover Statistics for Hoover (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010) ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-	3378.9	3.93	5868.45	6.84	6866.91	8.00	9951.23	11.6	+234.72
Water bodies	650.32	0.75	716.04	0.83	539.59	0.62	422.15	0.49	-8.14
Others	81733.1	95.30	79177.83	92.32	78355.8	91.36	75388.92	87.9	-226.57
Total	85762.32	100	85762.32	100	85762.3	100	85762.3	100	

2.3.2 Montgomery, Alabama

Montgomery is the capital of Alabama. The city started growing at the intersection of I-65 and I-85 in 1982. Since then it has spread towards the east and south. Gradually Montgomery took the form of a grid (Rodrigue 2013) and gradually filling in over the years. Urban built-up area grew almost double between 1982 and 2010 (table 6).

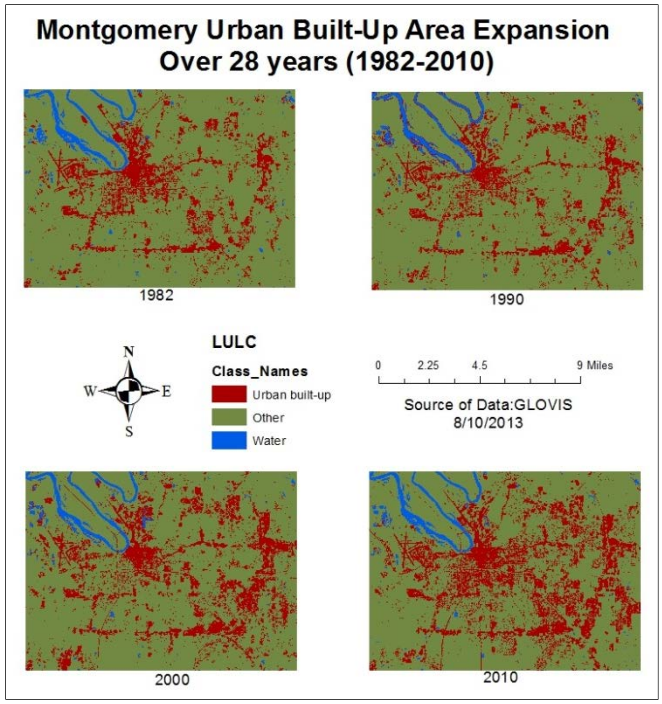


Figure 6.Urban Built-up Expansion for Montgomery.

Table 6.Land Use Land Cover Statistics for Montgomery (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-	3823.55	13.	3992.92	14.3	5096.34	18.29	6073.47	21.7	+80.35
Water	833.94	2.9	705.96	2.53	764.19	2.742	744.97	2.67	-3.17
Others	23204	83.	23162.62	83.1	22001	78.96	21043.1	75.5	-77.17
Total	27861.49	100	27861.5	100	27861.5	100	27861.54	100	

2.3.3 Mobile, Alabama

Mobile urban area mainly situated near the banks of several rivers (Alabama River, Mobile River, Tombigbee River). Initially it grew near the rivers and later it spread from east to west. Mobile shrunk 2.7 percent in terms of population from 1982 to 2010. But it’s urban built up area increased significantly which highlight urban expansion or sprawl.

The net addition to urban built-up was 130 percent which is quite high.

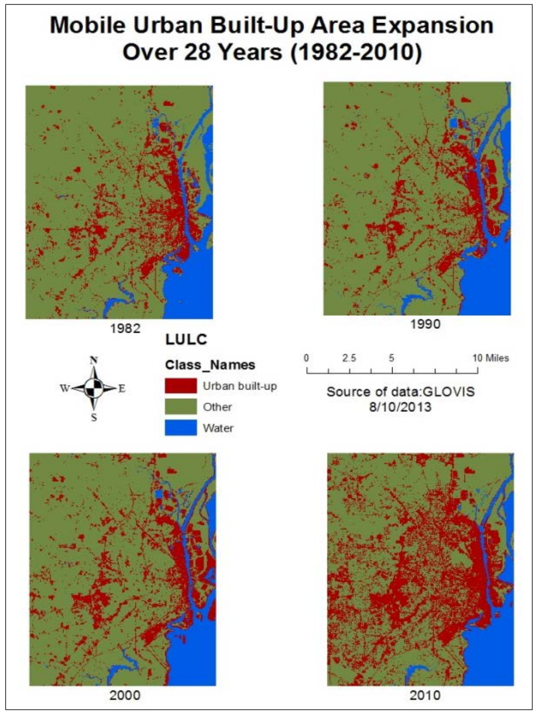


Figure 7. Urban Built-up Expansion for Mobile.

Table 7. Land Use Land Cover Statistics for Mobile (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	5509	13.58	5875.07	14.48	7166.7	17.66	12719.3	31.35	+257.51
Water bodies	4962.6	12.23	4793.5	11.81	4577.67	11.28	4445.1	10.95	-18.48
Others	30096.27	74.18	29899.3	73.70	28823.5	71.05	23403.47	57.68	-239.02
Total	40567.87	100	40567.87	100	40567.87	100	40567.87	100	

2.3.4 Dothan, Alabama

Urban expansion of Dothan mainly followed a radial pattern. It spread from central part to periphery of the study area along US highways 431, 231 and 84.and state highways 1 and 53. This kind of expansion is mainly the consequences of centrifugal forces (Colby

1933). In 1982, the concentration was in mainly central part of the study area. From 1990, it started to spread towards periphery (figure 8) along several transportation routes. The net addition of urban built area was also high for Dothan. It is approximately 146 percent (table 8). Water bodies also decreased in significant amount (318.7 hectares).

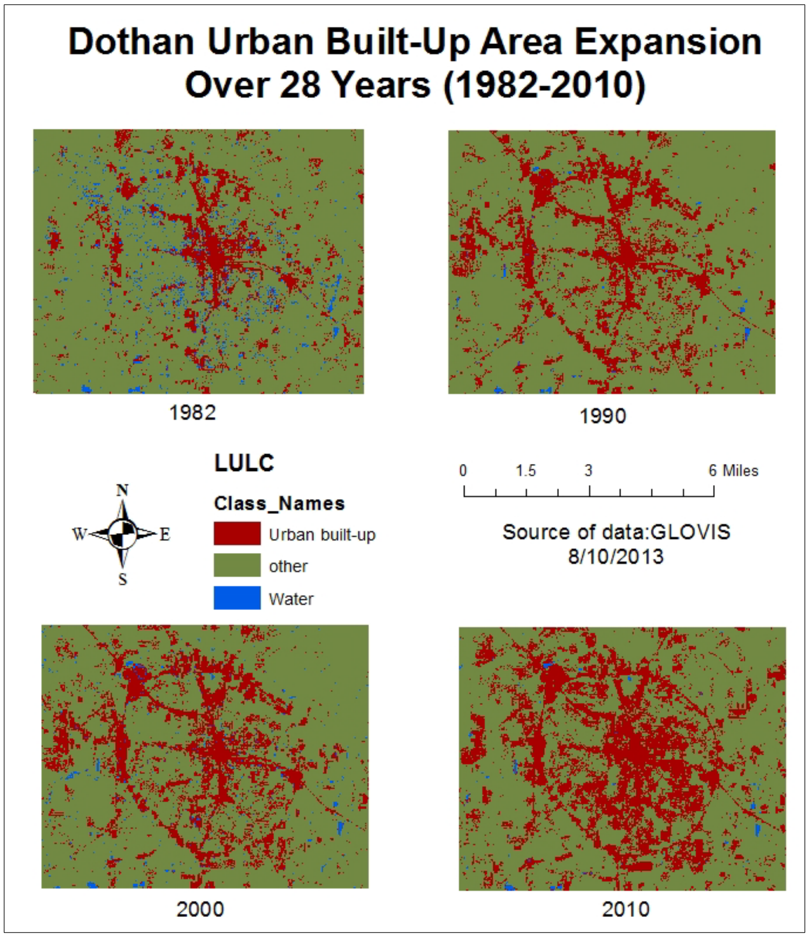


Figure 8.Urban Built-up Expansion for Dothan.

Table 8.Land Use Land Cover Statistics for Dothan (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	1501.02	11.62	2311	17.89	2531	24.53	3694.61	28.61	+78.34
Water bodies	377.46	2.92	163.17	1.263	66.33	0.64	58.59	0.45	-11.38
Others	11034.7	85.45	10439.01	80.84	10315.85	79.88	9159.98	70.93	-66.95
Total	12913.18	100	12913.18	100	12913.18	100	12913.18	100	

2.3.5 Decatur, Alabama

It is noticeable from figure 9 that urban growth of Decatur was along water bodies. In 1982, urban expansion was limited to the river side (Tennessee River) and along I-65 which runs in a north to south direction. Since 1990 Decatur started to spread in all directions. Not much of the water bodies were transformed to built-up (table 9), the expansion was beyond the river (figure 9). Rather the ‘other’ category got more replaced by urban built-up. In 1982 the total urban built-up area was almost 8 percent of the whole study area which increased to almost 20 percent in 2010 (table 9).

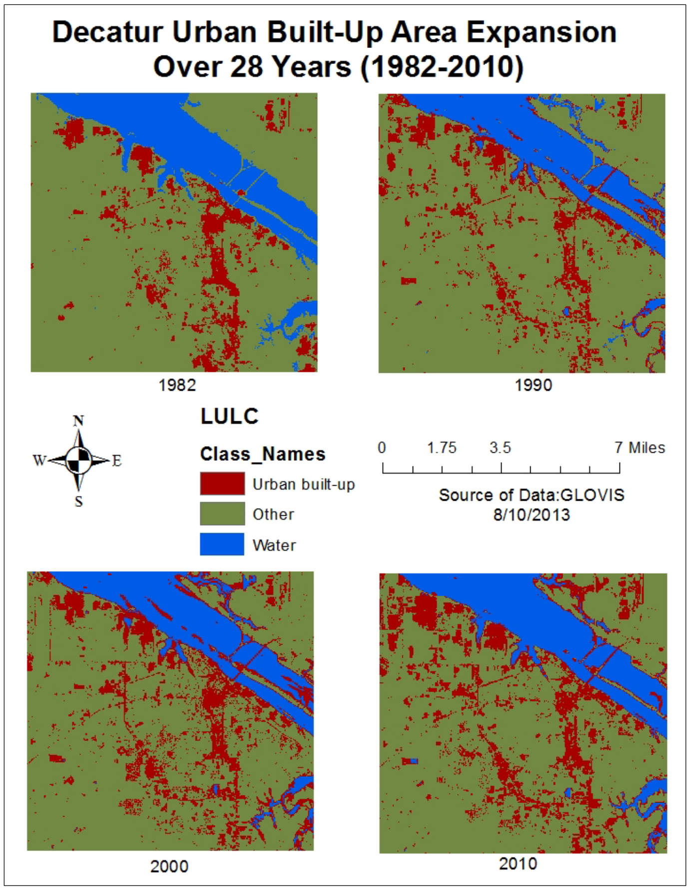


Figure 9. Urban Built-up Expansion for Decatur.

Table 8.Land Use Land Cover Statistics for Decatur (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	1729.98	7.80	3102.12	17.02	3205.66	17.59	3519.57	19.31	+63.91
Water bodies	3165.57	17.37	2597.83	14.25	2305.11	12.65	2132.02	11.70	-36.91
Others	13326.2	73.13	12521.8	68.71	12710.98	69.7	12570.16	68.98	-26.99
Total	18221.75	100	18221.75	100	18221.75	100	18221.75	100	

2.3.6 Huntsville and Madison, Alabama

Spatial expansion of urban or built-up areas of Huntsville is distinctly shown in figure 10. In 1982, the urban built-up area occupied only 3.15 percent of the total land area for Huntsville and was mainly located along the interstate 565 corridor. Significant urban expansion was shown to have taken place in 1990, 2000, and 2010, with net addition of 4578, 520, and 603.6 hectares, respectively. The outward expansion of built-up areas (table 10) in these three decades tends to follow major transportation routes and is highly concentrated in central and western part of the study area (figure 10 left).

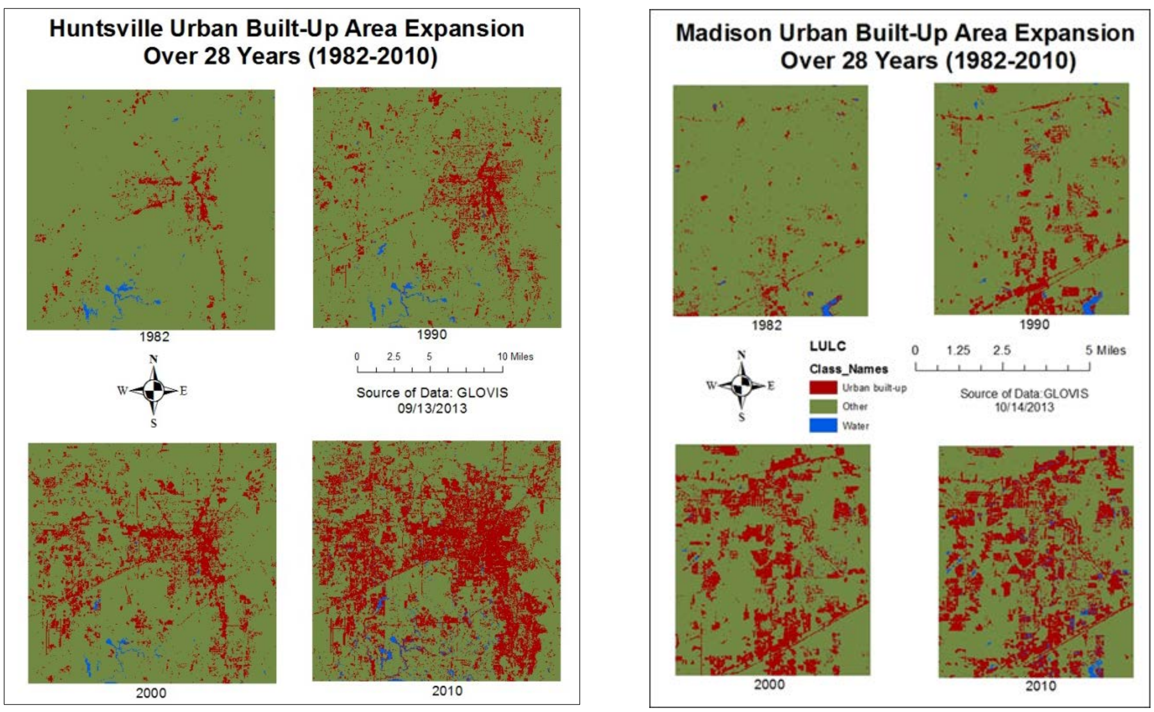


Figure 10.Urban Built-up Expansion for Huntsville (left) and Madison (right).

Table 9. Land Use Land Cover Statistics for Huntsville (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	2462.67	3.15	7040.79	9.1	7561.37	9.68	8165	10.5	+203.6
Water bodies	489	0.62	461	0.6	407.5	0.52	386	0.5	-3.7
Others	75124.5	96.21	70574.3	90.3	70107.3	89.8	69525.2	89.0	199.97
Total	78076.17	100	78076.17	100	78076.17	100	78076.17	100	

For Madison, in 1982 urban built-up areas were mainly concentrated near I-565. From 1990, it started to spread towards north. In 2010, it dispersed all over the study area (figure 10 right). Population grew over 900 percent from 1980 to 2010. Net addition of urban built-up area is 2551.81 hectares (over 600 percent).

Table 10. Land Use Land Cover Statistics for Madison (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-	376.85	3.88	1000.8	10.31	2283.86	23.5	2928.66	30.	+91.13
Water	84.25	0.86	65.43	0.75	32.38	0.33	25.32	0.2	-2.10
Others	9237.12	95.24	8631.9	89.0	7381.98	76.1	6744.24	69.	-89.03
Total	9698.22	100	9698.22	100	9698.22	100	9698.22	100	

2.3.7 Auburn, Alabama

Based on figure 11, urban built-up expansion for Auburn mainly follows north-east to south-west direction. From 1982 to 2010, it has taken place both side of I-85. Urban expansion mainly concentrated in the central place of study area (due to presence of urban functions, such as schools) and expansion was more southern part than the northern part (figure 11).

In 1982, total urban built-up area was approximately 5.4 percent and in 2010, it was 33.7 percent (table 12). So the net addition was over 600 percent.

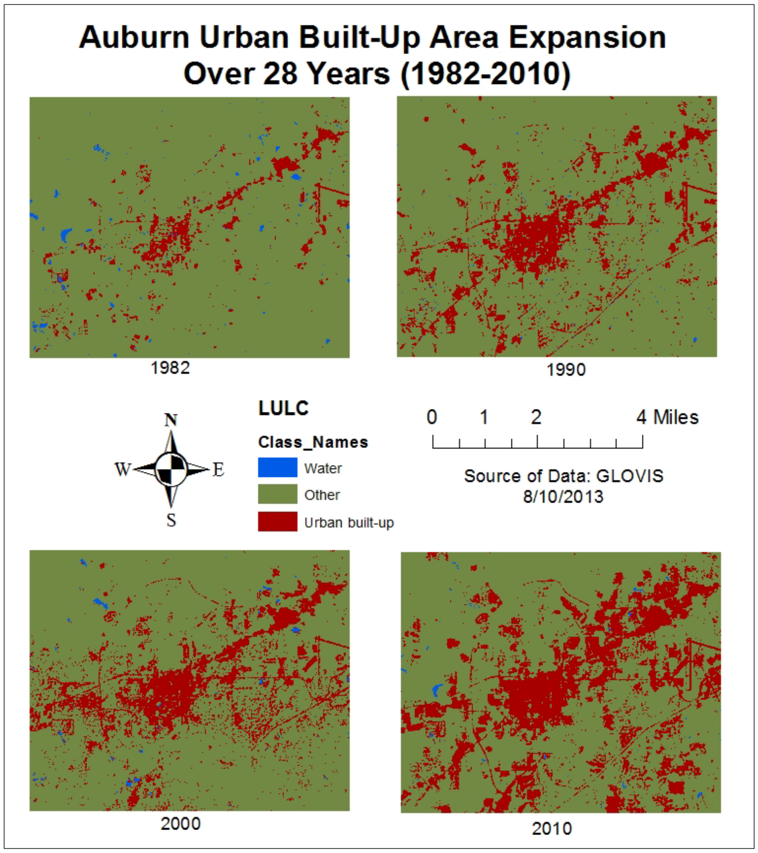


Figure 11. Urban Built-up Expansion for Auburn.

Table 11. Land Use Land Cover Statistics for Auburn (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	423.18	5.36	1084.59	13.76	1288.8	16.35	1985.31	33.78	+55.79
Water bodies	64.35	0.81	35.4	0.523	30.6	0.388	19.71	0.33	-1.59
Others	7394.31	93.81	6761.85	85.79	6562.44	83.26	5876.82	74.56	54.19
Total	7881.84	100	7881.84	100	7881.84	100	7881.84	100	

2.3.8 Tuscaloosa, Alabama

Based on figure 12, the nature of change is quite clear. Spatial expansion of urban built-up area was mainly determined by the presence of large water body (Black Warrior River). Most of the expansion took south of the water body. It did not follow any significant transportation route. From 1982 to 2010, water bodies decreased gradually although built-up did not increase significantly. The net addition was 30 percent for Tuscaloosa urban area (table 13).

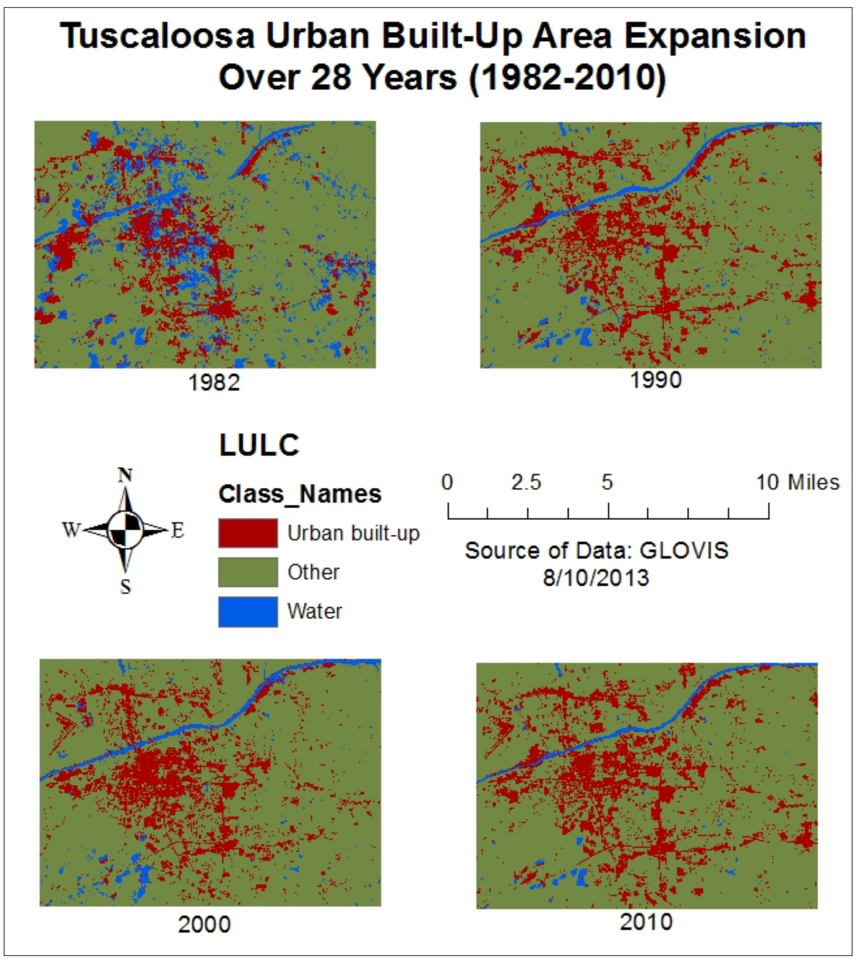


Figure 12. Urban Built-up Expansion for Tuscaloosa.

Table 12. Land Use Land Cover Statistics for Tuscaloosa (1982-2010).

LULC	1982		1990		2000		2010		Annual growth rate (1982-2010)ha
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	
Urban built-up	3222.36	15.17	3308.4	15.57	3712	17.47	4210	19.88	+35.27
Water bodies	653.94	3.07	617.4	2.90	401	1.88	256.23	1.20	-14.20
Others	17361.9	81.74	17312.4	81.51	17125.2	80.63	16771.97	78.97	21.06
Total	21238.2	100	21238.2	100	21238.2	100	21238.2	100	

2.4 Accuracy Assessment of Classified Images

Because of the limited availability of ground reference data, it was impossible to perform accuracy assessment for all images with authenticity. The strategy which is adopted here to assess the accuracy is to calculate using stratified random sampling method and Kappa statistics were also computed.

The supervised classification of each image consisted of three classes. Using the stratified random sampling a total of 50 random points were created for each image. Once the points were created for each image, the accuracy assessment was initiated. Because of the limited availability of ground reference data, the accuracy of these images is limited. The minimum accuracy was 75 percent and the maximum accuracy was more than 80 percent (table 14).

Various literatures (Yang 2002, Matlab *et al* 2005, Trousdale 2010) mentioned that the ‘other’ land cover type caused most of the error because it contains different types of land use (table 3).

Table 13. Accuracy Assessment and Kappa Statistics of Classified Image.

Urban Built-up Area	Accuracy Assessment (%)				Kappa Statistics			
	1982	1990	2000	2010	1982	1990	2000	2010
Auburn	76.1	75.3	79.1	78.0	.755	.744	.789	.779
Dothan	75.3	77.8	78.5	77.2	.745	.767	.788	.771
Tuscaloosa	77.4	77.3	75.7	75.4	.777	.756	.749	.749
Mobile	77.2	80.1	75.6	75.4	.773	.799	.766	.755
Huntsville	75.2	78.1	76.2	76.7	.765	.773	.766	.766
Decatur	79.7	75.3	76.1	77.2	.779	.742	.763	.777
Birmingham	77.5	75.1	75.2	77.9	.789	.755	.746	.771
Montgomery	79.7	76.2	78.2	78.1	.799	.771	.779	.779

2.5 Summary

In conclusion, supervised classification technique applied to quantify urban expansion in the ten study areas. Figure 13 represents graphical representation of urban built-up area expansion from 1982 to 2010.Graph is very steep for Auburn and Madison whereas Tuscaloosa, Birmingham grew very gradually.

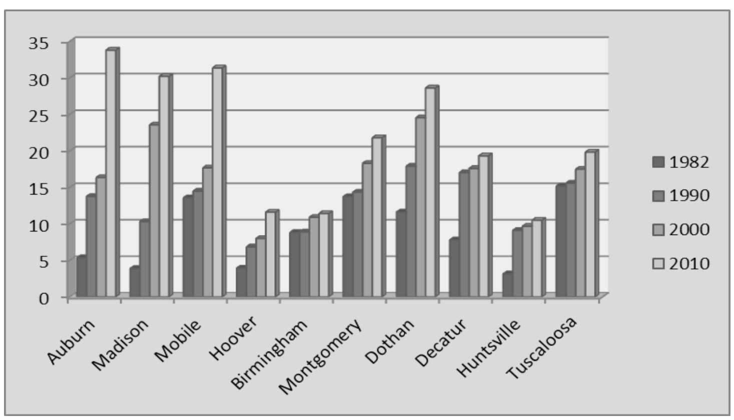


Figure 13. Urban Built-up Area Statistics (1982-2010)

Different urban areas showed varied spatial patterns of growth due to influential factors like presence of transportation routes and water bodies. Literatures also found to support this statement (Li *et al* 2003, Meng *et al* 2003,Peng *et al* 2006, Yang 2002). Birmingham, Montgomery, Dothan, Huntsville, Madison and Auburn showed significant patterns of growth around transportation routes such as interstate highways and state highways. This expansion can be attributed to economic activities that highways attract. On other hand, water bodies dominated the growth of urban areas like Mobile, Decatur and Tuscaloosa.

Chapter 3: Urbanization and Impact on Environment

3.1 Introduction

Previous research has highlighted how different environmental parameters (temperature, precipitation, and air quality: ozone and $PM_{2.5}$) are changing with time over urban areas and their correlation with built up expansion globally (Tayanc and Toros 1997, Mitra *et al* 2011, Superczynski and Christopher 2011, Babatola 2013). Temperature and precipitation are fundamental components of environment and changes in their pattern can affect human health, ecosystems, plants, and animals. These two variables are also interconnected. An increase in Earth's temperature leads to more evaporation and cloud formation, which in turn, increases precipitation (Tabari *et al* 2013). So it is important to understand and quantify the variability or anomaly in these weather elements over time especially for urban areas where change is very rapid.

This chapter focuses on trend detection in annual temperature, precipitation and air quality (O_3 and $PM_{2.5}$) of all study areas from 1980 to 2010 using Mann-Kendall (MK) trend test and examines whether urban built-up expansion has an impact on environmental parameters using multiple linear regression.

3.2 Temporal Trends of Environmental Parameters

The temporal trends of some random variables exhibit a trend such that there is a significant change (negative or positive) over time. Statistical procedures are used for the detection of the gradual trends over time (Bayazit and Onoz 2003). The purpose of trend testing is to determine whether the values of a random variable generally increase or decrease over some period of time in statistical terms (Helsel and Hirch 1992; Bayazit and Onoz 2003).

Trend analysis is an active area of interest in climatology, hydrology, water quality, and other natural sciences for over three decades (Mustapha 2013). Detection of temporal trends is very important to monitor environmental parameters because these kinds of data are often carried out to assess the human impacts on the environment (Libiseller and Grimvall 2002) and also because some projects mainly based on historical pattern of environmental behaviors (Mustapha 2013).

Non parametric trend tests require data which are independent and can tolerate outliers in data (Onoz and Bayazit 2003). There are many non- parametric trend tests use to analyze the temporal trends. The Mann Kendall (MK) test (Mann 1945; Kendall 1955; Mitra *et al* 2011) is one of the widely used non-parametric tests to detect the significant trends in the time series (Hameed 2008, Mustapha 2013). MK test to detect trend in environmental data (temperature, precipitation, and air quality) have been used by many scholars (Gilbert 1987, Serrano *et al* 1999, Yue *et al* 2002, Libiseller and Grimvall 2002, Kahya and kalayci 2004, Hameed 2008, Buhairi 2010, Mitra *et al* 2011, Mustapha 2013, and Lunge and Deshmukh 2013).

Yue *et al* (2002) documented the power of two trend tests (Mann–Kendall test and Spearman's rho test) in their paper. According to them, power of trend tests depends on the pre-assigned significance level, magnitude of trend, sample size, and the amount of variation within a time series meaning the bigger the absolute magnitude of trend the more powerful are the tests. With a large sample size, the tests become more powerful and as the amount of variation increases within a time series, the power of the tests decrease (Yue *et al* 2002). Another study by Kahya and Kalayci (2004) examined four non-parametric trend tests (the Sen's T, the Spearman's Rho, the Mann-Kendall, and the Seasonal Kendall) to understand the trend analysis of stream flow in Turkey. In order to detect possible trends in precipitation over the Iberian Peninsula, the Mann-Kendall test was applied to the annual and monthly series (Serrano *et al* 1999).

In this study, Mann-Kendal test was performed to understand the temporal trends of environmental parameters (temperature, precipitation, ozone, and particulate matter 2.5) for ten study areas from 1980 to 2010 which are non-parametric. Here observations were made annually from one single station for each study area.

3.3 Relationship between Environmental Parameters and Urban Built-up Area

A study by Mitra *et al* (2011) suggests that there is a positive relationship between growth of a city and rainfall amount. Particularly the findings of their study indicated that urban land cover change has had a positive effect in increasing pre-monsoon rainfall in Kolkata, India. Babatola (2013) also found in his study that urbanization increases relative-humidity and that relative humidity has corresponding influence on rainfall in Ibadan, Nigeria. Another study in Turkey reveals that four urban measurement stations and their neighboring rural sites for the 1951-1990 time periods have experienced a shift towards the warmer side with respect to the frequency distributions of daily minimum temperature (Tayanc and Toros 1997).

Kalnay & Cai (2003) estimated the impact of urbanization and other land uses on climate change by comparing trends observed by surface stations with surface temperatures over a 50 year period. Their results indicate that half of the observed stations experienced a decrease in diurnal temperature range due to urban and other land-use changes.

Studies that attempt to relate air pollution and urban growth are limited in number (Superczynski and Christopher 2011). Weng *et al* (2006) however, investigated the relationship between pollutant particles (SO_2, NO_x, dust) and urban infrastructure in China. They used Geographic Information System (GIS) as a technique to correlate urban concentration and pollution. They found that pollution levels were significantly correlated to the regions around the pollution centers. Another study also found connection between pollutant material ($PM_{2.5}$) and LULC in Birmingham, AL (Superczynski and Christopher 2011). In this study the researchers used GIS and remote sensing techniques to determine the relationship between $PM_{2.5}$ and urban area in 1998 and 2010 and they found moderate to strong impact.

In this research, relationship between urban built up expansion and environmental parameters has been established through multiple linear regression analysis (Appendix B). This model also provides a module of ANOVA that gives the information whether model itself is statistically significant or not (Sundari *et al* 2013). Many scholars used regression in urban environment study (Fushimi *et al* 2005, Denby 2008, Manquiz *et al* 2010, Sundari *et al* 2013, Mekparyup 2013, and Hug *et al* 2013) and their results support the reliability of the model.

3.4 Data and Data Sources

The data for this study were collected from different sources from 1980 to 2010. Temperature and precipitation data were collected mainly from National Weather Service (NWS), National Climatic Data Center (NCDC), and Environmental Protection Agency (EPA) (Appendix A). The datasets were not normally distributed though they are randomly distributed.

3.5 Methodology

3.5.1 MK Trend Test

There are two advantages of using the MK test. First it does not require the data to be normally distributed (distribution of normal variables as a symmetrical bell shaped curve). Second it is less affected by outliers because its statistic is based on the sign differences, not directly on the values of the random variables (Kahya and kalayci 2004, Tabari *et al* 2011). According to this test, the null hypothesis H_0 assumes that there is no trend (the data is independent and randomly ordered) and this is tested against the alternative hypothesis H_1, which assumes that there is a trend (Onoz and Bayazit 2003).

The basic principle of MK test is based on statistics (S). MK (S) statistic is computed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k)$$

S= Mk test value

X_j and X_k = Sequential data values

K and n = length of data

S value is assumed to be 0 (no trend). A very high positive value of S indicates an increasing trend and a very low negative value indicates a decreasing trend.

The MK test also computes Kendall's Tau nonparametric correlation coefficient. It measures the strength of relationship between two variables (Gilbert 1987). The value ranges from +1 to -1. Positive correlation indicates both of the variables increase together whereas negative correlation indicates that if one variable increases; the other decreases (Gilbert 1987).

Software used for performing the statistical Mann-Kendall test is Addinsoft's XLSTAT 2013 (figure 14). On running the Mann-Kendall test on environmental parameter data, if the p value is less than the significance level α (alpha) = 0.05, H_0 is rejected. Rejecting H_0 (accept H_1) indicates that there is a trend in the time series, while accepting H_0 indicates no trend was detected. On rejecting the null hypothesis, the result is said to be statistically significant.

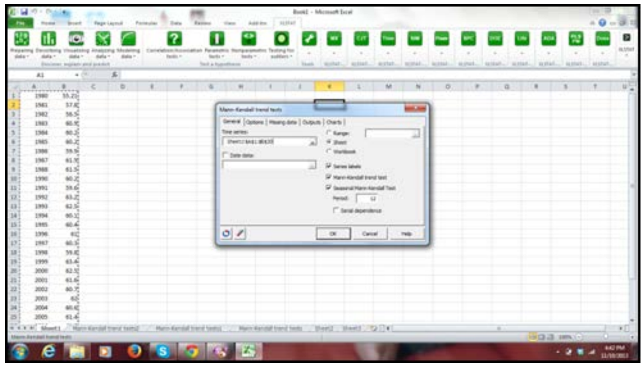


Figure 14. Screen Shot of MK test in Addinsoft's XLSTAT 2013.

In this study, it is hypothesized that all the environmental parameters should has an increasing trend with time.

3.5.2 Multiple Linear Regression

In statistics, linear regression is an approach to modeling the relationship between a dependent variable and one or more explanatory variables. The case of one explanatory variable is called simple linear regression. For more than one independent variable, it is called multiple linear regressions (Jolliffe 1982).

In a simple linear regression model, a single response measurement Y is related to a single predictor X for each observation. Here the critical assumption of the model is that the conditional mean function is linear: $E(Y|X) = \alpha + \beta X$. In most problems, more than one predictor variable will be available.

For this research, the equation should be:

$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$

Y= Temperature, precipitation, ozone and PM $_{2.5}$

X_1=Urban built-up

X_2=Water

X_3=Other

There should be a linear relationship between independent and dependent variables (Denby 2008, Manquiz *et al* 2010, Sundari *et al* 2013). It means if the dependent variable increases, independent variable will increase too. For instance, in this study if urban built-up area increases temperature will also increase.

Table 14 : Variables and their Indicators

Classes	Variables	Indicators	Assumptions
Dependent Variables	Temperature	Average temperature in year (^{0}F)	Urban built-up area is expected to positively relate to temperature, precipitation, PM 2.5 and Ozone.
	Precipitation	Average precipitation in year (inch)	
	PM 2.5	Annual concentration in air (µg/m 3)	
	Ozone	Annual concentration in air (ppm)	
Independent Variables	Urban built- up	Size in hectors	Water bodies and other LULC are expected to negatively relate to temperature, precipitation, PM 2.5 and Ozone.
	Water bodies	Size in hectors	
	Other	Size in hectors	

Results can be explained by R square value, P value and coefficient value. R square value indicates how much of the variation in the dependent variable can be explained by variations in the three independent variables. If the F significance value is less than 0.05, the regression equation is effective as a whole. If p value is less than 0.05 for a variable, it has an impact on dependent variable. Coefficient value indicates how the variables are correlated: positively or negatively.

This model has been run four times for four dependent variables. The reason for choosing the four environmental parameters as dependent variables is because they can vary with changing LULC. The model was obtained by data analysis using Microsoft excel (figure 15).

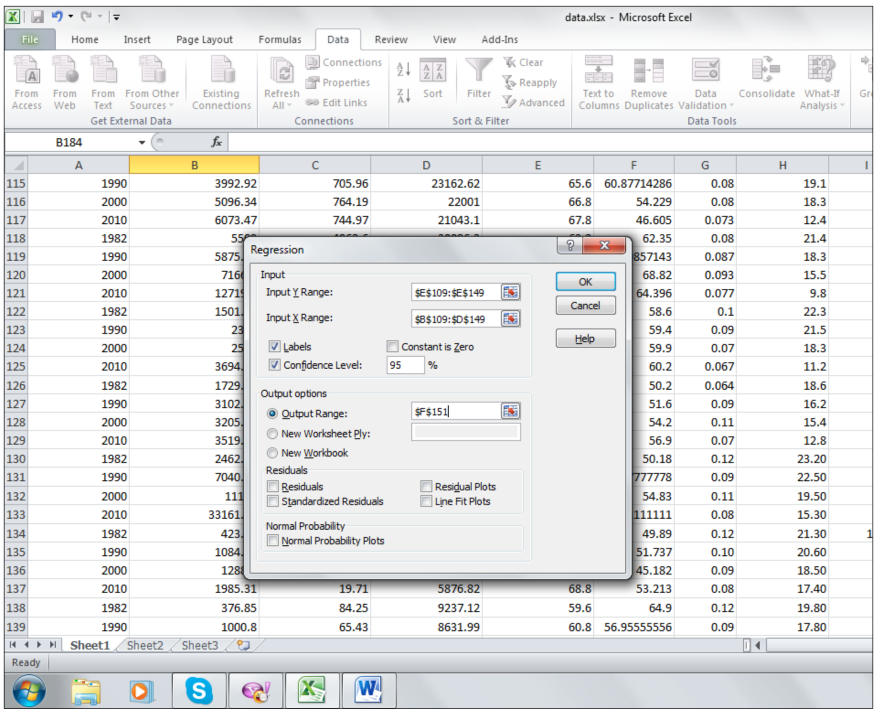


Figure 15. Multiple Linear Regression in Excel.

3.6 Results

3.6.1 Trend Analysis using MK Trend Test

Man-Kendall test was applied to the environmental parameters data (temperature, precipitation, ozone, and $PM_{2.5}$) to verify the increasing or decreasing trends for 1980 to 2010. In this study X variable is time and Y variables are environmental parameters (figure 16).

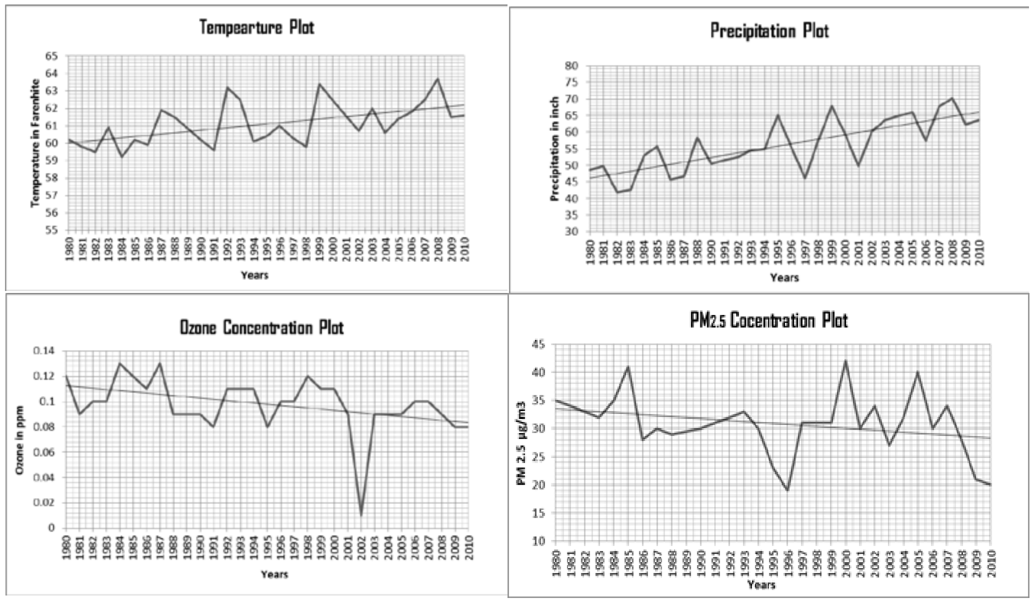


Figure 16. Temporal Trends for Madison, Alabama (1980-2010).

Temperature

On running the MK test on temperature data, the following results in Table 16 were obtained for ten study areas.

The Mann-Kendall test confirmed that the positive trend observed in temperature data is statistically significant (p values are less than 0.05). S values are also positive and much higher than 1, it indicates an increasing trend in temperature data for every study area. Kendall’s tau values are also positive; it proves that temperature has increased from 1980 to 2010.

Table 15. Mann-Kendall Summary of Temperature Data for the Ten Study Areas (1980-2010).

Study Area	Results of MK trend test for temperature					
	Mann-Kendall Statistics (S)	Kendall's Tau	P value	alpha	Test interpretation	Trend
Birmingham	40	0.354	.0045	0.05	Reject H_0	↑ Increasing
Montgomery	43	0.222	.0013	0.05	Reject H_0	↑ Increasing
Mobile	31	0.256	.0002	0.05	Reject H_0	↑ Increasing
Huntsville	33	0.344	.0001	0.05	Reject H_0	↑ Increasing
Tuscaloosa	48	0.211	.0004	0.05	Reject H_0	↑ Increasing
Hoover	40	0.354	.0045	0.05	Reject H_0	↑ Increasing
Dothan	52	0.347	.0015	0.05	Reject H_0	↑ Increasing
Decatur	22	0.214	.0001	0.05	Reject H_0	↑ Increasing
Auburn	28	0.365	.0001	0.05	Reject H_0	↑ Increasing
Madison	33	0.344	.0001	0.05	Reject H_0	↑ Increasing

This increased trend in temperature is attributed to concrete surface and greenhouse gas emission (Han *et al* 2013 and Buhairi 2010). Various urban heat island studies revealed that temperature in the urban are is higher than its surround rural area (Garstang 1975, Morris and Simmonds 2000).

Precipitation

For precipitation (1980-2010) data in ten study areas shows an increasing trend (table 17). Here p values are less than 0.05 for every study area. Thus null hypotheses are rejected. On rejecting the null hypothesis, the result is said to be statistically significant. Kendall's tau and S values also (both values are positive) revealed a positive trend in data set.

Under thermodynamic conditions that are conducive to moist convection, the urban heat island-induced updrafts act as dynamic forcing to initiate moist convection and produce surface precipitation. Surface precipitation is likely to further increase under higher aerosol concentrations if the air humidity is high and deep and strong convection occurs (Han et al 2013, Babatola 2013).

Table 16. Mann-Kendall Summary of Precipitation Data for the Ten Study Areas (1980-2010).

Study Area	Results of MK trend test for Precipitation					
	Mann-Kendall Statistics (S)	Kendall's Tau	P value	alpha	Test interpretation	Trend
Birmingham	66	0.142	.0015	0.05	Reject H_0	↑ Increasing
Montgomery	61	0.211	.0012	0.05	Reject H_0	↑ Increasing
Mobile	98	0.155	.0001	0.05	Reject H_0	↑ Increasing
Huntsville	68	0.356	.0001	0.05	Reject H_0	↑ Increasing
Tuscaloosa	25	0.222	.0056	0.05	Reject H_0	↑ Increasing
Hoover	66	0.142	.0015	0.05	Reject H_0	↑ Increasing
Dothan	20	0.255	.0011	0.05	Reject H_0	↑ Increasing
Decatur	45	0.125	.0001	0.05	Reject H_0	↑ Increasing
Auburn	98	0.211	.0036	0.05	Reject H_0	↑ Increasing
Madison	68	0.356	.0001	0.05	Reject H_0	↑ Increasing

Ozone Concentration

The trend analysis of Ozone concentration in ten study areas over 1980-2010 indicated a decreasing trend (S values and tau values are negative). P values are also less than 0.05. Thus the null hypotheses are rejected here. That means there are trends (reject H_0) in ozone concentration which are decreasing as S values and tau values are negative.

Table 17. Mann-Kendall Summary of Ozone Data for the Ten Study Areas (1980-2010).

Study Area	Results of MK trend test for Ozone					
	Mann-Kendall Statistics (S)	Kendall's Tau	P value	alpha	Test interpretation	Trend
Birmingham	-58	-0.211	0.008	0.05	Reject H_0	↓ Decreasing
Montgomery	-44	-0.104	0.035	0.05	Reject H_0	↓ Decreasing
Mobile	-65	-0.233	0.018	0.05	Reject H_0	↓ Decreasing
Huntsville	-61	-0.365	0.002	0.05	Reject H_0	↓ Decreasing
Tuscaloosa	-48	-0.296	0.044	0.05	Reject H_0	↓ Decreasing
Hoover	-58	-0.211	0.033	0.05	Reject H_0	↓ Decreasing
Dothan	-22	-0.122	0.030	0.05	Reject H_0	↓ Decreasing
Decatur	-47	-0.452	0.027	0.05	Reject H_0	↓ Decreasing
Auburn	-22	-0.366	0.032	0.05	Reject H_0	↓ Decreasing
Madison	-61	-0.365	0.019	0.05	Reject H_0	↓ Decreasing

Particulate Matter 2.5 ($PM_{2.5}$)

This following table represents the results of $PM_{2.5}$ concentration in air for ten study areas (1980-2010). Here P values are less than 0.05. It indicates the result is statistically significant. S values (negative) and tau values (negative) also proved that $PM_{2.5}$ has a decreasing trend in 30 years in all the study areas.

Table 18. Mann-Kendall Summary of $PM_{2.5}$ Data for the Ten Study Areas (1980-2010).

Study Area	Results of MK trend test for PM 2.5					
	Mann-Kendall Statistics (S)	Kendall's Tau	P value	alpha	Test interpretation	Trend
Birmingham	-36	-0.320	0.025	0.05	Reject H_0	↓ Decreasing
Montgomery	-47	-0.213	0.029	0.05	Reject H_0	↓ Decreasing
Mobile	-27	-0.278	0.019	0.05	Reject H_0	↓ Decreasing
Huntsville	-51	-0.388	0.043	0.05	Reject H_0	↓ Decreasing
Tuscaloosa	-33	-0.359	0.045	0.05	Reject H_0	↓ Decreasing
Hoover	-36	-0.320	0.036	0.05	Reject H_0	↓ Decreasing
Dothan	-39	-0.345	0.005	0.05	Reject H_0	↓ Decreasing
Decatur	-88	-0.356	0.029	0.05	Reject H_0	↓ Decreasing
Auburn	-47	-0.334	0.027	0.05	Reject H_0	↓ Decreasing
Madison	-51	-0.388	0.033	0.05	Reject H_0	↓ Decreasing

3.6.2 Multiple Linear Regressions

Model 1: Temperature as Dependent Variable

A multiple regression was conducted to understand how temperature can vary with different land use land cover. The overall model was significant (F value is less than .05) and accounted for the 72.36 percent of the variance (table 20). That means 72.3 percent of the variation in the temperature explained by urban built-up, water and other LULC.

The results indicated that urban built-up, and other LULC were significant variables of the temperature variation (p value is less than 0.05). Water bodies were not significant variable (p value is more than 0.05) (table 20).

At the significant level of 0.05, positive and small coefficient of urban built-up indicates that higher urban built-up area is associated with higher temperature (table 20).

Table 19. Regression Results for Temperature.

Variables	Coefficients	P-value
Intercept	64.1501642	3.17744E-47
Urban Built-up	**0.000180636**	**0.032674734**
Water body	-0.000228902	0.429368727
Other	-2.87942E-05	0.005284124
R Square Value	0.723632792	
F Significance	0.026322768	

Model 2: Precipitation as Dependent Variable

From the ANOVA table (table 21), F significance is less than 0.05. The mode is highly significant. The R square value means that 65.94 percent of the variation in precipitation can be attributed to three independent variables (table 21). This is not a very high percentage as roughly 34 percent is left unexplained.

Regression results also revealed that urban built-up is a significant variable to determine the amount of precipitation. Positive coefficient value and P value support this statement (table 21).

Rest of the variables (water bodies and other) was also significant. However other category is negatively correlated with precipitation whereas water bodies are positively correlated (table 21).

Table 20. Regression Results for Precipitation.

Variables	Coefficients	P-value
Intercept	54.48773419	6.38519E-34
Urban Built-up	**0.000253938**	**0.027448967**
Water body	0.001500062	0.012901341
Other	-4.12031E-05	0.040740165
R Square Value		0.659446819
F Significance		0.011957406

Model 3: Ozone as Dependent Variable

The F value (more than 0.05) of the model indicates that this model is not significant (0.200075634). Thus independent variables are not significant for ozone concentration in air at all.

Model 4: $PM_{2.5}$ as Dependent Variable

For this regression model, R square value is a very high. 86.2 percent of the variation in $PM_{2.5}$ concentration can be explained by three independent variables (table 21 a). F value (less than 0.05) from ANOVA table also proved the effectiveness of this model (table 22)

Positive coefficient and P value (0.004) of urban built-up also suggest that if urban built-up area goes high, the concentration of $PM_{2.5}$ in air also goes high (table 22). ‘Other’ variable have negative effect on $PM_{2.5}$ (table 22). However water body was not significant for $PM_{2.5}$ since p value is more than 0.05 thought it has negative coefficient value (table 22).

Table 21. Regression Results for PM $_{2.5.}$

Variables	Coefficients	P-value
Intercept	18.5005228	2.30993E-22
Urban Built-up	**0.000363319**	**0.004234144**
Water body	-0.000458622	0.283836639
Other	-7.94683E-05	2.37939E-06
R Square Value		0.861704408
F Significance		1.33E-06

The main reason for the improved air quality in Alabama is the 'Revisions to the Clean Air Act' in 1990 required each state to develop a State Implementation Plan (SIP) describing how it will reach and maintain the national standards (EPA 2012a). These SIPs vary by state, but generally include local monitoring of air quality levels, strategies to reduce emissions, and steps to evaluate these strategies. Individual actions that can also make a difference include recycling, using energy-efficient products and appliances, planting deciduous trees, and driving less.

3.7 Summary

This chapter briefly analyzed temporal trends of environmental parameters and how they vary with urban built-up expansion. A gradual increase in temperature and precipitation and a decrease in ozone and $PM_{2.5}$ were observed for study areas over a period of 1980 to 2010.

Results of multiple linear regression revealed that variation in temperature, precipitation and $PM_{2.5}$ can be explained by urban built-up expansion. So the results fulfill the assumptions that there is a cause and effect relationship between urban built-up expansion and environmental parameters. However, variation in ozone cannot be explained by urban built-up expansion (F value was not significant).

Chapter 4: A Peek into Future Urban Growth

4.1 Introduction

Predictions say that urban population will rise to 70 – 80 percent globally of the total population (UN 2007). Thus it would be interesting to see how present urban areas will look like in next 30 – 40 years. To run these futuristic predictions it is important to use reliable LULCC models. These models can predict the spatial distribution of the specific LULC classes for future years by utilizing the knowledge gained from previous years (Behera *et al* 2012). LULC models are different from each other and have their own capabilities and limitations (Chen and Pontius 2006). There are various land use change models: DELTA, Land change modeler, What If, SLEUTH, LTM, Markov model and others (EPA 2000). Cellular Automata Markov chain is one of the accepted methods for modeling LULCC (Mitsova *et al* 2011; Kityuttachai *et al* 2013).

In this study the IDRISI CA (Cellular Automata) – Markov model has been used to predict the future growth of the Alabama urban areas. CA-Markov method has two techniques: Markov chain analysis and CA. The spatial character in a model is introduced by CA component. It allows the transition probabilities of one pixel to be a function of the neighboring pixels. CA-Markov models the change of several classes of cells by using a Markov transition matrix; a suitability map and a neighborhood filter (Eastman 2000).

The IDRISI Selva, an integrated GIS and Image Processing software, has a built-in CA Markov model that can be used to project the future growth of urban built-up areas of the State of Alabama. The literature has shown that CA Markov models have been successful in predicting future growth of urban areas. Araya and Cabral (2010), Guan *et al* (2011) Behera *et al* (2012), and Kityuttachai *et al* (2013) used the CA Markov model to predict future urban growth of various global cities and highly recommend the use of the model.

4.2 Future Urban Growth using CA Markov Model

Future growth of five urban built-up areas has been predicted using cellular automata IDRISI Selva model for the next 30 years from 2010 based on the results from the supervised classification shown in chapter 2: three of which showed highest growth in population (Madison, Hoover and Auburn) and two which showed decrease in population in 30 years (Birmingham and Mobile) from 1982 to 2010. The two classified (1982 and 2010) Landsat images derived from objective 1 and accuracy assessment of the classifications both were required to run the model (Behera *et al* 2012). To predict the future growth, it is important to know the extent of built-up area and vegetation/agricultural land on which development can occur and water on which development cannot occur.

To run the model, the images should be: (1) derived from grids in the same projection, (2) derived from grids of the same map extent, (3) verified to be of the same resolution (row x column count is consistent), and (4) verified to be of the same class value. The next step was to import the images into IDRISI Selva and convert them to

*.rst images because it does not accept *.img images. Then, a Markov chain analysis was run on both images. The output from the Markov chain analysis was used to initialize the CA – Markov analysis (Guan *et al* 2011). The images run through a series of tasks to get the projection of the urban built-up areas in Alabama up to 2040. Classified images from objective one was used here to predict future urban expansion. Figure 17 displays a flow diagram of the CA-Markov modeling process.

4.2.1 Cross Classification of Two Images

Cross classification is a common application in land cover change analysis where a cross tabulation is done between two qualitative maps of two different dates that targets on the same features (IDRISI 2012). It is used to compare two classified images where the classification assigns the same unique and distinct identifier to each class on both the dates. The aim is to evaluate whether the areas fall into the same class on the two dates or a change to a new class has occurred (IDRISI 2012). By running a CROSSTAB module in IDRISI SELVA it is possible to get a new image based on all the unique combination of values from the two images in which each unique combination of input values has a unique output value and a cross tabulation table.

Cross correlation images show all possible combinations that are used to produce two types of change images. These relative frequencies are known as transition probabilities and are an underlying basis for Markov Chain prediction of future transitions (Mitsova *et al* 2011; IDRISI 2012).

In this study cross classification was run between classified images of 1982 and 2010 for five study areas.

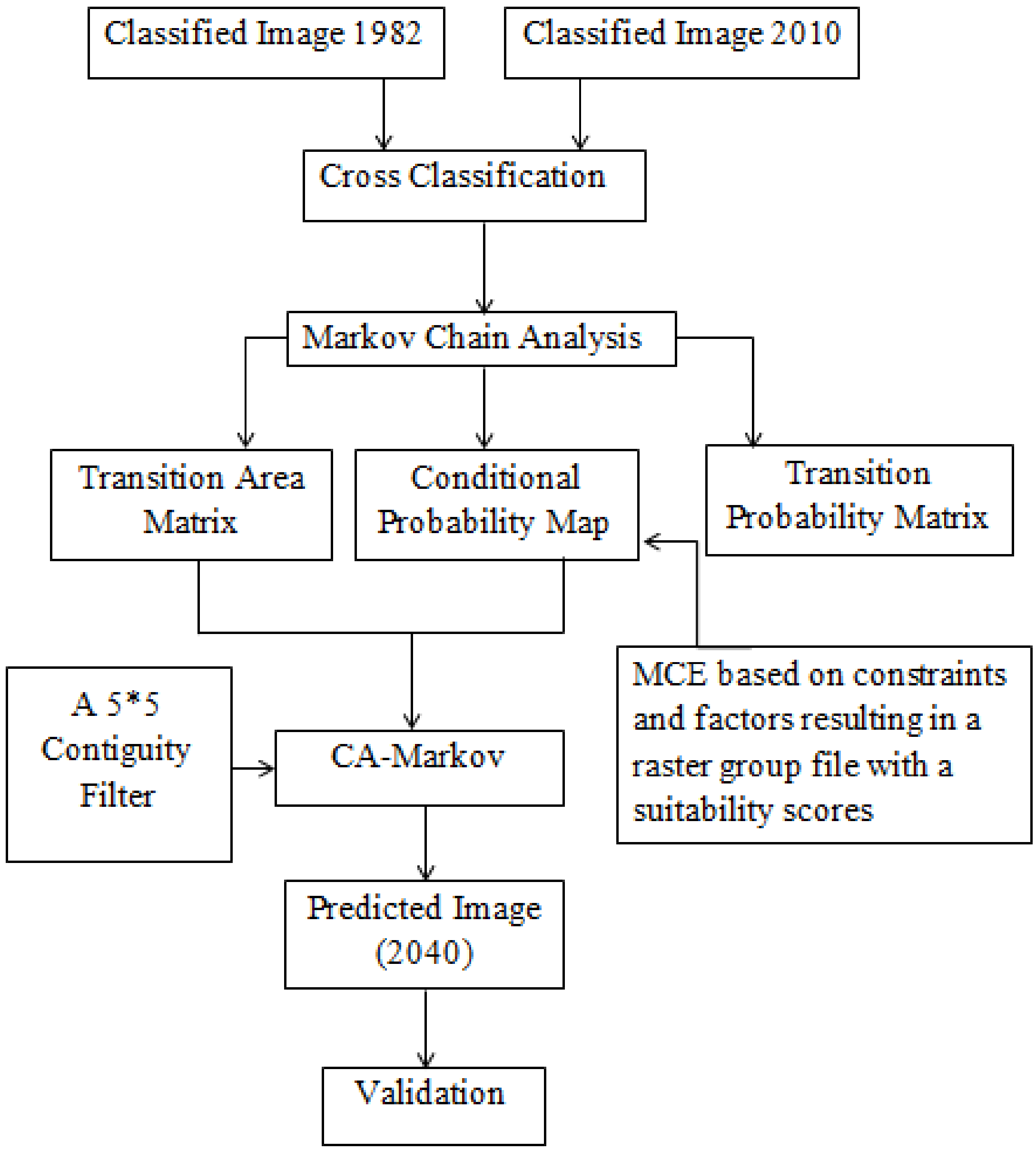


Figure 17. Flow diagram showing this study's CA-Markov Model Design.

4.2.2 Markov Chain Analysis

The Markov chain analysis describes the probability of land cover change from one period to another by developing a transition probability matrix (Eastman 2000). The output of this step are a transition probability matrix, a transition area matrix and a set of transition probability maps by analyzing two qualitative land use images (Islam and Ahmed 2011). The transition probability matrix records the probability of each land use category to change into the other category. This matrix is produced by the multiplication of each column in the transition probability matrix be the number of cells of corresponding land use in the later image (Islam and Ahmed 2011). The transition areas matrix is a text file that records the number of pixels that are expected to change from each land cover type to the other land cover type over the specified number of time units (Adhikari and Southworth 2012). It will be used as an input to run CA-Markov model. Transition probability maps were created for every category of LULC.

The Markov chain analysis though one of the best has its limitations. Markov analysis does not account the causes of land use change. It ignores the forces and processes that produced the observed patterns (Adhikari and Southworth 2012). It assumes that the forces that produced the changes will continue to do so in the future. An even more serious problem of Markov analysis is that it is insensitive to space: it provides no sense of geography (Mubea *et al* 2010, Adhikari and Southworth 2012). Using cellular automata adds a spatial dimension to the model (Mubea *et al* 2010).

4.2.3 Cellular Automata (CA)

Cellular automata (CA) are spatially dynamic models frequently used for land-use and land-cover change studies (Mitsova *et al* 2011). In a CA model, the transition of a cell from one land-cover to another depends on the state of the neighborhood cells. A CA model can add spatial character to a Markov model and make it a dynamic spatial model (Mubea *et al* 2010, IDRISI 2012).

4.2.4 CA Markov Model

A combined Markov and CA model was used to predict the future LULC of the five urban areas of Alabama. Transition area matrix (output of Markov model) was used here. In addition, to get the suitable image collection, multi-criteria evaluation (MCE) has been run. MCE is a common method for assessing and aggregating many criteria (IDRISI 2012). Two types of criteria (constraints and factors) were developed to determine which lands were more suitable for future development or not. The constraints were standardized into a Boolean character of 0 and 1 and the factors were standardized to continuous scale of 0 (least suitable) to 255 (more suitable). Here the constraints were water bodies and existing urban areas. Factors were presence of water bodies, road network, slope and elevation. Three types of fuzzy membership functions were used to rescale the factors into the range 0-255: sigmoidal, linear and symmetrical. Analytic hierarchy process (AHP) was used to determine the weight of factors (Mitsova *et al* 2011).

The CA-Markov model is based on the first law of geography by using a contiguity rule. That means, a pixel that is near one specific LULC is more likely to become that category than a pixel that farther (Araya and Cabral 2010). Here, a contiguity filter of 5*5 pixels was applied.

4.2.5 Model Validation

Model validation is very important step in the modelling process (Araya and Cabral 2010). The location accuracy of land use change was done on Neural Network built-in module in the IDRISI (IDRISI 2012). The input for this method was 2010 and 2040 image. This method was able to provide the accuracy of future location compare to recent location on the basis of constraints (water body and existing urban built-up area) and factors (presence of water bodies, road network, slope and elevation).

In this study, another accuracy assessment was also performed on the 2013 CA-Markov output image and the Google earth image to understand how accurate the prediction is for 2040. 65 random points were used for each study area to perform the accuracy assessment. In this case only 50 could be plotted as the other points were outside of the image. A visual assessment of the points on both the images were done and compared with the help of the classification error matrix.

4.3 Results

4.3.1Transition Probability Matrix

The Markov model calculates transition probabilities (table 23) as a txt file with the number of transitioning cells from one LULC to another. Another output is raster grids, indicating transition areas (Mitsova *et al* 2011). The later one was used for CA-Markov model. Markov transition probability matrix is computed from cross classification of two classified images (1982 and 2010). Transition areas are derived by multiplying each column representing LULC in probability matrix (Mitsova *et al* 2011).

The transition probability matrices of LULC for Madison, Hoover, Auburn, Birmingham, and Mobile for 1982-2010 calculated on the basis of the Markov model are shown in table 23. The diagonal cross section of each study area (shown in bold in table 23) represents the probability of a LULC remaining the same whereas the off diagonal values (not in bold) indicate the probability of a change occurring from one LULC to another (table 23).

Table 22. Transition Probability Matrix of Markov Model for Five Study Areas.

Study Area	Given (1982-2010)	Probability of changing to -		
		Class 1: Water	Class 2: Other	Class 3: Urban built-up
Madison	Class 1: Water	**0.9989**	0.001	0.0001
	Class 2: Other	0.0005	**0.7452**	0.2543
	Class 3: Urban built-up	0.0006	0.012	**0.9472**
Hoover	Class 1: Water	**0.4053**	0.3072	0.2075
	Class 2: Other	0.0316	**0.5434**	0.4250
	Class 3: Urban built-up	0.0121	0.2569	**0.7310**
Auburn	Class 1: Water	**0.7870**	0.1066	0.1064
	Class 2: Other	0.0048	**0.5999**	0.3953
	Class 3: Urban built-up	0.0033	0.1754	**0.8213**
Birmingham	Class 1: Water	**0.8833**	0.0545	0.0622
	Class 2: Other	0.0127	**0.6599**	0.3274
	Class 3: Urban built-up	0.0815	0.0284	**0.8901**
Mobile	Class 1: Water	**0.9045**	0.0007	0.0948
	Class 2: Other	0.0640	**0.7631**	0.1729
	Class 3: Urban built-up	0.1189	0.0047	**0.8764**

From the table 23 it is evident that most of the LULC remained same except the ‘other’ category. The transition rules allowed water pixels to remain almost unchanged.

Other LULC was converted mostly to urban built-up area but the rate varied with every study area. May be the reason was ‘other’ category includes vacant land and various types of vegetation which is more vulnerable to convert. Urban built-up area remained unchanged since it is very rare to convert built-up area to vegetation or water body.

Table 23 indicates that during 1982-2010 there was 25.4 percent chance that ‘other’ category would transform to urban built area for Madison. Percentage was highest for Hoover (42.5 percent) and lowest for Mobile (17.3 percent). The rate was 39.5 and 32.7 percent for Auburn and Birmingham respectively. On the other hand, water bodies transformed to urban built-up area (10 and 6 percent for Auburn and Birmingham respectively) and ‘other’ (30 percent for Hoover) in a very low rate. The rate of transformation for urban built-up area to water body and ‘other’ was also very low (0 percent and 17 percent respectively of for Auburn).

As a result urban built-up increased continuously and ‘other’ category decreased. Water body remained unchanged. The increasing source for conversion to urban area was ‘other’ category.

4.3.2 Urban Built-Up Area Prediction for the year 2040

After running cross classification and Markov model, it was interesting to examine the pattern and tendency of the change of built-up area for the future. Prediction for the 2040 was carried out for five selected study areas considering transition area matrix, a contiguity filter and the transition suitability collection.

Here the two constraints were water bodies and existing urban built-up area. It means that future urban could not take in these two specified place. The factors were slopes, elevation, roads, and distance for water body of the study areas. These factors determine the quantity and location of future change of LULC (Guan *et al* 2011). The sum of the factors should be 1 (IDRISI 2012). Smaller weight is less effective to determine the predicted LULC compare to higher weight. It means, roads and water bodies were more effective than other two (table 24).

Table 23. Factors Controlling Future Growth (derived from MCE).

Study Area	Factors	Weight
Madison	Slope	0.16
	Elevation	0.20
	Roads	0.31
	Water bodies	0.33
Hoover	Slope	0.18
	Elevation	0.14
	Roads	0.31
	Water bodies	0.37
Auburn	Slope	0.19
	Elevation	0.21
	Roads	0.28
	Water bodies	0.32
Birmingham	Slope	0.10
	Elevation	0.25
	Roads	0.26
	Water bodies	0.39
Mobile	Slope	0.21
	Elevation	0.12
	Roads	0.29
	Water bodies	0.38

Based on these predicted LULC of 2040 was produced for five areas. Visual analysis of the predicted results indicates that built up area will take at a very high rate (table 25).

Table 24. Predicted Urban Built-up by 2040.

Study Area	LULC	Area 2010 (hectors)	Area 2040 (hectors)	Difference		Annual rate of change (2010-2040) in hectors	Annual rate of change (1982-2010) in hectors
				Hectors	Perce ntage		
Madison	Urban built-up	2928.66	4902.91	1974.25	67.4	65.8	91.3
Hoover	Urban built-up	9951.23	14560.77	4609.54	46.3	153.6	234.2
Auburn	Urban built-up	1985.31	3878.96	1893.65	95.4	63.1	55.8
Birmingham	Urban built-up	37136.1	46056.12	8920.02	24.1	297.3	301.7
Mobile	Urban built-up	12719.3	20040.66	7321.36	57.5	244.1	257.5

From the table 25, the projected 2040 urban built-up area shows a significant increase over water bodies and 'other' category. Since water body is a constraint, most of the urban built-up expansion will take place in 'other' category. But the amount of change varies with different study areas. The projection of the future growth of urban area of Madison shows an increase of 1974.25 hectors followed by 4609.54 hectors for Hoover, 1893.65 hectors for Auburn, 8920.02 for Birmingham, and 7321.36 hectors for Mobile (Table 25).

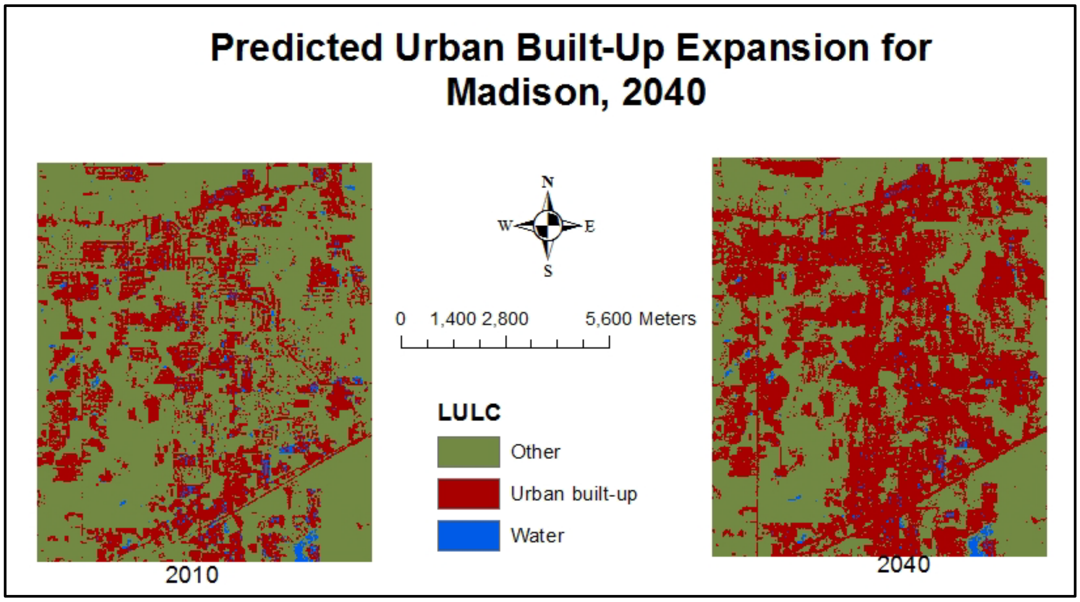


Figure 18. Predicted Urban Built-up Expansion for Madison, 2040.

Annual growth in future will be 65.8 hectors (2010-2040) for Madison whereas the growth was 91.3 hectors for last 28 years (table 25). It means that Madison will grow less compared to last 28 years. On the other hand, Auburn will grow faster (63.1 hectors) than before (55.8 hectors). Birmingham and Hoover will grow slowly than previous year. For Mobile the rate of growth per year will be 244.1 hectors compared to 257.5 hectors in the past.

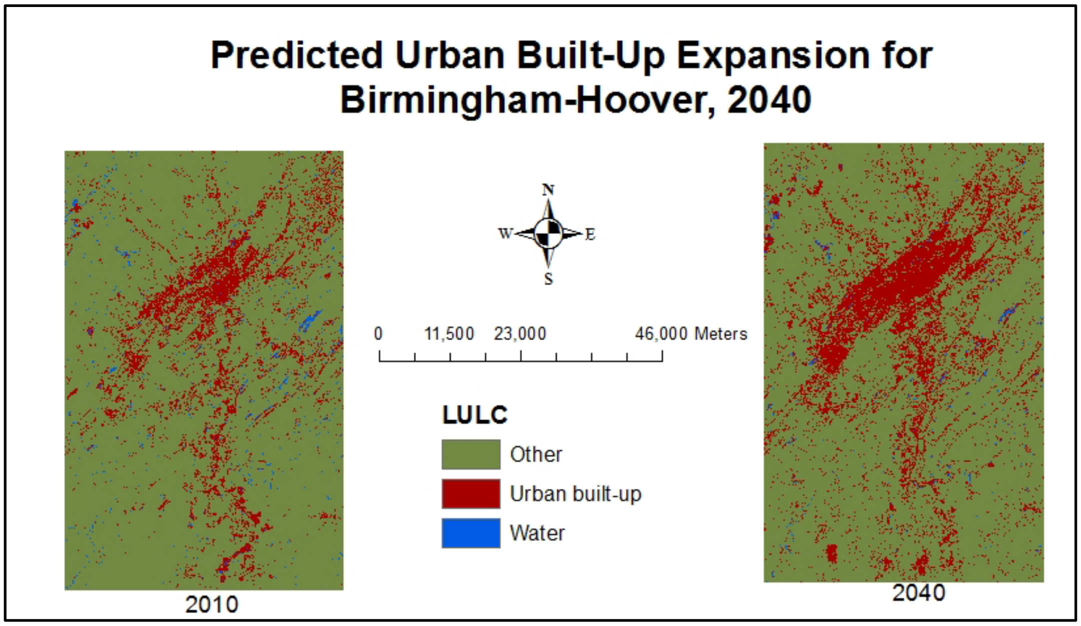


Figure 19. Predicted Urban Built-up Expansion for Birmingham-Hoover, 2040.

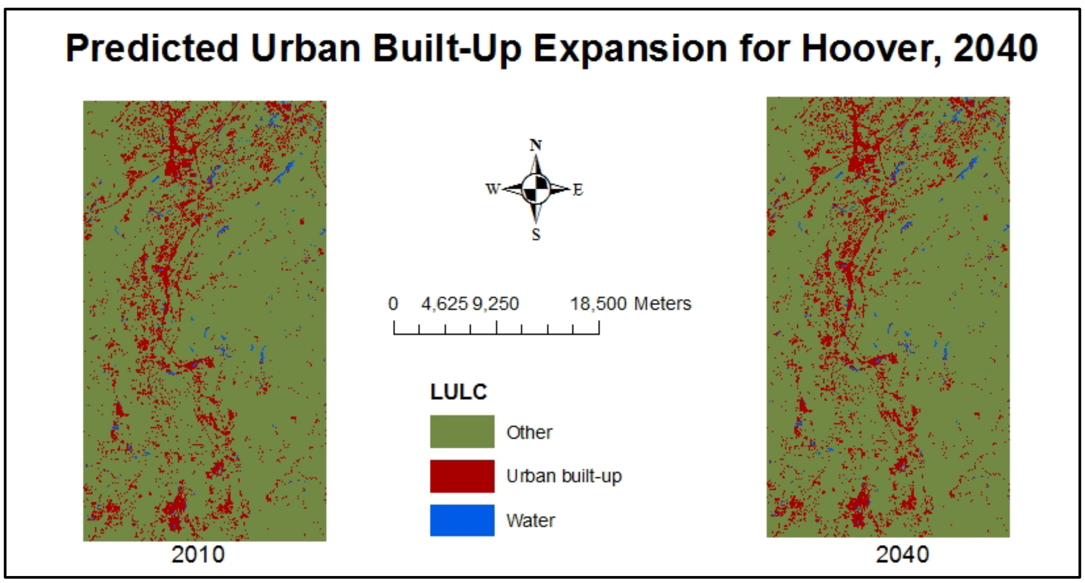


Figure 20. Predicted Urban Built-up Expansion for Hoover, 2040.

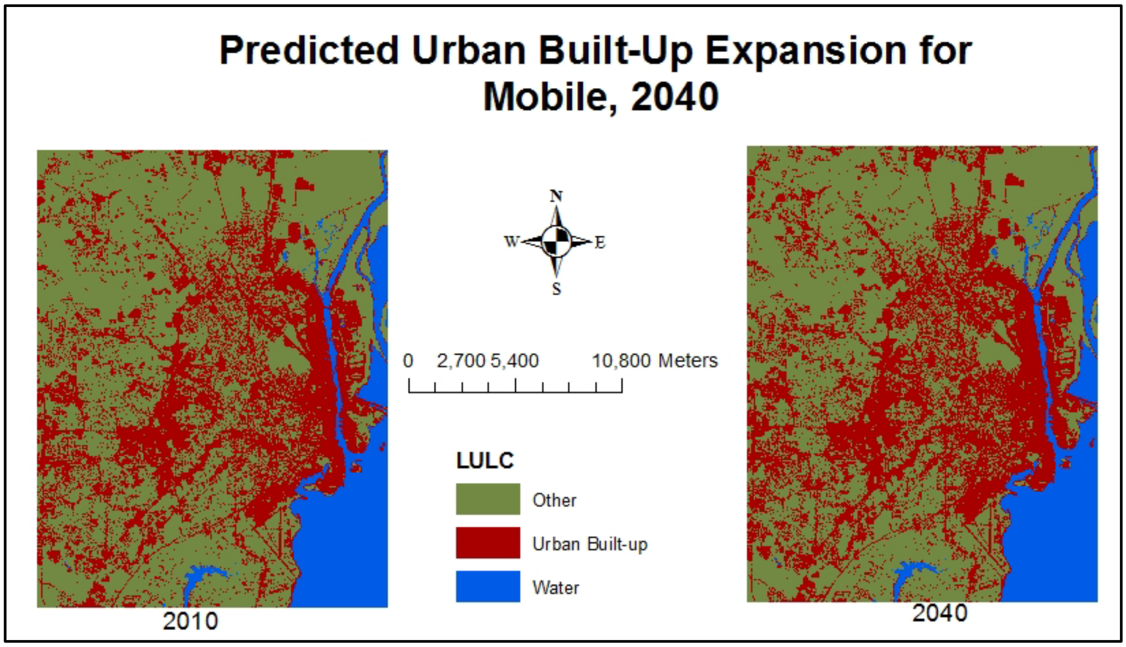


Figure 21. Predicted Urban Built-up Expansion for Mobile, 2040.

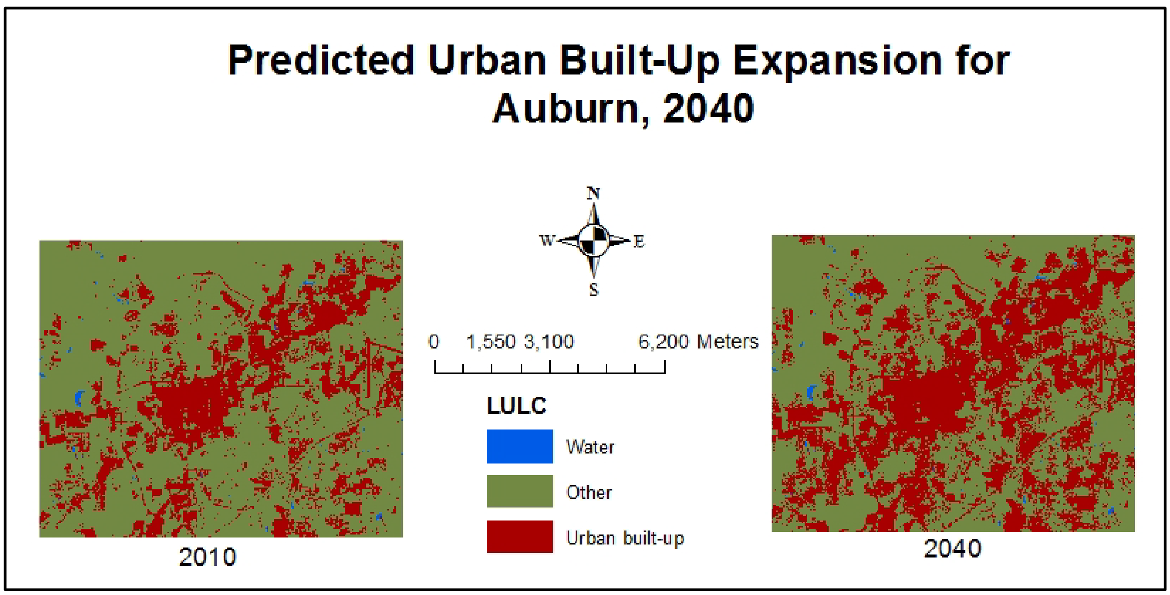


Figure 22. Predicted Urban Built-up Expansion for Auburn, 2040.

4.3.3 Validation of CA-Markov Model

The accuracy was not standard as per regular system (percentage was low as literature indicated) (Araya and Cabral 2010, Guan *et a*l 2011, Behera *et al* 2012, and Kityuttachai *et al* 2013) using IDRISI SELVA software. The accuracy is highest for Hoover 75.24 percent followed by 73.63 percent for Mobile, 69.4 percent for Auburn, 69.32 percent for Madison, and 68.48 percent for Birmingham. Absence of sufficient number of influencing factors (demography, economy of study areas) may influence the accuracy levels in this study.

A visual validation technique was also performed to compare a CA-Markov projected 2013 image with a present Google Earth scenario. Accuracy was more or less same as IDRISI SELVA software produced. The accuracy is highest for Mobile 71.00 percent followed by 70.1 percent for Auburn, 69.5 percent for Madison, 69.03 percent for Hoover, and 67.22 percent for Birmingham.

On the basis of 2013 validation, it has been assumed that 2040 output images are also accurate into same extent.

4.4 Summary

The chapter briefly described the CA-Markov model that is used for this study to predict future urban expansion for five study areas of the state of Alabama. The significance of cross classification and transition probability matrix is also discussed here to CA-Markov model perform better.

Results of transition probability matrix revealed that ‘other’ LULC category was more vulnerable to change to urban built-up for all five urban areas. The most controlling factors for future growth were water bodies and road network. Which means most of the urban expansion will take place following the transportation lines and water bodies will act as restricted zones to built-up expansion.

Future prediction for 2040 revealed that only Auburn will grow more in next 30 years compare to last 28 years. On the other hand, Madison, Hoover, Birmingham, and Mobile will grow slowly in future.

Chapter 5: Conclusion and Summary

Massive urban growth is a common reality in all countries throughout the world. It has a myriad of impacts on environment and the quality of life for both humans and nature are affected. It is a challenge to understand the complexities of urban patterns and how they interact with each other. This requires proficient utilization of methodologies and technologies to monitor expansion and changes in LULC of the urban spaces. By utilizing satellite image and GIS techniques, it is possible to monitor temporal patterns of urban expansion over long periods of time. Remote sensing helps to observe the pattern changes in urban expansion and help in predicting future growth too.

This research was mainly dealt with three major issues: How urban area is growing in present times, whether it has an impact on environment and how it will grow in future. A summary of findings are discussed below.

5.1 Urban Built-up Expansion

This study monitored urban expansion of ten urbanized areas of the state of Alabama over 28 years. Many previous studies proved the efficiency of satellite image and remote sensing classifying LULC. For this study a supervised classification approach was used in which random training samples were collected from each image. After that an accuracy assessment was performed to validate the classification of each image.

Table 25. Net Addition of Urban Built-up from 1982-2010 for Ten Study Areas.

Study Areas	1982		2010		Net addition (%)
	Area(ha)	%	Area(ha)	%	
Auburn	423.18	5.36	1985.31	33.78	369.14
Dothan	1501.02	11.62	3694.61	28.61	146.13
Tuscaloosa	3222.36	15.17	4210	19.88	30.64
Mobile	5509	13.58	12719.3	31.35	130.88
Huntsville	2462.67	3.15	8165	10.5	231.54
Madison	376.85	3.88	2928.66	30.19	677.14
Decatur	1729.98	7.80	3519.57	19.31	103.41
Birmingham	28687.35	8.82	37136.1	11.42	29.40
Hoover	3378.9	3.93	9951.23	11.60	194.51
Montgomery	3823.55	13.72	6073.47	21.79	58.84

The expansion of urban areas was clearly demarcated from 1982 to 2010 by using the supervised classification technique (table 26). Table 26 also indicates that Madison was the fastest growing study area and Birmingham was the slowest growing up to 2010. Most of the expansions of urban areas follow the lines of major transportation routes. As a result sometimes spatial pattern of growth was linear and sometimes radial or grid (Furundzic and Furundzic 2012). Some of the highlights of the classification of urban areas are:

1. Mainly forest, barren land, and grassland have been urbanized.

2. Most of the urban expansion took place along the interstates. As a result most of the study areas exhibited linear pattern of urban expansion such as Birmingham, Hoover, and Auburn.

3. Some areas are the results of centrifugal force (Colby 1933) for instance Dothan, Mobile, Huntsville and Montgomery. Some urban areas exhibited dispersed pattern such as Tuscaloosa, Madison and Decatur.

There are two adjacent urbanized areas. One is Birmingham and Hoover and another one is Huntsville and Madison. Though Birmingham is losing population, Hoover is gaining but for urban expansion both are gaining at a different rate. The annual growth of urban built-up for Hoover (234.72 hectors) is much more than Birmingham (30.74 hectors). Similar is the case with Huntsville and Madison, both expanding along I-565. Net addition of urban area over 28 years for Huntsville was 231 percent whereas for Madison it was 677 percent (table 26).

This study also reveals more conversions in certain categories. Mostly the 'other' category of LULC has been encroached by urban built-up area. For example in Montgomery 83 percent of the 'other' category was converted to urban built-up in 1982 and 75 percent was transformed to built-up in 2010. On the other hand in 1982 water body had only 3 percent conversion to built-up and in 2010 only 2.6 percent. Generally water bodies are restricted from encroachment by urban built-up. Another example in this study is Decatur with net growth of 103.41 percent.

One of the main focuses of this study was urban expansion of mid and small sized areas. Birmingham, Tuscaloosa and Montgomery are three largest urban areas in Alabama have shown steady growth than the excessive growth in the mid-sized urban areas (Auburn, Madison, and Hoover).

5.2 Environmental Parameters

It has been established that the Earth's atmosphere is warming and that humans have substantially contributed to this warming since industrial revolution (IPCC 5th report 2013). Warming of the atmosphere affects the temperature of air, land, and water, which in turn affects patterns of precipitation, evaporation, and wind, as well as ocean temperature and currents (Buhairi 2010). World-wide interest in global warming and climate change has led to numerous trend analysis studies to quantify the anomalies in precipitation, temperature and pollution level. Anthropogenic interference with environment is one of the main causes for weather and climate changes in several regions of the world (Buhairi 2010).

In this study statistical techniques like temporal trend analysis has been performed on various environmental parameters from 1980-2010. Also to understand whether there is any dependency between the variables, multiple linear regressions has been conducted.

There was conformity in the trend results obtained from the Mann-Kendall test for temperature-precipitation and air quality in ten study areas. For temperature and precipitation, the trend line indicates that it is increasing for all the ten areas. On the other hand ozone and $PM_{2.5}$ concentration is decreasing in air.

The main reason for the improved air quality in Alabama is the ‘Revisions to the Clean Air Act’ in 1990 required each state to develop a State Implementation Plan (SIP) describing how it will reach and maintain the national standards (EPA 2012a). These SIPs vary by state, but generally include local monitoring of air quality levels, strategies to reduce emissions, and steps to evaluate these strategies. Individual actions that can also make a difference include recycling, using energy-efficient products and appliances, planting deciduous trees, and driving less. Efforts by EPA and other organizations have successfully improved air quality in the United States. State of Alabama is not an exception. These declines are regionally uneven: some areas experienced bigger declines while others actually experienced increases in air (EPA 2012b).

The proposed multiple linear regressions depicting the influence of all variables of interest (environmental parameters, urban built-up, water body, and other) presented as the relationship between the dependent variable (environmental parameters) and the rest as independent variables (urban built-up, water body and other). Multiple linear regression models have been run four times for four different environmental parameters. Results of multiple linear regression revealed that variation in temperature, precipitation and $PM_{2.5}$ can be explained by urban built-up expansion. However variation in ozone cannot be explained by any LULC change (F value was not significant in ANOVA test). For this study linear regression model has proved its efficiency to determine the correlation between environmental parameters and variable LULC. That means increasing trend in temperature and precipitation can be explained by urban built-up expansion (explained by P value and coefficient). Though air quality is improving in study area but urban built-up area effects $PM_{2.5}$ concentrations in air significantly.

5.3 Future Urban Built-up Expansion

Future growth prediction for urban areas is important to know and help better adapt and mitigate some of the impacts of increasing anthropogenic activities in cities. Results from first two objectives in this study have established dependency of LULCC on precipitation, temperature and air quality patterns. Thus having knowledge of how the urban areas will look in next few decades will benefit planning the cities.

The CA-Markov model is used predict future growth of the five study areas in Alabama. The results for the CA-Markov model revealed that predicted urban built-up expansion for 2040 and the recent urban built-up followed a similar pattern of growth (constraints and factors were same).

The results of the simulation indicate that there will be a significant urban built-up expansion in the future. As discussed in chapter l, transportation and physical landform acted as driving forces for urban built-up expansion. Accessibility to main road, slopes, and altitude will also act as driving forces for urban built-up expansion in the future.

Future prediction for 2040 revealed that only Auburn will grow more in next 30 years (63.1 ha annually) compare to last 28 years (55.8 ha annually). On the other hand, Madison, Hoover, Birmingham, and Mobile will grow at a slower pace in the future.

Results of transition probability matrix revealed that ‘other’ LULC was more vulnerable to transform to urban built-up for all study areas. It shows a high interclass mobility such as a high persistence of urban area to stay in its own class from 2010-2040 and ‘other’ category being transformed to urban area. From 1982-2010 there was 25.4 percent chance that ‘other’ LULC would transform to urban built area for Madison. Percentage was highest for Hoover (42.5 percent) and lowest for Mobile (17.3 percent).

5.4 Conclusion and Significance

In this study, urban expansion has been quantified in ten mid-sized urban areas and it combined with environmental parameter to understand whether built-up has an impact on them or not. Later CA-Markov model was used to project future urban expansion for five urban areas.

This study has led to the following conclusions at the technological, theoretical, and application levels. At the technological level, the study has demonstrated the usefulness of satellite remote sensing and digital image processing for LULC classification. The Mann-Kendal trend test has proved its efficiency to analysis increasing or decreasing trends in environmental parameters. Multiple linear regressions have also conducted successfully to understand the dependency of the variables. For future growth projection CA-Markov model proved its effectiveness.

At the theoretical level, this study has examined the evolution of urban spatial form for urban built-up areas in state of Alabama. Significant growth pattern of urban expansion was found in every study area. Predicted urban growth also represented same kind of pattern in study areas (follow the transportation routes and water bodies). Temperature, precipitation, and $PM_{2.5}$ have been influenced by urban built-up expansion but variation in ozone concentration cannot be explained by urban built-up area.

At the application level, this study has established a well-documented regional case focusing on Alabama. Findings of this study should be useful in future urban planning strategies. And also useful to manage resources and provide direction in a rapidly changing environment. Urban growth is a complex phenomenon with myriad implications. Regardless, the study can provide a changing image of actual urban area, and projected urban expansion that is useful for town planners and policy makers who can then decide on the direction of urban mobility, as well as the trend of urban growth (Yang 2002).

5th Intergovernmental Panel on Climate Change (IPCC) report mentioned that many global risks of climate change are concentrated in urban areas and will be on the rise in future. For example, heat stress, extreme precipitation, flooding, air pollution, drought, and water scarcity pose risks in urban areas for people. So it is important to understand the impacts, vulnerabilities and adaptation measures suitable to improve life on Earth (IPCC 5th report 2014). Techniques like CA-Markov future growth model and GIScience are effective tools to aid sustainable planning and development because they can illustrate the foreseeable changes. A well planned sustainable development can decelerate the negative impacts of modern era urban growth thus highlighting the importance and need of studies like the one done here.

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Appendices
Appendix A

Environmental Parameters Data

Huntsville and Madison (1980-2010)

Year	Temperature	Precipitation	PM2.5	Ozone
1980	60.21	48.65	35	0.12
1981	59.8	49.65	34	0.09
1982	59.5	41.81	33	0.1
1983	60.9	42.59	32	0.1
1984	59.2	52.89	35	0.13
1985	60.2	55.69	41	0.12
1986	59.9	45.7	28	0.11
1987	61.9	46.66	30	0.13
1988	61.5	58.3	29	0.09
1990	60.2	50.54	30	0.09
1991	59.6	51.56	31	0.08
1992	63.2	52.48	32	0.11
1993	62.5	54.57	33	0.11
1994	60.1	54.87	30	0.11
1995	60.4	65.06	23	0.08
1996	61	55.6	19	0.1
1997	60.3	46.03	31	0.1
1998	59.8	57.61	31	0.12
1999	63.4	67.85	31	0.11
2000	62.5	59.37	42	0.11
2001	61.6	49.65	30	0.09
2002	60.7	60.18	34	0.01
2003	62	63.61	27	0.09
2004	60.6	64.9	32	0.09
2005	61.4	66.07	40	0.09
2006	61.8	57.39	30	0.1
2007	62.5	67.7	34	0.1
2008	63.7	70.25	28	0.09
2009	61.5	62.26	21	0.08
2010	61.6	63.58	20	0.08

Mobile (1980-2010)

Year	Temperature	Precipitation	PM 2.5	Ozone
1980	64.8	75.6	44	0.14
1981	64.8	62.5	44	0.12
1982	65.4	79.2	43	0.12
1983	64.4	83.46	42	0.14
1984	66.4	53.82	43	0.12
1985	66.9	69.97	42	0.12
1986	67.9	59.34	42	0.11
1987	66.7	67.12	43	0.101
1988	66.6	62.25	43	0.12
1990	66.7	64	41	0.1
1991	68.7	55.97	40	0.12
1992	67.8	81.67	41	0.11
1993	66.8	70.46	42	0.1
1994	66.4	60.4	41	0.12
1995	67.5	54.92	42	0.11
1996	66.2	80.49	42	0.1
1997	66.6	66.73	43	0.12
1998	68.6	80.14	42	0.11
1999	68.1	86.52	41	0.9
2000	67.7	50.9	40	0.12
2001	67.3	45.74	27	0.1
2002	67.1	54.65	28	0.1
2003	67.5	72.48	31	0.1
2004	68	70.93	36	0.9
2005	67.7	66.16	29	0.09
2006	67.8	63.83	28	0.11
2007	66.8	49.35	24	0.1
2008	67.8	55.25	22	0.09
2009	67.6	59.1	22	0.09
2010	66.4	56.47	19	0.09

Birmingham-Hoover (1980-2010)

Year	Temperature	Precipitation	Pm 2.5	Ozone
1980	63.2	60.2	49	0.16
1981	62.5	60.1	49	0.16
1982	62	57.82	48	0.15
1983	60.2	65.96	49	0.15
1984	62.2	47.62	48	0.16
1985	61.8	50.67	48	0.15
1986	63.5	41.07	47	0.15
1987	62.5	45.32	48	0.14
1988	61.5	43.97	45	0.14
1990	61.5	53.71	48	0.122
1991	64.7	47.46	48	0.133
1992	64	53.49	41	0.123
1993	61.6	55.6	41	0.123
1994	62	39.2	40	0.13
1995	62.8	60.25	40	0.13
1996	63	55.12	40	0.13
1997	61.9	62.91	39	0.11
1998	61.8	55.49	39	0.12
1999	64.9	67.27	38	0.12
2000	64.4	48.77	35	0.12
2001	63.4	50.24	34	0.13
2002	62.5	66.73	30	0.11
2003	63.3	64.41	30	0.12
2004	62.5	65.58	31	0.1
2005	63.5	61.32	28	0.1
2006	63.3	49.2	29	0.1
2007	64.7	56.56	31	0.1
2008	65.4	28.86	28	0.08
2009	63.5	55.09	28	0.09
2010	62.9	71.66	30	0.1

Auburn (1980-2010)

Year	Temperature	Precipitation	PM 2.5	Ozone
1980	62.9	51.62	60	0.15
1981	62	46.62	60	0.15
1982	64	57.8	60	0.15
1983	61.6	62.49	60	0.16
1984	63	43.96	58	0.14
1985	63	45.26	58	0.14
1986	64.8	53.01	59	0.14
1987	63.2	45.43	59	0.14
1988	61.6	53.74	59	0.14
1989	62.3	65.63	59	0.16
1990	65.4	43.43	59	0.15
1991	64.2	54.14	60	0.13
1992	62.6	31.03	60	0.14
1993	64.9	37.43	55	0.13
1994	63.6	57.24	55	0.14
1995	64.6	49.07	53	0.13
1996	63	22.71	53	0.13
1997	62.6	62.92	52	0.13
1998	65.4	49.03	54	0.15
1999	64.6	45.85	54	0.14
2000	63.8	42.4	53	0.16
2001	63.4	50.36	42	0.12
2002	63.9	48	40	0.11
2003	62.8	66.57	34	0.13
2004	63.6	49.06	31	0.13
2005	63	71.32	30	0.13
2006	65	45.67	30	0.1
2007	65.9	28.44	30	0.1
2008	63.2	45.73	28	0.12
2009	62.9	81.58	28	0.11
2010	62.6	45.4	25	0.11

Montgomery (1980-2010)

Year	Temperature	Precipitation	PM 2.5	Ozone
1980	65	75.8	58	0.15
1981	64.8	75.6	58	0.145
1982	64.5	75.46	58	0.142
1983	63.5	75.47	57	0.16
1984	65.3	53.86	57	0.13
1985	65.5	48.34	59	0.13
1986	66.2	52.53	54	0.14
1987	65.1	55.02	54	0.12
1988	64.1	65.43	52	0.11
1990	64.5	75.49	52	0.1
1991	67	53.38	52	0.11
1992	66	67.6	50	0.12
1993	64.1	65.55	50	0.101
1994	64.8	52.94	45	0.12
1995	66.1	59.22	48	0.13
1996	65.6	43.8	47	0.1
1997	63.6	63.09	47	0.1
1998	64.2	47.3	46	0.1
1999	67	44.46	45	0.09
2000	65.7	44.95	42	0.08
2001	64.6	37.95	37	0.101
2002	65.5	47.51	39	0.09
2003	64.6	38.96	40	0.1
2004	66.9	47.86	42	0.1
2005	65.4	49.59	40	0.09
2006	66.1	49.54	42	0.11
2007	66.9	44.71	34	0.09
2008	65.4	36.75	27	0.08
2009	65.2	51.77	21	0.08
2010	64.8	61.41	24	0.09

Tuscaloosa (1980-2010)

Year	Temperature	Precipitation	Pm 2.5	Ozone
1980	63.9	66.62	48	0.17
1981	64	41.73	47	0.17
1982	64.7	62.22	47	0.16
1983	62.2	78.35	46	0.1
1984	62.8	46.4	46	6.154
1985	62.8	50.31	47	0.152
1986	64.7	36.04	45	0.122
1987	64	43.29	45	0.12
1988	62.9	51.15	43	0.1
1989	62.8	64.42	45	2.11
1990	65.6	58.31	45	0.11
1991	65.4	55.93	45	0.1
1992	63.2	51.28	41	0.1
1993	63.4	45.93	40	0.1
1994	53	55.3	43	0.12
1995	64.9	58.3	41	0.101
1996	64.3	56.44	41	0.11
1997	64.2	72.17	40	0.12
1998	67.1	60.61	40	0.1
1999	66.3	54.4	40	0.09
2000	66	49.25	38	0.09
2001	65	63.78	36	0.08
2002	65.9	52.62	36	0.08
2003	64.8	62.54	33	0.09
2004	65.2	59.3	35	0.08
2005	66.2	58.43	28	0.08
2006	66.8	55.83	30	0.07
2007	54.9	47.25	27	0.07
2008	64.8	49.66	25	0.06
2009	64.8	75.03	25	0.07
2010	60	48.41	26	0.07

Decatur (1980-2010)

Year	Temperature	Precipitation	PM 2.5	Ozone
1980	66.9	79.7	58	0.16
1981	65.8	72.6	58	0.13
1982	65.5	77.3	57	0.13
1983	66.4	81.5	54	0.14
1984	66.4	73.72	54	0.13
1985	66.9	69.17	57	0.12
1986	67.9	69.34	57	0.101
1987	67.7	67.34	52	0.111
1988	66.3	65.45	56	0.102
1990	65.9	66.25	52	0.1
1991	68.7	55.97	51	0.12
1992	67.8	81.67	51	0.11
1993	66.8	70.46	51	0.1
1994	66.4	62.31	50	0.12
1995	67.5	54.92	45	0.11
1996	66.2	80.49	41	0.1
1997	66.6	66.73	41	0.12
1998	68.6	80.14	41	0.11
1999	68.1	86.52	42	0.12
2000	67.8	61.91	41	0.12
2001	67.4	45.74	40	0.1
2002	67.1	54.65	40	0.11
2003	67.5	72.48	40	0.11
2004	68.1	68.93	38	0.08
2005	67.7	66.16	39	0.09
2006	67.8	63.83	30	0.11
2007	66.8	49.35	30	0.11
2008	66.9	65.25	27	0.1
2009	66.8	69.1	23	0.1
2010	65.3	66.47	21	0.08

Dothan (1980-2010)

Year	Temperature	Precipitation	PM2.5	Ozone
1980	63.31	75.91	41	0.16
1981	61.81	51.81	41	0.14
1982	60.51	60.65	40	0.14
1983	61.9	65.39	40	0.12
1984	59.4	77.03	40	0.13
1985	61.4	57.06	38	0.12
1986	60.9	77.57	38	0.11
1987	63.5	57.85	38	0.1
1988	62.4	66.66	37	0.1
1990	61.2	73.58	37	0.1
1991	59.6	72.26	38	0.08
1992	63.2	70.25	38	0.11
1993	62.5	68.6	40	0.11
1994	60.1	68.56	40	0.11
1995	60.4	66.07	37	0.08
1996	61	62.48	37	0.1
1997	60.3	60.18	35	0.1
1998	59.8	57.61	36	0.12
1999	63.7	45.7	30	0.11
2000	62.2	45.69	28	0.11
2001	61.6	42.89	28	0.1
2002	60.5	63.61	28	0.01
2003	62	50.54	27	0.09
2004	60.7	54.87	25	0.09
2005	61.5	59.37	20	0.08
2006	62.8	39.65	20	0.11
2007	60.5	42.59	19	0.11
2008	61.7	28.65	18	0.09
2009	60.5	48.3	18	0.07
2010	59.6	47.7	18	0.07

APPENDIX B

Multiple Linear Regression Data

Year	Built-up	Water	other	Temperature	Precipitation	O3(ppm)	PM2.5(ug/m3)
1982	28687.35	1422.15	294832	59.9	50.25	0.07	30.2
1990	28916.4	1367.1	294658	61.2	50.7675	0.106	26.5
2000	35419.6	1169.91	288352	62.5	54.556	0.13	23.89
2010	37136.1	1155.42	286650	64.3	56.965	0.1	30.2
1982	3823.55	833.94	23204	62.3	60.5	0.09	20.5
1990	3992.92	705.96	23162.62	65.6	60.87714286	0.08	19.1
2000	5096.34	764.19	22001	66.8	54.229	0.08	18.3
2010	6073.47	744.97	21043.1	67.8	46.605	0.073	12.4
1982	5509	4962.6	30096.3	63.2	62.35	0.08	21.4
1990	5875.07	4793.5	29899.3	66.5	65.70857143	0.087	18.3
2000	7166.7	4577.67	28823.5	67.5	68.82	0.093	15.5
2010	12719.3	4445.1	23403.5	68.9	64.396	0.077	9.8
1982	1501.02	377.46	11034.7	62.3	58.6	0.1	22.3
1990	2311	163.17	10439.01	63.3	59.4	0.09	21.5
2000	2531	66.33	10315.9	65.7	59.9	0.07	18.3
2010	3694.61	58.59	9159.98	67.9	60.2	0.067	11.2
1982	1729.98	3165.57	13326.2	60.2	50.2	0.064	18.6
1990	3102.12	2597.83	12521.8	61.5	51.6	0.09	16.2
2000	3205.66	2305.11	12710.9	66.5	54.2	0.11	15.4
2010	3519.57	2132.02	12570.2	67.9	56.9	0.07	12.8
1982	2462.67	489	75124.5	60.2	50.18	0.12	23.20
1990	7040.79	461	70574.3	61.5	50.37777778	0.09	22.50
2000	11165	386	66525.2	63.5	54.83	0.11	19.50
2010	33161.37	267.5	53864.67	64.9	57.71111111	0.08	15.30
1982	423.18	64.35	7394.31	62.3	49.89	0.12	21.30
1990	1084.59	35.4	6761.85	63.5	51.737	0.10	20.60
2000	1288.8	30.6	6562.44	67.4	45.182	0.09	18.50
2010	1985.31	19.71	5876.82	68.8	53.213	0.08	17.40
1982	376.85	84.25	9237.12	59.6	64.9	0.12	19.80
1990	1000.8	65.43	8631.99	60.8	56.95555556	0.09	17.80
2000	2283.86	32.38	7381.98	62.3	57.74	0.11	16.30
2010	2928.66	25.32	6744.24	63.2	49.817	0.08	14.60
1982	3222.36	653.94	17361.9	63.9	66.62	0.075	19.3
1990	3308.4	617.4	17312.4	64.7	53.222	0.074	15.7
2000	3712	401	17125.2	65.6	55.961	0.077	13.2
2010	4210	256.23	16771.97	66.9	57.285	0.06	12.1
1982	3378.9	650.32	81733.1	61.5	50.4	0.07	30.2
1990	5868.45	716.04	79177.83	63.3	50.3	0.106	26.5
2000	6866.91	539.59	78355.8	64.8	54.9	0.13	23.89
2010	9951.23	422.15	75388.92	68.8	56.2	0.1	30.2