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HUMAN IMPACTS STUDY ON CUYAHOGA VALLEY NATIONAL PARK USING GIS AND REMOTE SENSING (130 pp.)

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Cuyahoga Valley National Park (CVNP) is located between Cleveland and Akron in North Ohio and is the only national park in Ohio. Even though it is within a short distance of the metropolitan areas, the wilderness inside of the park has been preserved through Cleveland Metroparks, Metroparks Serving Summit County, Cuyahoga Valley National Park, non-profit organizations, and community efforts. However, outside the park boundaries, urban extent and population have increased progressively outside the park potentially providing stresses to the park environment.

CVNP receives over 3,000,000 visitors every year, and is a primary recreation area in the region. In this thesis, human impacts on CVNP are analyzed using geographic information systems (GIS) and remote sensing to determine how the impacts have influenced the park environment. The main goal is to detect urban expansion patterns around CVNP from 1987 to 2006. In order to do this, the object-oriented classification (OOC) and pixel-based classification (PBC) were compared to determine which method provided a higher accuracy. The results showed that the OOC maps showed higher accuracies in their results than the PBC maps, and, using the OOC maps, more urban expansions were recognized in the direction to CVNP in the last 20 years.

HUMAN IMPACTS STUDY ON CUYAHOGA VALLEY NATIONAL PARK USING GIS AND REMOTE SENSING

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by

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CHAPTER 1

INTRODUCTION

Since Yellowstone National Park was established in 1872 as the world first national park, 58 national parks have officially been designated in the U.S (*National Park Service*). The National Park System comprises 391 acres including national parks, monuments, battlefields, military parks, historical parks, historic sites, lakeshores, seashores, recreation areas, scenic rivers and trails, and the White House (*National Park Service*). Cuyahoga Valley National Park (CVNP) is the only national park in Ohio and is located in the northeast of the State (Figure 1.1).

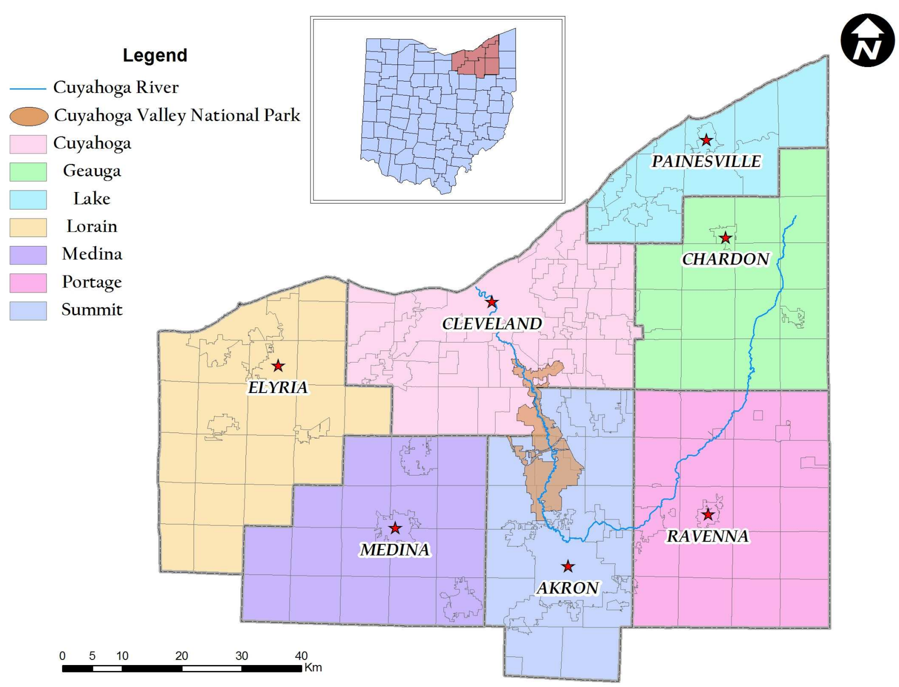


Figure 1.1 Map of Cleveland and Akron Metropolitan Area in Northeast Ohio

The CVNP was first created through legislation as a National Recreation Area by President Gerald Ford in 1974 and redesignated as a National Park in 2000 (*Cockrell, 1992*). The CVNP stretches between Cleveland and Akron in heavily urbanized northeastern Ohio (*Platt*, *2006*), but the park is very isolated from the crowd and noise of the cities. The CVNP has received more than 2.0 million visitors since 1993 (*National Park Service*), and there are many activities people can enjoy in all seasons. There are over 125 miles of hiking trails, Ohio & Erie Canal Towpath Trail - about 20 mile long bike paths beside the Ohio and Erie Canalway, golf courses, two ski resorts, and the Blossom Music Center, which is the summer home of Cleveland Orchestra (*Cockrell,*

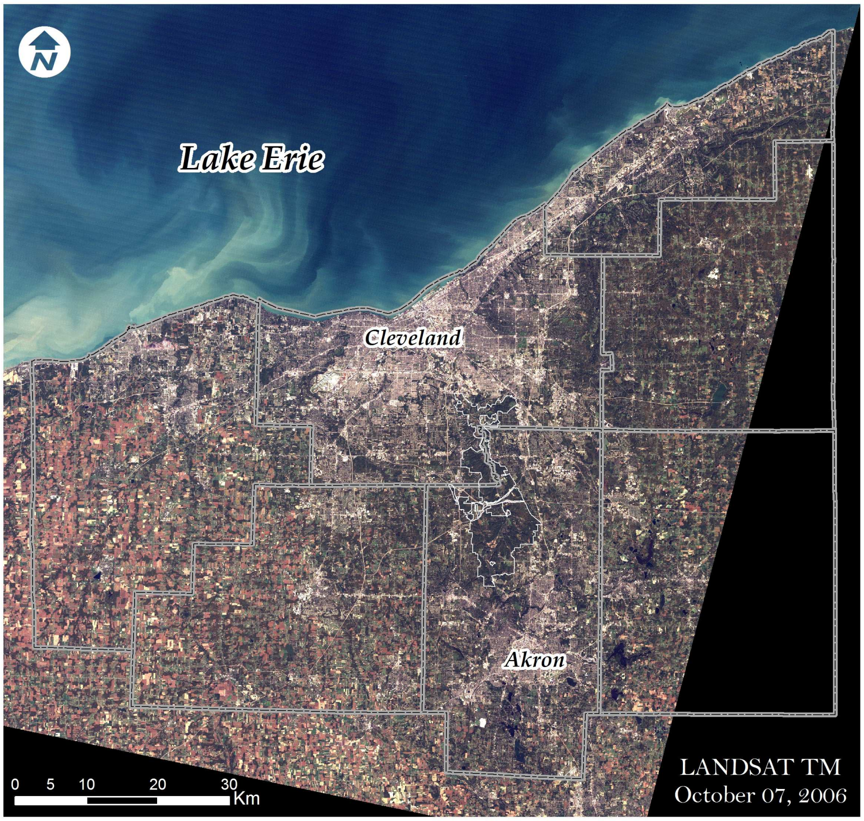


Figure 1.2 LANDSAT TM Image of Study Area

1992; Jackson and Newton, 1992; National Park Service). The CVNP is one of the most crowded and popular parks in northeast Ohio because of these varied activities and its unique geographic position between the metropolitan areas of Cleveland and Akron. The CVNP looks like "*an isolated island*" from Space (*Platt, 2006*) (Figure 1.2) as gradual urban expansion and population growth around the park.

The spatial land use changes due to human influence are caused by different factors in different regions. The CVNP influences are particularly complicated due to its proximity to Akron and Cleveland. Beside natural environmental factors, the history of human impact has also influenced the distribution of vegetation types (*Hoersch et al., 2002*) and the patterns of wildlife. The history of the CVNP has been closely related to human activities. A big boost to change the valley was the development of the Ohio and Erie Canalway, which connected the Ohio River at Portsmouth and Lake Erie at Cleveland in 1832 (*Cockrell, 1992; Platt, 2006*). After the boom era of the canal, the park continued to be changed by the introduction of a railroad system in the mid 19th century and massive constructions of major interstate and state highway roads through, inside, and outside of the park in 20th century. Many people in Cleveland started seeking their houses outside of the city because of ethnical problems, decay of Downtown Cleveland, slumps of iron and steel industries, and better accessibilities to commute to the center of cities in a short time using freeways. As the result, gradual urban expansion begun in the early 1930s around Cleveland, and it has been continued until now. Since the park was founded in 1974, the valley has been protected by efforts of government, state, and other non-profit organizations. However, even though construction in the park has stopped, it continues daily outside park bounds (*Platt, 2006*).

In this thesis, human impacts on the CVNP will be analyzed in terms of how they have influenced the park environment. The regions in the Cleveland and Akron Metropolitan Area are concerned about outmigration, which is the migration of households from the central city to the fringe of the metropolitan area (*EcoCity Cleveland*). Now the population in Cleveland and Akron cities is declining, but urban and suburban areas outside of these cities are expanding, and numbers of population around CVNP are growing simultaneously. It is believed that this trend will gradually cause severe environmental changes around CVNP, which will also influence the ecosystem of the park indirectly. To measure these trends, it is necessary to know the pattern of urban expansion to prevent environmental degradation around the park. The combination of remote sensing and Geographic Information System (GIS) is the best way to find spatial and temporal changes around CVNP. The overall goal of this thesis is to detect urban expansion around CVNP in the last 20 years (1987-2006) using remote sensing satellite data. To accomplish the objectives are,

(1) To test the object-oriented classification against the pixel-based classification method to determine which method accurately quantify land surface classification,
(2) To analyze patterns of urban expansion by the post-classification method and buffer zone analysis, examine population changes in Cleveland and Akron

Metropolitan Area using GIS, and analyze the relationship between urban increases and population growth around CVNP statistically,

(3) To determine areas of vulnerability in CVNP based on human impact factors from all analyses.

CHAPTER 2

BACKGROUND OF THE STUDY AREA

2.1 History of Cleveland and Akron Metropolitan Area

Cleveland, situated to the north of CVNP, is the county seat of Cuyahoga County (see Figure 1.1), the most populous county in Ohio (*US Census Bureau, 2007*). The city is spread along the shore of Lake Erie and the mouth of Cuyahoga River and used to be an industrial center of iron and steel manufacturing. Its population grew quickly because of the development of the Ohio and Erie Canalway (*Cockrell, 1992*) and railroads through the Cuyahoga Valley.

The Ohio & Erie Canalway which was begun in 1825 and completed in1832, linked Cleveland with Portsmouth on the Ohio River. Canal traffic reached its peak in the mid 1840s, but use declined from 1851 to 1860. Railroads revolutionized transportation in northeast Ohio, and Cleveland had become one of the major rail centers in the U.S. along with New York, Chicago, and St. Louis. In the late 19 century, the Civil War accelerated the growth industry in Cleveland, and the population in Cleveland increased. Because of its geographic location of Cleveland and transportation revolution in the early to middle 19th century, raw materials for iron and steel manufacturing was fluent and helped Cleveland's rise as a national industrial center (*Miller and Wheeler, 1997*).

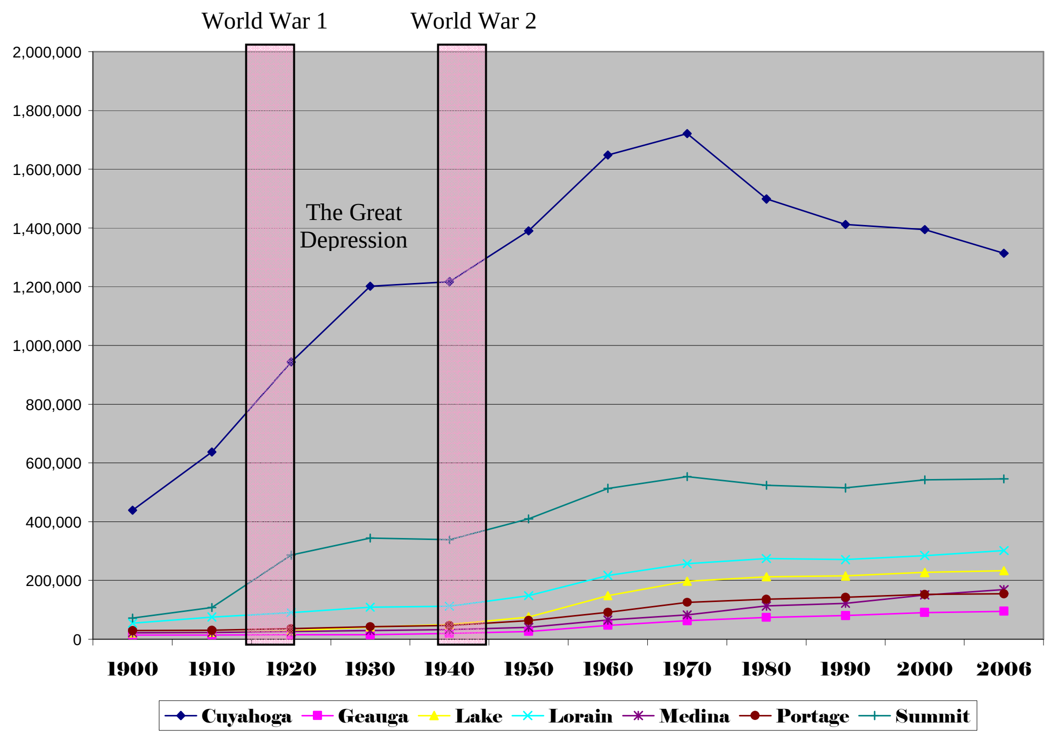


Figure 2.1 Population Changes from 1900 to 2006 in Cleveland Akron Metropolitan Area

In the early 20th century, the city continued to be one of the nation's most progressive and attractive cities (Figure 2.1). However, automobiles and paved highways stimulated metropolitan expansion around 1915 to 1929. The urban growth had been slow but continuously expanded in territory and population. Around this period, the suburbs of Cleveland Heights, Shaker Heights, Garfield Heights, and Parma grew rapidly, while the population in Cleveland decreased. The growing use of automobiles helped expansion of residential locations and created new roadside businesses – gas stations, auto showrooms, repair shops, and parking lots. At the same time, the situation widened the economic gap between city and suburb. In the early 1930s, Cleveland Metropolitan area was the 3rd most populated after New York and Chicago. However, population in Cleveland still kept decreasing and increased in speed after the Great Depression in 1929.

Cleveland industries in the 1940s expanded rapidly to meet demand for war material during World War II (in the late 1920s to 1945), but the speed of decline in Cleveland was not reduced after 1950. The decay of downtown was apparent, Slum areas and areas that threatened to become slums expanded, and a need for affordable private housing and new schools, parks, and more could not be developed in the city. Thousands of city residents left for new homes in the suburbs. Urban renewal and the construction of freeways dramatically and permanently changed Cleveland City (*Miller and Wheeler, 1997*).

The city used to be the fifth largest city in the US, and the Cuyahoga River was infamous as the biggest burning river in 1969 (*Beach, 1998*). By the 1960s, however, heavy industries began to slump (*Grabski, 2006*; *Platt, 2006*), because more companies started seeking their business in the south of the U.S. or abroad. There are many reasons why residents in Cleveland immigrated outside of Cuyahoga County, but the construction of highways caused significant alterations in traditional land-use patterns (*Miller and Wheeler, 1997*). The network of freeways led people outside cities but many people could still commute to their office in a short time. This movement brought a lot of commercial and industrial activities toward outside the city. By 1975, the interstate highway system completed and population loss in Cuyahoga County is significant (see

Figure 2.1). Since the 1970s, the population of Cuyahoga County has dropped dramatically. However, population in all adjacent counties (Geauga, Lake, Lorain, Medina, Portage, and Summit) has kept increasing gradually since the early 1900s.

Akron City is the county seat of Summit County (see Figure 1.1) and is located to the south of Cleveland, also along the Cuyahoga River and south of the CVNP. First, Akron prospered well because of its location, at the "summit" of the Ohio and Erie Canalway, and the city transformed to "the Rubber City" later. The world famous tire company, Goodyear Tire and Rubber Company, has its headquarters in Akron. The city's population reached close to 300,000 in 1960s. However, it has steadily declined to about 100,000 (*US Census Bureau, 2006*) since then. Although Akron City experienced decline in its population, population in Summit County has grown since the1990s. According to population data, both Cleveland and Akron experienced similar patterns in their population changes in the past while surrounding suburban cities grew in population.

Cleveland and Akron launched the Metropolitan Park Districts in 1911 and 1920 to design and manage parks around the cities because more people came to the Cuyahoga Valley to seek recreational areas. Cleveland Metroparks cover 19,000 acres in what is referred to as the "*Emerald Necklace*" around Cleveland. It protects stretches of the Chagrin River, Rocky River, Tinkers Creek, Euclid Creek, as well as other streams. Metro Parks serving Summit County cover 6,600 acres with 11 developed parks, a 23-

mile biking/hiking trail, nature center, arboretum and conservation areas around Summit County (*Beach, 1998*). These Metropolitan Park Districts also own parts of the CVNP and manage the park's environment.

2.2 History of the Cuyahoga Valley

Platt (2006) published the Cuyahoga Valley National Park Handbook which describes a brief history of the park from the American Indians' era to the present. In 1974 Congress created the park "for the purpose of preserving and protecting for public use and enjoyment, the historic, scenic, natural, and recreational values of the Cuyahoga River and the adjacent lands of the Cuyahoga Valley and for the purpose of providing for the maintenance of needed recreational open space necessary to the urban environment." (*Vasarhelyi, 2006*) Unlike other National Parks, many historical landmarks can be seen in the park – villages and towns; trails, roads, canals, and railroads; and farms, mills, and factories.

Early in its history, the park was used for agricultural, residential, and industrial purposes, but it has been rehabilitated by Cleveland Metroparks, Metroparks serving Summit County, National Park Service, nonprofit organizations, and many volunteers. Platt (2006) described in her book that the Cuyahoga Valley is not simply a natural landscape. The park has involved a long history with human activities. When American Indians were in the park first, they did not greatly alter the park's natural systems. Settlement was slow due to topographical obstacles, steep valleys, dense forests, and isolation to the outside of the park (*Cuyahoga Valley Historical Museum and Cuyahoga Valley National Park Association, 2004*). However, these topographical obstacles did not disrupt the European settlers. By the late nineteenth century they came to the valley and cut most of the forest cover for farming and for industries like milling, quarrying, brick making, and building. With the completion of the Ohio and Erie Canal, many industries were brought into the Cuyahoga Valley (*Cockrell, 1992; Platt, 2006*).

The Ohio & Erie Canalway launched the development of commerce in the Midwest. The canal brought more industries and farming to the valley, and more people settled inside the valley. By the 1860s, faster and more efficient railroad systems took the place of canal. Although the railroads were introduced to the valley, they didn't bring more prosperity than the canal did from 1827 to 1840 (*Platt, 2006*). In 1913 the great Flood destroyed most of the canal system, and the devastating flood ended the operation of the canal in the valley (*Cockrell, 1992*).

In the early 1870s, the Cuyahoga Valley was focused more as a recreational area for city dwellers in Cleveland and Akron (*Cockrell, 1992*). Many of people from Akron and Cleveland looked for a place to escape from the pressure of urban industrial life. In the early 20th century Cleveland and Akron Metropolitan Park Districts and other groups came to seek recreational opportunities in the Cuyahoga Valley. Both Cleveland Metroparks and Metro Parks, Serving Summit County also conserve and manage not only the Cuyahoga Valley environment but also other parks and preservation areas inside

Cuyahoga and Summit counties. The histories of both metro park systems are older than Cuyahoga Valley park system, and they manage natural resources to provide outdoor recreational and educational opportunities to city dwellers.

In the 1950s to early 1970s, many people built homes in and around the Cuyahoga Valley. The high-speed road system allowed people to live further out of the cities. Interstate Highway 77, 80 (the Ohio Turnpike), and 271 increased accessibilities to both the valley and cities, and these highways accelerated the rapid development around the valley. Now the CVNP is surrounded by these roads and resembles a spider web pattern. However, inside the valley is peaceful even though it is located in a short distance from urbanized areas.

CHAPTER 3

LITERATURE REVIEW

3.1 Introduction

Human impacts on national park environments can result in degradation of the environment, including species extinction and ecosystem degradation. These impacts can be internal or external to the parks. A significant amount of research has been undertaken on detecting forest changes or patterns in national parks (*Hong et al., 2004; Nepal SK and Nepal SA, 2004; Leung and Marion, 1999*), but much of these researches do not consider the specifics of internal and external impacts. There is also little research that has evaluated human impacts on the CVNP. In this literature review, I will review and consider the following topics.

1) Human impacts studies on national parks,
2) How remote sensing has been used to analyze landscape changes,
3) How remote sensing has been used to analyze forest regions,
4) Affect of roads on wildlife and vegetation areas,
5) Object-Oriented Image Analysis,
6) Geostatistical methods using GIS technologies.

3.2 Human Impact Studies on National Parks

Human impacts on CVNP is considered coming from various factors. The Cuyahoga Valley had been abused for agricultural, industrial, and recreational purposes for a long time in its history (*Miller and Wheeler, 1997; Platt, 2006; National Park Service*). The park has been protected by regulations recently, but a lot of people still come to the park for their recreational purposes and the park environment cannot be said a perfect condition compared with other National Parks. Park visitors enjoy the nature and recreation in the park throughout the year. While there has been urban and suburban development outside the park, the park itself has been protected by National Park Service, Cleveland and Summit Metropark systems, and other nonprofit organizations designed to protect the park.

These days urban sprawl can be the most influential human impacts on CVNP, but we need to first of all, define urban sprawl. Gillham and MacLean (2002) suggested that there is no single, clear, and succinct definition of sprawl that is shared by everyone. In their book they said that Reid Ewing's (*National Center for Smart Growth Research & Education*) definition of urban sprawl is widely more accepted, and it is defined by the following characteristics - 1) Leapfrog or scattered development, 2) Commercial strip development, 3) Low density development, 4) Large expanses of single-use development, 5) Poor accessibility (Automobile dominance), and 6) Lack of functional open space. Urban sprawl around the Cleveland and Akron areas seems to have similar these characteristics of urban sprawl. Ewing also said that sprawl simply would not happen without a transportation system capable of serving this pattern. Forman et al. (2003) noted that the road infrastructure is needed to connect communities to services and institutions as well as to one another as metropolitan regions sprawl outward. They also studied how road network patterns affect the ecological properties, watershed processes, and landscapes. The transportation infrastructure development may have had one of the biggest human impacts not only on CVNP but also most of cities in the U.S. Because people in the U.S. are very car-dependents, road developments are necessary to go anywhere in the region. From a satellite data, it is hard to find a wide natural or open space without any roads in Northeast Ohio.

There are many papers that have studied the human impact on national parks (e.g., *Floyd et al., 1997; Leung and Marion, 1999; Marion and Farrell, 2002; Nepal and Nepal, 2004; Hong et al., 2004; Southworth et al., 2004; Wiersma et al., 2004*). Southworth et al. (2004) attempted to examine the human impact of Celaque National Park on forest fragmentation in western Honduras in Central America. Celaque National Park has a relatively short history, and the accessibility to the park is not particularly good. However, deforestation, illegal logging, agricultural clearing, and coffee plantations can be found both outside and inside the park. In this study LANDSAT TM data and Fragstats software were used to analyze temporal and spatial changes in three different buffer zones (core zone, park boundary, and surrounding landscape).   By using remote sensing, they found that national park system in Celaque National Park was effective in preserving the forest and stopping land clearance for deforestation or coffee plantations. Remote sensing analysis helped to understand spatial and temporal changes inside and outside the national park effectively. However, they suggested that there is also a necessity for fieldwork to interpret human activities and incentives that relate to land cover change.

Some people have studied the human impacts on national parks by assessing visitor impacts on trails such as in the Great Smoky Mountains National Park (GSMNP) located between North Carolina and Tennessee (*Leung et al., 1999*), in the Sagarmatha (Mt. Everest) National Park (*Nepal and Nepal, 2004*), and in the Twelve Apostles National Park, Victoria, Australia (*O'Connor, 2005*). O'Conner (2005) placed an electronic device at one of popular trails in the park, to track visitors' patterns over 3 days. All of these studies focus on how park visitors influence the park trails including loss of vegetation cover, incision, soil loss on the tread surface, tread widening, soil compaction, the appearance of informal trails, and the results of various depreciative behaviors such as littering and cutting of trail switchbacks (*Nepal and Nepal, 2004*). Trail degradation is one of the important indicators to assess how people affect or change the park environment or its ecosystem because most parks restrict where people can walk and park trails are usually the main connection between the parks and people. Since these studies were concentrated in specific areas, their methods may not be very useful to analyze CVNP. People can enter to the park from many places by different ways – walking, biking, driving, and riding on a train. Therefore, methods using GIS and Remote Sensing will be considered more suitable to assess large-scale human impact inside and outside CVNP.

In urban areas, there are few green spaces for us to come into contact with nature, so areas such as CVNP are important to urban residents as recreational areas. It is very unusual to have a large natural recreation area like CVNP in a short distance from an urbanized society. Although there are other state parks or natural preservation areas in the Cleveland and Akron Metropolitan area, the Cuyahoga Valley is more popular than others because of its variety of outdoor activities and diversity of nature in the park. The popularity and attractiveness of parks is different for each visitor, but distance is thought to be one of the most influential factors in visitation rates for parks (*Ode and Fry, 2006*). The accessibility to parks is therefore an important indicator of human impact. Ode and Fry (2006) suggested that the accessibility and quality of woodlands in Sweden is a key component to measure visitor pressure on woodlands. They indicated that the degree to which woodlands can attract people within the urban area could be defined through a complex system of interacting factors such as woodland size, location, and structure with a mitigating element from its location relative to the population. It could be difficult to decide what important factor is the most influential to attract people, because CVNP is really multipurpose recreational areas.

3.3 How Remote Sensing Has Been Used to Analyze Landscape Change

Human activities typically result in land cover change and lead to biodiversity decline and species endangerment (*Wulder and Franklin, 2007*). Monitoring natural and human-caused land cover and forest changes, disturbance processes, and spatial pattern is relevant for the conservation of forest landscapes and their inhabitants (*Wulder and Franklin, 2007*). Remote sensing has been widely utilized to analyze environmental phenomena on our planet over the last few decades. It has been utilized to understand humid and arid lands, vegetation, snow and ice, the seasonal variation of atmospheric and oceanic circulation, atmospheric chemistry, geologic features and events, and the human activities that are producing global change (*Christopherson, 2002*). Among the many environmental issues, urban sprawl or landscape change is considered one of the biggest problems for the natural environment in the U.S, especially around major cities. Sprawl does not cause only landscape changes but also natural ecosystem alteration, habitat loss and degradation for many kinds of wildlife (*Gillham and MacLean, 2002*). Habitat loss and degradation of natural environments is a massive threat to the planet in the future. It is, therefore, important to understand the spatial and temporal characteristics of nature on landscape change patterns through time, and remote sensing is the best way to analyze landscape change patterns.

Today aerial and satellite remote sensing data are the primary data sources of spatial information of the land surface (*Schmidt and Skidmore, 2003*) because the information is very useful for detecting and monitoring spatial and temporal patterns of land surface changes over time. Remote sensing has been used for many landscape change studies *(e.g. Narumalani et al., 2004; Lunetta et al., 2004; Yuan et al., 2005; Im and Jensen, 2005; Nordberg and Evertson, 2005; Castellana et al., 2007; Shalaby and Tateishi, 2007*). Many change detection algorithms (e.g. image algebra, post-classification comparison, spectral change vector analysis, multidate composites, etc.) (*Jensen, 1996; Campbell, 2002*) have been developed by different scholars, and it is important to select an appropriate algorithm for a certain study area (*Jensen, 1996*). Urban expansion always results in changes to other land cover types (agriculture, pasture, shrubs, grass, etc.). Ji et al. (2006) said that effective forecasting of urban sprawl dynamics depends largely on the understanding of subtle spatial and temporal patterns of the built-up land. By detecting small changes around CVNP, the post-classification change will be the appropriate method to detect urban changes and understand its patterns.

Narumalani et al (2004) utilized the post-classification change detection algorithm, which is the most commonly used quantitative method of change detection (*Jensen, 1996*). It requires two or more independent classifications of each scene and compares them on a pixel-by-pixel basis to pinpoint any changes between the time periods (*Campbell, 2002; Narumalani et al., 2004*). The advantage of this algorithm includes the detailed "from-to" information that can be extracted and the fact that the classification map for the next base year is already complete (*Jensen, 1996*). We can examine what kind of land surface (agriculture, forest, ponds, etc.) has taken place. Yuan et al. (2005) also used the post-classification change detection algorithm to detect changes in the Twin Cities Metropolitan Area using four different time datasets of LANDSAT TM data and produced accurate landscape changes successfully. The post-classification change detection algorithm provides more useful results than some other methods, but the algorithm requires accurate classifications of individual scenes (*Jensen, 1996; Campbell, 2004*). Moreover, careful data pre-processing is needed for any multi-temporal analyses because small radiometric or geometric differences may cause a big difference in the results.

The major problem for mapping urban areas resides in the diversity and heterogeneity of their spectral response (*Martinuzzi et al*, *2007*). It is difficult to find a single pixel in an image covered by only one land classification especially for middle-resolution satellite images like LANDSAT TM/ETM+. Most urban areas show a variety of land surface types, and a single pixel, which is the smallest size on an image, can contain several of these different surfaces. These are referred to as “mixed pixels”, and they can be problematic for mapping when applying conventional classification methods. For example, in east of Cleveland many residential areas have a large number of trees and park areas, therefore lot of pixels have mixed urban, and vegetation classes that affect their reflectance values.

Martinuzzi et al. (2007) combined satellite information with population census data to study development, land use, and urban sprawl in Puerto Rico. In his study he used population census blocks and specified the specific conditions of urban areas throughout all of Puerto Rico. His method was effective in defining urban areas using remote sensed imagery because many urban pixels on aerial or satellite images contained mixed information within one pixel like agriculture, pasture, or bare soil, which are similar with urban pixels. For example, the size of single pixel for LANDSAT TM data is 30×30 m. For instance, if about half of one pixel is dominated by a stand of trees, and half by impervious surface how do we decide to which class that pixel is assigned to? We can better define land surface classes. Congalton and Green (1999) mentioned in their book the importance specifying the project’s classification schemes. First of all, it is necessary to decide on a solid set of labels (e.g. urban, forest, agriculture, etc), and then create a set of rules or definitions for each label. Congalton and Green (1999) also mentioned that the level of detail in the scheme strongly influences the time and effort needed. Since the minimum pixel sizes for LANDSAT TM and ETM+ are 30m square, it is necessary to remember that there is a limitation to seeing specific objects on ground.

Clapham (2003) also suggested that there is a problem of heterogeneity in urban areas using remote sensing. He uses a continuum-based classification, a normalization technique resulting in a curve with values from 0 to 1. This was applied to detect the urban changes in the Cuyahoga River watershed. The continuum classification emphasizes the location and depth of individual absorption features (*Schmidt and Skidmore, 2003*). Clapham (2003) noted that a disadvantage of the continuum classification is that a single conversion factor is assumed to apply equally to all pixels in the land-cover type. In this thesis, more specific landscape changes will be more useful to find the characteristics of Cleveland and Akron Metropolitan Area, so the post-classification change detection algorithm seems to be more suitable.

3.4 How Remote Sensing Has Been Used to Analyze Forests Regions

Remote sensing has been used to generate a wide range of estimates that are valuable to ecologists, including information on land cover, vegetation cover, habitat, forest structure, and forest function (*Wulder et al., 2004*). Forests are one of the most complicated land cover types to study, and many scholars have developed their ideas to include regional, national, and sometimes global issues. Since the 1970's there have been increased efforts to manage forest covered land using new technologies like GIS and remote sensing. These days many researchers have employed both GIS and remote sensing to manage changes and patterns of forest and wild habitat areas. Books by Franklin and Wulder (2003/2007) present ideas and tools for understanding and choosing remote sensing solutions to solve problems and discuss the future of remote sensing technologies. Franklin (2001) explained that the future of forest management still remains unclear and therefore there will be the need to adapt forest management continually to slow the current rate of species extinction.

With the advantage of GIS technology and development of faster computers, we are able to manage more data than we can handle these days. GIS is powerful to manage various dataset simultaneously, and remote sensing is very useful for monitoring large forest areas over long time spans. There are also many different satellite sensors that are appropriate for monitoring forest regions with their range of spatial resolutions and spectral band widths. Using higher spatial resolution data, it is possible to identify and map individual trees and groups of trees over large areas, or as part of a strategy for forest sampling (*Wulder et al., 2004*). However, the characteristics of individual trees are still difficult to detect even though the sensors are much improved because conditions of trees change day by day. Many researchers try to determine the radiometric characteristics of trees and improve their accuracy detection using high spatial resolution or hyperspectral remotely sensed data (*Franklin, 2001; Wulder, 2004; Soudani, 2006*). Franklin (2001) suggested that combining estimates of remote sensing attributes with the analytical utility of GIS and advanced forest process models give us a better understanding of the influence of disturbances and forest management.

Franklin (2001) noted that simple image transformations are very effective in understanding and enhancing differences between features in a scene and over time. Among the many available transformations, the Normalized Vegetation Difference Index (NDVI) is often used to look at the health of vegetation. In the near-infrared region of the spectrum, vegetation reflects high radiation. On the contrary, in the visible red of the spectrum, high absorption results in low radiation reflection. Consequently, changes in vegetation amount and cover are related to an increase in the difference between near-infrared and red radiation (*Wulder and Franklin, 2007*). Franklin (2001) notes that corrections to NDVI values and the use of various other indices have been applied; for example, the soil-adjusted vegetation index (SAVI) accounts for soil effects. Richards and Jia (2006) said that ratios of different spectral bands from the same image find use in reducing the effect of topography and for enhancing subtle differences in the spectral reflectance characteristics for rocks and soils.

3.5 How Roads Affect Wildlife and Vegetation Habitats

As urban areas spread, traffic congestion increases. Gillham and MacLean (2002) noted that approximately 91 % of all the person miles traveled in the United States are in privately owned automobiles. Trains, bikes, walking, airplanes, and other forms of transportation make up the remaining 9 %. Automobile dependency in the U.S. has influenced the U.S. transportation infrastructure and associated urban/suburban development. New houses, shopping malls, and office parks are opened, leading to further cycles of road building followed by more development.

Without developments of the high-speed traffic system around CVNP, people in the Cleveland and Akron Metropolitan Areas would inhabit an entirely different world, and landscape in the region would be completely unlike now. The environment of the valley changed significantly after infrastructure upgrades (e.g. the Ohio & Erie Canalway and railroads beside the canal) through the Cuyahoga Valley (*Platt, 2006*). In North America, roads and vehicles have expanded the web of our interactions and activities (*Forman et al., 2003*), and vehicles are indispensable for many city dwellers living out of urban areas. Forman et al. (2003) examined how road network patterns influence the ecological properties, watershed processes, and land uses at a broader landscape scale. This expansion of road networks has allowed more people to live on the periphery of urban areas or even outside of urban areas, and it can be considered one of the main reasons for urban sprawl in the U.S (*Forman et al., 2003; Miller and Wheeler, 1997*). They suggested three major road system properties that determine ecological responses – road density, road surface area, and traffic volume. Among these, the impact of road density relates to fragmentation of landscape and wildlife habitats, which results in increased vehicle accidents with wild animals on roads and reduces the wildlife habitat quality around the area (*Forman et al., 2003*). The changes in the Cuyahoga Valley started with the development of the Ohio & Erie Canalway, railroads system, and high-speed traffic system connected to outside Cleveland. The concern of transportation influence to the park is necessary to understand the change of the park environment.

3.6 Object-Oriented Image Analysis

Most land classification methods using remote sensing data are based on pixel-by-pixel analysis. These traditional land classification methods explore the spectral differences of various features to extract the thematic information. Although there are some “objects” that can be identified by a single pixel, most of land features are comprised from multiple pixels, comprising the larger objects. The traditional land classification methods mentioned earlier in this chapter, like supervised and unsupervised classification, have their limitations to obtain a high accurate classification image by distinguishing land surface features. All landscapes are characterized by degrees of heterogeneity (patchiness) at different scales because of differing substrates (soils, bedrock), natural disturbances (fire, insect outbreaks), and human activity (forestry, road building) (*Wulder and Franklin, 2007*). Heterogeneity in urban areas is even more complicated with different demands on land use. It is therefore difficult to obtain higher accuracies in classification maps using pixel-based classification in these urban areas. Most recently, object-oriented image analysis has been getting more and more attention as a new classification method in remote sensing.

The biggest advantage of the object-oriented classification (OOC) is that it not only looks at spectral properties of objects but also spatial patterns of object relationships such as shape, size, and relationships to surrounding objects or pixels (*Benz et al., 2004; Hay et al., 2005*). By analyzing spatial patterns, the OOC can distinguish features of objects that traditional classification can not (e.g. the difference between a river and a lake because they are different shapes). The OOC is being used more now because of the availability of higher resolution satellite data. Since 1999, several high-resolution sensors have been launched on commercial satellites. These sensors are better able to see smaller objects on ground. Hay et al. (2007) noted that a key driver in the object-based shift has been the dramatic increase in commercially available high resolution digital remote sensing imagery that is characterized by spatial resolutions 5.0m and finer (e.g. IKONOS – multispectral 4m and panchromatic 1m; QuickBird – multispectral 2.44m, and panchromatic 0.61m). The diversity and heterogeneity of land surface in human dominated places is more complicated with developments of our needs. It is more difficult for remote sensing analysts to classify aerial or satellite images by pixel-based classification techniques because of their heterogeneities.

The flexibility of the OOC can be very powerful and useful to classify complicated urban areas. However, Hay (2006) notes that a weakness of the OOC method is that object-oriented software provides overly complicated options in their analyses. Benz et al. (2004) described the main requirements of the information extraction process - 1) understanding of the sensor characteristics, 2) understanding of appropriate analysis scales and their combination, 3) identification of typical context and hierarchical dependencies, and 4) consideration of the inherent uncertainties of the whole information extraction system.

3.7 Geostatistical Methods Using GIS Technologies

Nowadays computer-based systems, GIS, are used to store and manipulate geographic information (*Franklin, 2001*). The multiple functions to manipulate geographic data are effective in many complex areas and give us more possibilities to solve environmental and social issues at different scales over time. Many phenomena on this earth are rarely understood based on just one or two observations. Most things are interrelated, and it is important to understand the interrelatedness. For example, the environment of Cuyahoga Valley has been influenced from different types of human activities (historical, recreational, agricultural, and transportation influences) for a long time. There are many human impacts that we cannot see usually. It is necessary to store and analyze all influences we can consider. The advantage of using GIS is not only to store and manipulate geographic information, but to spatially analyze natural phenomena statistically and assess the complex interconnections among the different components (*Christopherson, 2002*). In many cases, spatial statistics have been used to digest large quantities of information and to provide better understanding of spatial relationships (*Wong and Lee, 2005*). With the development of computers, GIS is able to handle larger quantities of information in a shorter time.

When landscape changes occur, there should be certain patterns of change. These characteristics of landscape changes give us a better understanding of how urban expansion patterns in a region have developed. Now many land classification and change studies use landscape metrics that address spatial landscape patterns based on analyzing the geometry and spatial arrangement of land use/land cover patches (*Narumalani et al., 2004; Novak and Wang, 2004; Yuan et al., 2005; Ji et al., 2006*). Frequently, Fragstats software (*McGarigal and Marks, 1995*) is used to compute landscape metrics and analyze patch sizes or spatial distribution.

Both Hoersch et al. (2002) and Hong at al. (2004) utilized Digital Elevation Model (DEM) data to consider their characteristic regions, which are mountain areas in Switzerland and South Korea. Elevation, slope, and aspect are important factors controlling the spatial heterogeneity of the landscape (*Hoersch et al., 2002*). Hoersch et al. (2002) said that the geographic space of vegetation types or species is equal to its spatial distribution, caused by natural factors and human impact. The regions like Switzerland and Korea, need to consider landform parameters (e.g. elevation, slope, and aspect) to model of vegetation distribution in mountain landscapes, because their influence on vegetation caused many difference in vegetation distribution. In their studies, Principal Components Analysis and regression methods were used, and their results showed high correlations between landform parameters. Their analyses using remote sensing and GIS with DEM data were able to create more information to the explanation of vegetation in their study areas. It can be interesting to apply this method in the Cuyahoga Valley because elevation inside the park changes quite much. However, it will be necessary to use higher resolution of dataset for the park.

Jiang (1995) utilized GIS to develop a tourist resort and decide day use site selection in the Cuyahoga Valley National Recreation Area with eleven factors – topography, slope, aspect, soil, vegetation, transportation, water, historical sites, land ownership, disturbance areas, and infrastructure. These days many forest remote sensing studies use statistical methods with GIS to analyze spatial patterns of anthropogenic phenomena on this earth. GIS can deal with complex and constantly changing data and geographic information, and enables us to respond rapidly to changing conditions (*Maantay and Ziegler*, *2006*).

CHAPTER 4

METHODOLOGY

4.1 Introduction

In this study, LANDSAT Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) remote sensing data were used to analyze spatial patterns of urban growth in seven counties around CVNP. Remote sensing is a powerful tool for studying environmental changes and the effects of urban development (*Martinuzzi et al., 2007*). Its ability to analyze the land surface spatially and to also analyze a wide range of spectral reflectance of earth materials helps us to better understand landscape and ecological changes. GIS was also used to analyze spatial and temporal changes of land surface around the park.

CVNP is a human-dominated environment (transportation, industry, agriculture, and recreation), and the valley is bound to be affected by these different impacts from human demands. It is therefore important to know the factors affecting the park environment (*Store and Kangas, 2001*) and create a new approach for both natural and historical preservation in the Cuyahoga Valley. However, there are so many human influence factors through its history inside the Cuyahoga Valley. Therefore, environmental changes both inside and outside the park will be considered how they changed differently through the past, and, at the same time, key human influence factors will be analyzed in this study. In this chapter, methodologies will be discussed under two main headings:

- The Extraction of Urban Expansion using Remote Sensing
- Landscape Change and Population Growth Analysis using GIS

4.2 The Extraction of Urban Expansion using Remote Sensing

4.2.1 Satellite Image Preprocessing: Geometric and Radiometric Correction

The remote sensing analysis in this study requires LANDSAT 5 TM and 7 ETM+ images between 1987 and 2006. Around CVNP, both Path18/Row31 and Path19/Row31 LANDSAT image scenes cover the majority of Cleveland and Akron Metropolitan Area. However, only images from Path19/Row31 cover all of Cuyahoga and Summit Counties, which include most of the major cities and townships around CVNP, Cleveland, and Akron, and also their adjacent counties (Geauga, Lake, Lorain, Medina, and Portage County – both Geauga and Portage include only parts of their areas (see Figure 1.2)). Therefore, Path 19/Row 31 LANDSAT TM and ETM+ images in April/10/1987, September/26/1999, and October/07/2006 were used for this study.

To analyze temporal changes around CVNP, it is better to use data from similar times of the year. However, because Northeast Ohio is often covered by clouds (especially around Lake Erie), and it is difficult to get completely cloud free images of different years in same month. Cloud presence can result in misclassification of the datasets. The satellite images for this study were the best cloud-free datasets that covered the timeframe of the study (Table 4.1). They were downloaded from the Ohioview website (*www.ohioview.org*) which provides free LANDSAT coverage of Ohio. The 1987 LANDSAT TM image is the oldest image with cloud cover free from the Ohioview website. The 1999 LANDSAT ETM+ shows the CVNP immediately before it was designated a National Park. The 2006 LANDSAT TM image is the latest cloud-free image over the CVNP. By improving accuracies of each classification image, the problem of different seasons will be considered less influential to the final results of this study.

Table 4.1 Satellite Data Used in This Study

Date	Satellite Type	Cloud Cover %
1987 April 10	LANDSAT TM	0
1999 September 26	LANDSAT ETM+	0
2006 October 07	LANDSAT TM	0

Remote sensing data usually contain both systematic (scan skew, platform velocity, Earth rotation, etc.) and unsystematic (altitude, attitude, etc.) geometric errors (*Jensen, 1986*). To obtain higher accuracy in the data sets it is necessary to correct these errors. All images were already geometrically rectified by USGS (the United States Geological Survey), therefore, no geometrical correction was applied for these images. Obtained LANDSAT TM/ETM+ images were projected as the World Geodetic System (WGS) 1983 Universal Transverse Mercator (UTM) Zone 17 North first. To fit all GIS data and remote sensing data, all LANDSAT images were transformed to the North American Datum (NAD) 1983 UTM Zone 17 North using PCI Geomatica.

Additionally, when satellite sensors record reflected or emitted radiation from land surface objects, atmospheric interference causes distortion in the satellite data. This distortion is unavoidable, but must be accounted for before further analysis. Correction of radiometric distortion is important for preparing the datasets for analysis, but the process of removing distortion is time-consuming and not an easy task. For this study, the Dark Object Subtraction (or histogram minimum method) is applied to all satellite data to reduce the atmospheric scattering. Dark Object Subtraction sets the lowest values (usually in water) to zero. The dark black color is therefore assumed to be the correct tone for a dark object in the absence of atmospheric scattering (*Campbell, 2002*). This procedure forms one of the simplest, most direct methods for adjusting digital values for atmospheric degradation. The minimum digital number (DN) value in the histogram from the entire scene is attributed to the effect of the atmosphere and is subtracted from all the pixels (*Song et al., 2001*). In this study the minimum DN value was selected as the darkest DN with had at least a thousand pixels in the entire of image assigned to it (after *Song et al. 2001*).

4.2.2 The Pixel-Based Classification Method

Remote sensing data of the Earth may be analyzed to extract useful thematic information. Multispectral classification is one of the most often used methods of information extraction (*Jensen, 1998*). Traditionally, there are two basic ways to assign pixels into thematic categories – supervised and unsupervised classification. Supervised classification procedures require considerable interaction with the analyst, who must guide the classification by identifying areas on the image that are known to belong to each category. The analyst selects the training sites, and the statistical analysis (minimum distance to means, parallelepiped classifier, maximum likelihood classifier, and others) is performed on the multiband data for each class (*Navulur, 2007*). On the other hand, unsupervised classification proceeds with only minimal interaction with the analyst, in a search for natural groups of pixels present within the image (i.e. generally groups that are not known a priori because information is lacking) (*Campbell, 2002*). Although supervised and unsupervised classifications are widely used, they have an inherent limitation in being based solely on the spectral characteristics of each individual pixel (*Aronoff, 2005*). Kuemmerle et al. (2006) suggested that it may be the best to combine both supervised and unsupervised techniques to improve data accuracy and he ended up showing better results in his study. Therefore, in this study, a hybrid classification, which uses both supervised and unsupervised classification techniques, was applied to the three satellite images in the study area.

First, unsupervised classification with the Iterative Self-Organizing Data Analysis Technique (ISODATA) was applied with the maximum cluster numbers (255 for PCI Geomatics: Geomatica 10.1) to all images to determine their clusters. Table 4.2 shows results of cluster reports for each unsupervised classification map. Second, the statistical classified data were put into seven categories (urban, forest, grassland, water, bare land, agriculture, and no data) using available ground truth or reference data, associate clusters with each ground cover types.

Table 4.2 Unsupervised Classification Cluster Report

Date	Algorithm	Input Channels	Number of Clusters
1987 April 10	Isodata Unsupervies	1, 2, 3, 4, 5, 6, 7	100
1999 September 26	Isodata Unsupervies	1, 2, 3, 4, 5, 61, 62, 7	116
2006 October 07	Isodata Unsupervies	1, 2, 3, 4, 5, 6, 7	98

Table 4.3 shows details of the land surface categories used in this study. This Land Use/Land Cover Classification scheme is adapted from the U.S. Geological Survey Land Use/Land Cover Classification System (*Anderson et al., 1976*). Most important for this study is the understanding of urban and forest land cover changes but many of urban areas in Cleveland and Akron Metropolitan Area are covered by trees making classification more difficult. For this reason, many of low density residential areas are recognized as forest by satellite sensors. It is therefore necessary to create a more specific definition of urban areas in Cleveland and Akron Metropolitan Area. In this study, if there was more than approximately 10 percent of tree cover visible on higher resolution aerial photographs or by recognitions of colors on LANDSAT TM/ETM+ data, a pixel (cluster/objects) was assigned to forest area. If there is exposure of impervious surface or domination by residential housing, a pixel was assigned to urban area.

Table 4.3 Land Use/Land Cover Classification

Land Class	Types of Land Surface
Urban Area	Residential, commercial and services, industrial, transportation area
Forest Area	Evergreen, deciduous, mixed forest (tree canopy accounts for more than approximately 10 percent of the cover)
Grassland Area	Grass, bush, pasture, orchards, shrub, wetland covered by grass
Water Area	Stream, canals, lakes, ponds, ocean, reservoirs
Bare Land Area	Beaches, sand and gravel, exposed rock, rock quarry area
Agriculture	Tillage, cropland (exposed more soil)
No Data	No data value

4.2.3 The Object-Oriented Classification Method

The object-oriented classification (OOC) takes a different approach to classifying satellite imagery. It uses a series of decisions similar to the human brain. For example when we survey a region with our eyes, we register that a certain area has a particular size, form, and color (*Definiens, 2007*). We usually don't focus on single objects but also consider relationships with other objects by breaking down those into various objects (*Navulur, 2007*). It is more natural for us to understand a scene by breaking the image up to recognize it by color, size, shape, and relationship between specific objects. People interpret remote sensing images the same way. We do not usually focus on single objects (or pixels) on a remote sensing image; we usually see surface objects like buildings, roads and fields that can be recognized by their shape, size, color, texture, and relationships with other objects. In remote sensing, an object can be defined as a grouping of pixels of similar Digital Numbers (*Navulur, 2007*). Traditional land classification methods assigns a pixel to a definite class by distinguishing the spectral reflectance from a specific area on the land surface but it does not have the ability to group pixels together as an object by using only spectral differences. By creating objects, not only spectral difference but also spatial differences, like area, length, width, or direction, can be considered to distinguish features more effectively. The object-oriented approach can also count interrelationships with other objects and use thematic GIS layers (*Definiens, 2007; Navulur, 2007*). In other words, there are various ways to classify or recognize land surface features by different aspects. The ability of the OOC to distinguish objects is very powerful against heterogeneity of land surface classification.

In object-oriented analysis, segmentation of images is the first processing stage and it is important for creating objects from groups of pixels. Segmentation is a process that aggregates homogenous neighboring pixels by computing internally three criteria: color, smoothness, and compactness (*Definiens, 2007*). In the other words, it minimizes the average heterogeneity of image objects and reduces number of heterogeneity on land surfaces. Figure 4.1 shows an example of image segmentation into objects from the study area. The size of the image objects is determined by the scale parameter, which is related to the image resolution that describes the maximum allowable heterogeneity of image objects (*Platt and Rapoza, 2008*). Hay et al. (2005) noted that the real challenge of object-oriented analysis is to define appropriate segmentation parameters (typically based on spectral homogeneity, size, or both) for the varying size, shape, and spatially distributed image-objects composing a scene, so that segments can be generated that satisfy user requirements. Platt and Rapoza (2008) suggested trying different parameters iteratively until the resulting objects are approximately sized and shaped for the particular task of interest.

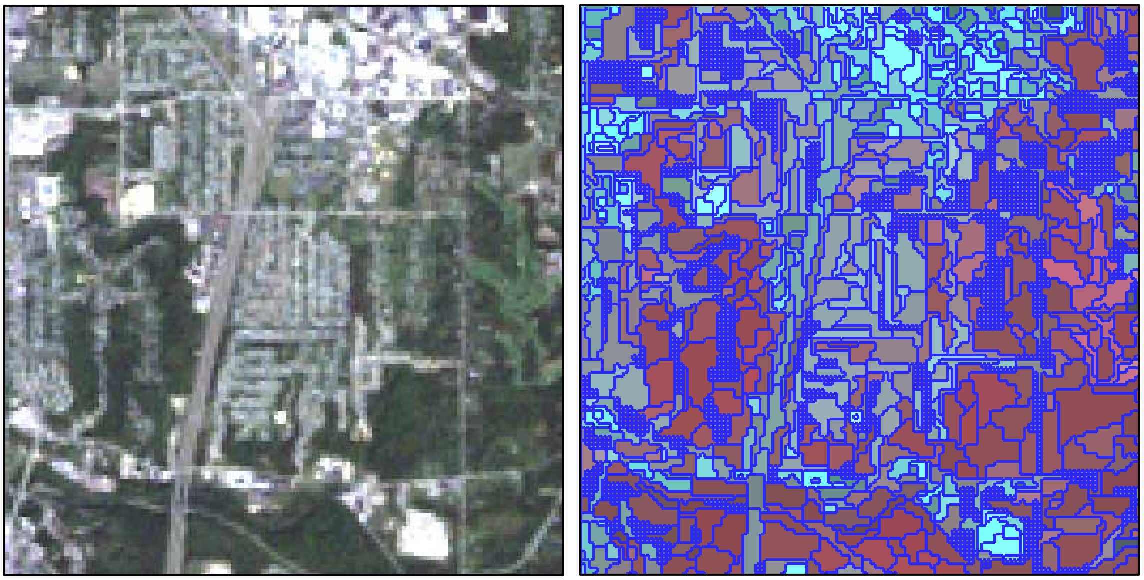


Figure 4.1 Segmentation of Satellite Image into Objects
(The left image shows LANDSAT TM true color image. The right image shows segmented image with Infrared color image.)

.

Furthermore, object-oriented analysis is able to build two or more image object levels called an image object hierarchy. Image object hierarchies can be created either above or below a current level, creating a simultaneous representation of image features at various scale levels that can then be used towards image classification (see Figure 4.2). An image object hierarchy is linked to neighbor objects within a same image object level horizontally and also a different image object level vertically. The lowest image object level has the finest image object resolution (smallest objects) and the highest image object level has the coarsest resolution (largest objects) (*Definiens, 2007*). Image object hierarchies are powerful in identifying certain characteristics on the ground, and they can be used to extract various features at different object sizes (*Navulur, 2007*). For example it is first easier to classify an image at a higher scale parameter (bigger objects), and then assign other hierarchies into newly created classes at different scales (smaller objects).

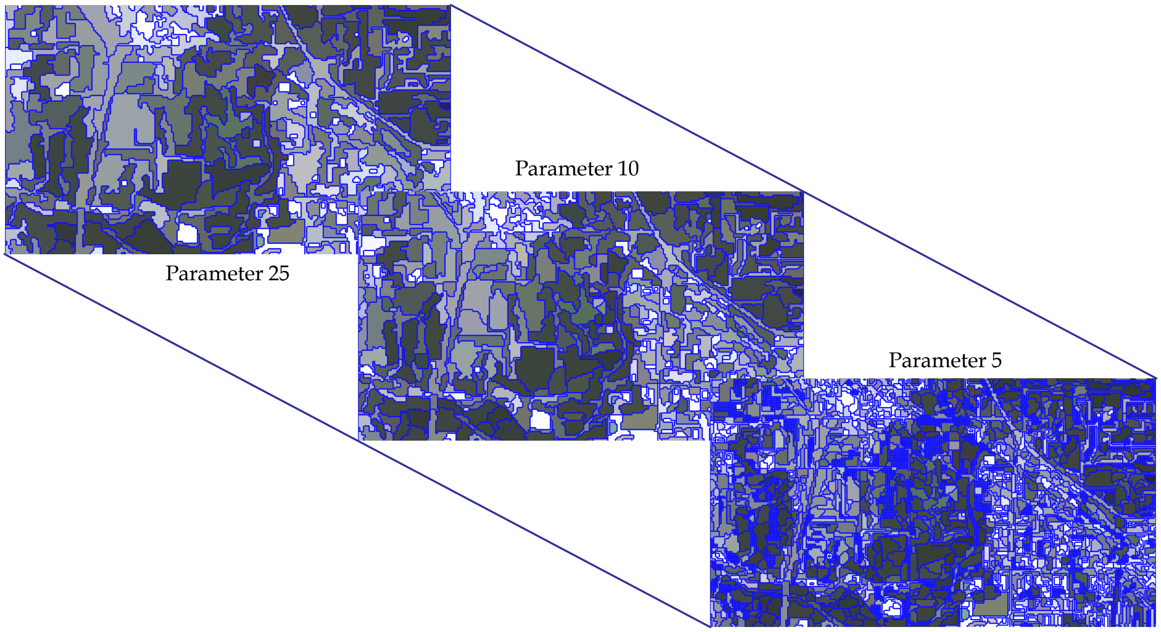


Figure 4.2 Image Objects Hierarchy

Image object hierarchies can reduce processing time to classify images by applying multiple scales, but the user input takes a longer time which many analysts do not like. Table 4.4 shows results of image segmentation from three satellite images.

Table 4.4 Results of Image Segmentation

Date	Level	Scale Parameter	Shape/Compact	Number of Objects
1987/4/10	1	5	0.3/0.5	771,297
	2	10	0.1/0.5	87,144
	3	15	0.1/0.5	41,185
	4	20	0.1/0.5	37,510
1999/9/26	1	5	0.3/0.5	927,135
	2	10	0.1/0.5	92,522
	3	15	0.1/0.5	41,674
2006/10/7	1	5	0.3/0.5	1,422,671
	2	10	0.1/0.5	73,899
	3	15	0.1/0.5	30,129

After creating image objects at different levels, image objects are classified according to their shapes, sizes, colors, textures, reflectance values, or relationships with neighbor objects. To begin the classification process, it is necessary to examine the attributes of image objects to decide what features can be distinguished through objects. Definiens Professional, which is the first general object-oriented image analysis software on the market (*Benz et al., 2004*), called an image object attribute a 'feature.' The available features are divided into four big categories – Object Features, Class-Related Features, Scene Features, and Process-Related Features. Table 4.5 shows some examples of object features. Using these object features, it is possible to develop a rule set for image classification that can result in aggregation of heterogeneous land surface characters into meaningful classes for their study areas.

Table 4.5 Object Features using in Definiens Developer Ell Earth

Object Features	customized	NDVI	(B4-B3)/(B4+B3)
		Simple Ratio	B4/B3
		Band Diff.	B4-(B3+B2)
			B3-(B2+B1)
	Layer Values	Mean	B1 to B7, Brightness, Max. Diff.
		Standard Deviation	B1 to B7
		To neighbors	mean diff. to neighbors
		Hue, Saturation, Intensity	
	Shape	Generic	Area, Asymmetry, Border length
			Density, length, width,
			Rectangular fit, …
		Position	x, y position
	Texture	texture after Haralick	GLCM: Gray Level Co-occurrence Matrix
			GLDV: Gray Level Difference Vector
Class-Related Features	Customized		
	Relations to neighbor objects		
	Relations to sub-object		
	Relations to super-object		
	Relations to classification		

After creating image object features, the Nearest Neighbor Classifier (NNC) was used to select feature classes. The NNC utilizes samples (typical representatives for each class) to search for the closest sample image object in the feature space (*Definiens, 2007*). Samples for each land classification were chosen from objects which are the most representative of land surface class category, and then the NNC was applied to other objects in a certain level. It is necessary to continue this process until you satisfy the classification image iteratively. After creating basic classification maps by the NNC, new levels of image object hierarchy were applied as super-object (bigger objects) or sub-object (smaller objects). The major reasons to create new levels are,

1. Reflectance values from bare fields and urban areas are very similar. First about the half of agricultural area in Lorain and Medina Counties was classified as urban because of this similarity of reflectance values. To distinguish these areas, segmentation in level 3 is easier to classify by rule-set classification (specification of features).
2. Residential areas in east and south Cleveland, Cleveland Heights and North Royalton, have dense tree cover. These areas tend to classify as forest, but they are highly populated areas. It was therefore necessary to create smaller objects and also chessboard segmentations for these forest and urban mixed areas, which must be analyzed pixel-by-pixel in specified areas.

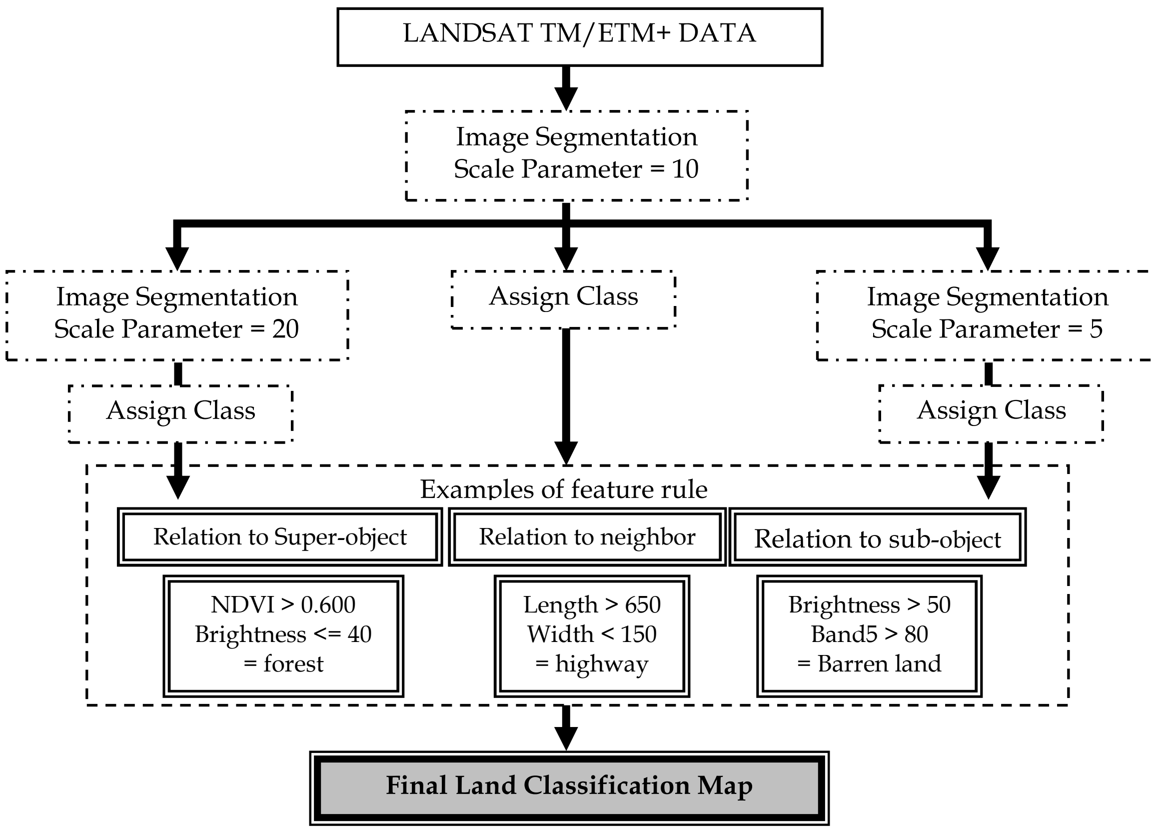


Figure 4.3 Workflow for the Object-Oriented Classification Maps

Figure 4.3 shows a workflow for object-oriented classification of the three image sets. Rule sets which were developed in this workflow were different by LANDSAT images because of differences in ground conditions when the images were recorded. For example, the image in 1987 shows very low reflectance in vegetation areas because it was recorded in early spring before grass or leaves were mature. Most of deciduous tree still did not have leaves on their branches, so soil dominated reflectance in forest areas, making it difficult to distinguish between forest and agriculture. The image in 2006 showed lower reflectance values in Band 4 for vegetation. The scene was recorded in early October, when fall foliage was starting. In contrast, the 1999 image was recorded in late September. The fall foliage was not started yet in the season, and most of forest showed greener forest areas (higher reflection in near-infrared) than the image in 2006. To account for these differences, segmentation of image objects was determined by image. Careful development of rule sets was required to obtain high accuracy in each classification map.

4.2.4 Assessing the Accuracy of Classification Maps

After completing the classification, accuracy assessments were undertaken. Accuracy assessments determine the quality of the information derived from remote sensing data (*Congalton and Green*, *1999*) and can reduce errors that lead to misinterpretation or inaccurate land classification change calculations (*Aronoff, 2005*). Errors are mostly caused by misidentification of parcels, excessive generalization, errors in registration, and variations in detail of interpretation (*Campbell, 2002*). Accuracy assessment needs reference data such as existing maps, high resolution aerial/satellite images, and field data. In this study topographical maps from the U.S. Geological Survey and high resolution satellite maps (the 2006 OSIP (Ohio Statewide Imagery Program) digital color infrared orthophotography and Google Earth), and field surveying data on different date (see Table 7.1) were used to determine the accuracy of classification maps. The assessment proceeds by an error matrix, which consists of an n×n array (n represents the number of categories). An error matrix identifies not only overall errors for each category but also misclassifications by category (*Campbell, 2002*). The columns usually represent the reference data, while the rows indicate remote sensing classification data. An error matrix also shows the errors of inclusion (commission errors) and errors of exclusion (omission errors). A commission error is simply defined as including an area into a category when it does not belong to that category, and an omission error is excluding that area from the category in which it truly does belong (*Congalton and Green, 1999*).

To do the accuracy assessment, random samples were collected from the classification maps. Accuracy assessment requires that an adequate number of samples per map class be gathered so that any analysis performed is statistically valid (*Congalton and Green, 1999*). The number of sample size differs by data size or number of classification categories. Jensen (1996) and Congalton and Green (1999) noted that a minimum of 50 samples for each category is a good rule of thumb. For this reason, I chose 300 samples for accuracy assessment to each classification map. However, the total number of pixels in each category is very different by regions. For example, pixels that are categorized as ‘bare land’ only add up to 3,135 out of 6,938,115 pixels (only 0.04% of the image). Therefore, the sample size for each category is statistically calculated and assigned depending on total percentage of pixels in each class by Geomatica 10.1.

After an initial inspection of the error matrix reveals the overall nature of the errors present, there is often a need for a more objective assessment of the classification (*Campbell, 2002*). The KAPPA ($\hat{K}$: K_{hat}) statistic is computed as

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}$$

where r is the number of rows in the matrix, x_{ii} is the number of observations in row i and column i, and x_{i+} and x_{+i} are the marginal totals for row i and column i, respectively, and N is the total number of observations (*Jensen, 1996*). The KAPPA statistic is a discrete multivariate technique used in accuracy assessment for statistically determining if one error matrix is significantly different than another (*Congalton and Green, 1999*). Overall accuracies include only diagonal elements (corrected samples), but the KAPPA statistic incorporates the off-diagonal elements (row and column) (*Jensen, 1996*). The value can range from +1 to -1. Congalton and Green (1999) noted that a value greater than 0.80 represents strong agreement; a value between 0.40 and 0.80 represents moderate agreement; and a value below 0.40 represents poor agreement.

4.2.5 Image Enhancement and Transformation

Vegetation change is not easy to detect unless there are large clear-cuts or wildfire burns in forests which we can easily recognize. It is therefore useful to use simple arithmetic ratios of pixel values from two bands of image data and transform those to a new image. To measure forest health, vegetation indices (VI) are widely used in remote sensing analyses. Ratios of different spectral bands from the same image, such as vegetation indices, tend to reduce the effect of topography, and enhance subtle differences in the ground spectral reflectance characteristics (*Richards and Jia, 2006*). The VI method reduces the multiple bands of data down to a single number per pixel that predicts vegetation conditions (*Jensen, 1996*).

Healthy green vegetation generally reflects 40% to 50% of the incident near-infrared energy (0.7 to 1.1μm), with the chlorophyll in the plants absorbing approximately 80% to 90% of the incident energy in the visible (0.4 to 0.7μm) part of the spectrum (*Jensen, 1996*). Using this spectral reflectance characteristics of vegetation, the near infrared band (Band 4 for TM and ETM+) and visible red band (Band3 for TM and ETM+) are utilized to show vegetation health on image screens. Among the many VI, a simple ratio (SR) and normalized difference vegetation index (NDVI) are commonly used to analyze vegetation using satellite data. These are characterized as:

$$SR = Band4/Band3$$

$$NDVI = (Band4-Band3)/(Band4+Band3)$$

Tasseled cap transformation and principal component analysis are also applied to help map vegetation (cf. *Jensen, 1996*). NDVI and SR are mostly used to create the OOC images, but other arithmetic transformations are used to detect subtle differences in images. For example, in this study, LANDSAT TM/ETM+: Band3 - (Band2 + Band1) is used to distinguish between urban and agriculture area in 2006 and 1999 images. A lot of tillage area emits similar spectral reflectance from the ground. However, tillage area shows more brown colors in a true color image (B: Band1, G: Band2, and R: Band3). Image transformation Band3 - (Band2 + Band1) enables to distinguish between urban and agriculture area well in this study area.

4.3 Landscape Change and Population Growth Analysis using GIS

4.3.1 The Post-Classification Analysis

Land classification change analysis is a useful way to see spatial changes over time. In this study three time difference images (1987, 1999, and 2006) are used to detect land classification changes around CVNP. There are many different types of change detection methods using satellite data developed *(Narumalani et al., 2004; Lunetta et al., 2004; Yuan et al., 2005; Im and Jensen, 2005; Nordberg and Evertson, 2005; Castellana et al., 2007; Shalaby and Tateishi, 2007*), but, among of these, the post-classification change detection algorithm is the most useful and appropriate to obtain quantitative changes in the Cleveland and Akron Metropolitan Area. This method requires careful rectification and classification of two images which can be compared on a pixel-by-pixel basis using a change detection matrix (*Jensen, 1996*). The post-classification analysis is useful to obtain specific land surface changes by each pixel and analyze patterns of regional and local changes.

In this thesis, land classification changes in three different geographic scales (metropolitan, county, and census subdivisions (cities/townships) level) were examined by the post-classification data. The study area includes Cuyahoga, Geauga, Lake, Lorain Medina, Portage, and Summit counties, but parts of Geauga and Portage counties are excluded because of the geometry of the satellite data. Therefore, the total area that this thesis considers is smaller than the total area for these seven counties (see Figure 1.2).

4.3.2 Multi Buffer Zones Analysis

To understand the pattern of urban expansion, multi-buffer zones analysis is a useful method to determine the spatial change in areas adjacent to the park and then at set distances from the park. Buffers can be created around points, lines, and also polygons. In this study five different distance buffers (1 mile, 3 mile, 5 mile, 10 mile, and 15 mile) were created from the outer boundary of CVNP. After creating the buffer zones, they changed to a raster data. Together with the post-classification maps previously created, land classification change patterns inside these buffer zones were analyzed by using raster calculator of ArcMap.

4.3.3 Overlay Analysis using Ancillary Data

Environmental Systems Research Institute (ESRI) provides The Census 2000 TIGER/Line® shapefiles from the Topologically Integrated Geographic Encoding and Referencing (TIGER) database of the United States Census Bureau (*ESRI*). Most of GIS shapefiles were obtained from ESRI but some of data were modified by the author to improve their accuracies. The boundary line of CVNP was obtained from National Park Service Geography and Mapping Technologies Geographic Information Systems (*National Park Service*).

(1) Population Change

The ability of GIS to handle information from many different sources can address more complicated environmental and social phenomena on the Earth for their sufficient solutions. Urban growth is usually associated with population concentration in the regions (*Jat et al., 2008*). With the spatial analysis ability of GIS, information of land classification changes from remote sensing can be more useful. GIS overlay analysis can integrate multiple layers of data on one map simultaneously, and can help us see interrelationships between different regions. By overlaying population/population density changes of cities and townships with urban change data, we can recognize more detail of the movement of people around CVNP. The relationship between population growth and urban area changes in the past is examined in census subdivisions. U.S. Census Bureau provides population census data in every 10 years, plus they estimated U.S. population in 2006. Using population census data in 1990, 2000, and 2006, the relationship with urban area changes around CVNP was examined statistically.

(2) Traffic Impact

Better and faster highway systems enable people to live further out in the suburbs, which create more environmental degradation including fragmentation of the landscape, increasing wildlife mortality, and spreading of chemical pollution in the air, water, and roadside vegetation (*Forman, 1995*; *Forman et al., 2003; Wilson et al., 2003*). Many researchers have studied the influence of traffic on the environment (*Forman and Devlinger, 2000; Forman et al., 20003; Wilson et al., 2003; Hawbaker et al., 2004*), but influences on vegetation and wildlife are difficult to determine because they are different by traffic volume, time, and location. In Northeast Ohio, construction of the national interstate highway system (Interstate 77, 80 (the Ohio Turnpike), and 271) helps people to live further from their work places and invites more people to the CVNP from further distances. Also railroads have been utilized as transportation for people and many other materials. They do not cause many wildlife mortalities like vehicles do, but they widely spread more non-native species around railroads (*Forman*, *1995*).

Road files from ESRI contain different types of Census Feature Class Codes (CFCC) providing information on the classification of line features. Codes A and B provides road and railroad information respectively. Table 4.6 shows the details of CFCC for road.

Table 4.6 Details of Census Feature Class Codes for Traffic Roads

CFCC	Detail
A1	Primary road with limited access or interstate highway
A2	Primary road without limited access, U.S. and State highway
A3	Secondary and connecting road, state and county highways
A4	Local neighborhood, and rural road, city street
A5	Vehicular trail, road passable only by 4WD vehicle
A6	Special road feature, major category used when the minor category could not be determined
A7	Other thoroughfare, major category used when the minor category could not be determined

In this study, roads between A1 to A3 level, which are considered main commuter roads in the study area, were used to see why people concentrated outside of major cities in the past and discussed future vision of Cleveland and Akron Metropolitan Area.

CHAPTER 5

COMPARISON OF REMOTE SENSING CLASSIFICATION RESULTS

5.1 Introduction

This chapter presents the results of the two different methodological approaches to classifying LANDSAT TM/ETM+ datasets for the Cleveland and Akron Metropolitan Area. They are assessed both qualitatively and quantitatively. The detailed methods for the classification are outlined in Chapter 4. However in summary the two methods were:

- A hybrid supervised/unsupervised classification using the ISODATA method in PCI Geomatica;
- The object-oriented classification using Definiens Developer.

Using each method, classification maps were created of the study area for the three different years (1987, 1999, and 2006). Each map was assigned seven land surface classes (urban, barren land, agricultural area, grassland, forest, water, and no data). Overall, the object-oriented classification (OOC) maps show higher accuracy in their results than the pixel-based classification (PBC) maps (Table 5.1). The rest of this chapter details the difference in results between the two methods.

Table 5.1 Summary of Overall Accuracies for Land Classification Maps

Year	Object-Oriented	Pixel-Based
2006	88.0%	79.0%
1999	87.3%	77.0%
1987	86.3%	73.0%

5.2 Visual Comparison

First of all, visual comparisons between the two classification maps were undertaken for both methodologies. Figure 5.1 (a), (b), and (c) displays all land classification maps created by both the OOC and PBC methodologies for 1987, 1999, and 2006 respectively. Urban areas around Cleveland and Akron spread both northward and southward of the CVNP from1987 to 2006.

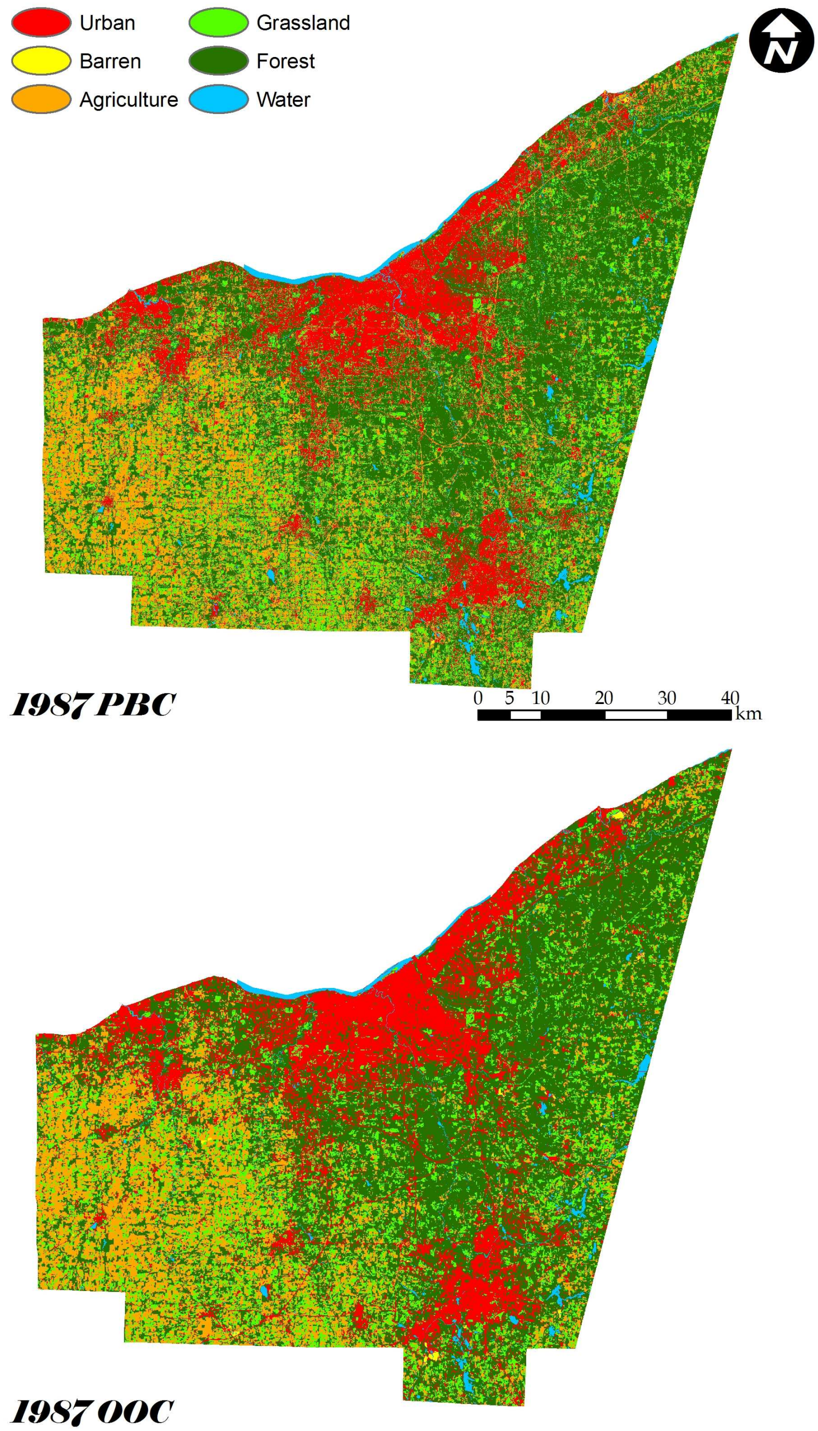


Figure 5.1 (a) Pixel-Based and Object-Oriented Classification Map in April 10, 1987

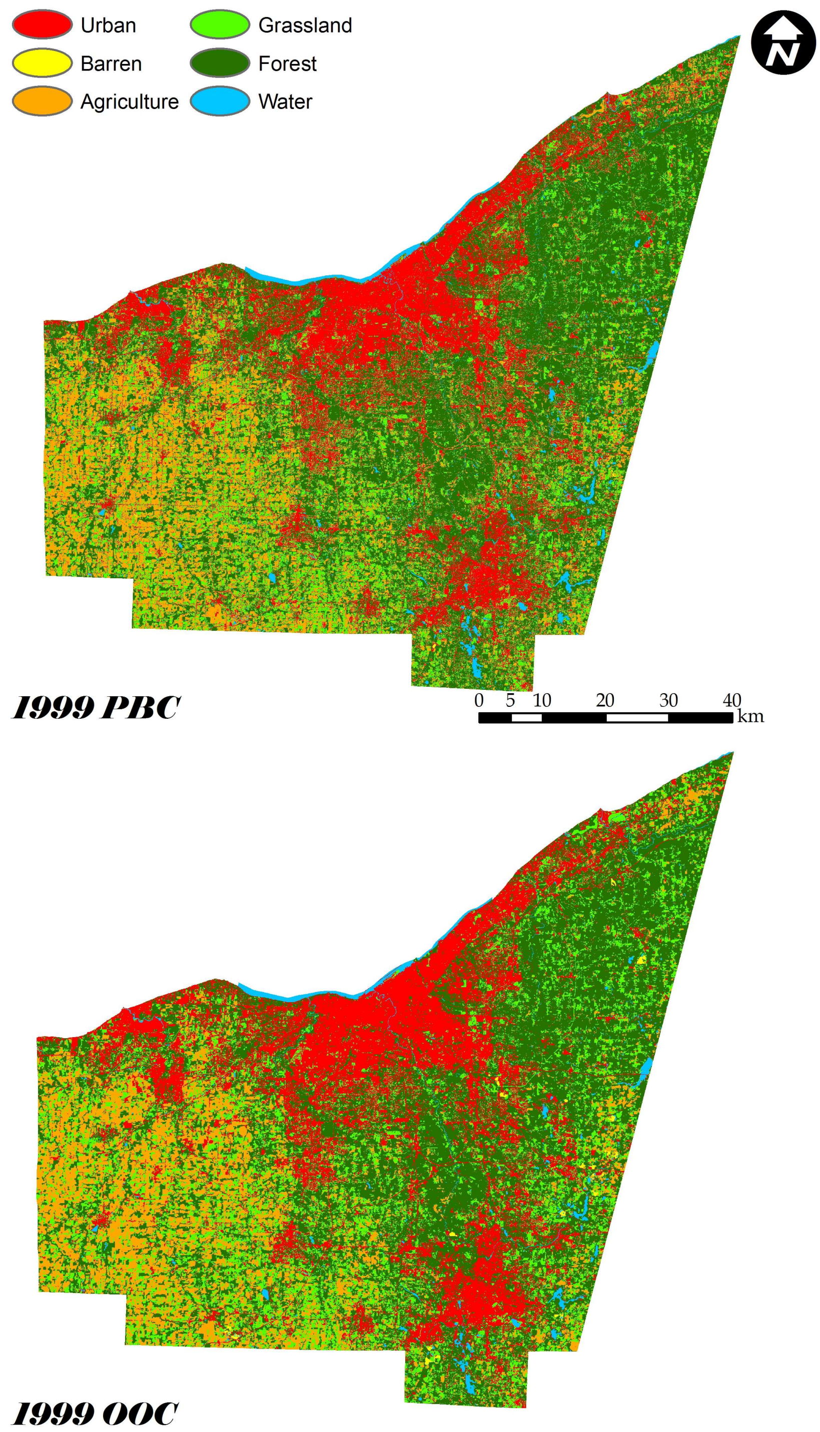


Figure 5.1 (b) Pixel-Based and Object-Oriented Classification Map in September 26, 1999

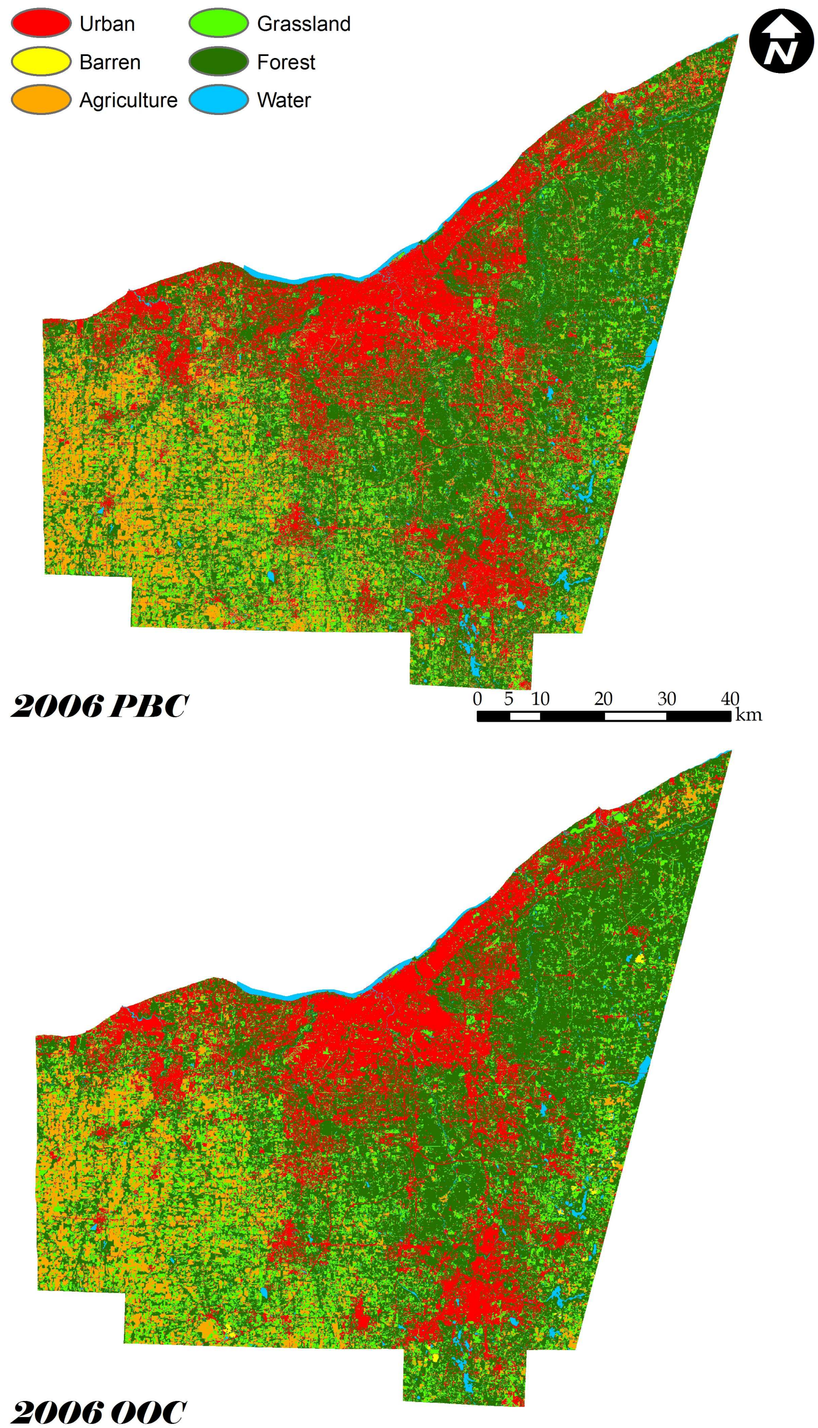


Figure 5.1 (c) Pixel-Based and Object-Oriented Classification Map in October 07, 2006

While these classification maps look quite similar, there are quite a few differences when each land classification category is carefully checked. The total land classification areas in each category of each year are summarized in Table 5.2. Table 5.3 shows the summary of land classification areas by county for each of the methods used.

Table 5.2 Total Land Classification Areas in Study Area

LULC Km^2	2006		1999		1987	
	OOC	PBC	OOC	PBC	OOC	PBC
Urban	1,468.6	1,476.8	1,454.4	1,276.8	1,227.8	1,111.2
Barren Land	9.8	2.8	11.4	8.4	9.5	8.3
Agriculture	535.6	726.1	848.1	988.6	1,007.9	1,035.6
Grassland	1,204.4	1,043.1	1,224.8	1,073.9	934.1	1,123.9
Forest	2,920.7	2,852.6	2,610.4	2,754.9	2,953.9	2,826.2
Water	105.1	142.9	95.2	141.7	110.9	139.1

Table 5.3 (a) Total Land Classification Areas in Each County for Object-Oriented Classification Maps

1987 OOC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	542.6	16.6	108.5	186.6	98.7	32.0	242.7	1,227.7
Barren Land	0.5	0.9	1.6	1.5	1.0	1.3	2.8	9.5
Agriculture	13.8	35.8	29.8	470.1	340.4	52.2	65.4	1,007.6
Grassland	94.9	82.8	54.8	209.6	263.5	79.4	148.9	933.9
Forest	531.0	447.9	337.7	400.6	383.8	247.2	605.3	2,953.4
Water	32.1	12.1	6.6	10.9	7.6	19.7	21.8	110.9
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

1999 OOC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	617.5	25.6	113.9	221.4	117.8	55.8	302.3	1,454.3
Barren Land	1.2	1.2	0.5	0.0	1.5	4.7	2.3	11.4
Agriculture	7.8	17.5	21.5	428.1	292.6	45.2	35.2	847.9
Grassland	126.9	111.8	96.6	280.8	315.3	104.5	188.5	1,224.4
Forest	431.7	429.6	301.0	342.6	360.9	204.1	540.1	2,610.0
Water	29.8	10.4	5.6	6.3	7.0	17.5	18.6	95.1
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

2006 OOC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	592.8	31.2	123.5	240.4	140.6	55.4	284.4	1,468.4
Barren Land	0.0	1.4	0.3	0.2	1.7	4.9	1.4	9.8
Agriculture	2.2	7.0	17.8	297.7	172.5	21.0	17.3	535.4
Grassland	105.5	95.2	70.7	320.9	342.6	99.4	169.7	1,204.1
Forest	483.0	449.3	319.7	412.0	429.7	231.7	594.7	2,920.1
Water	31.4	12.0	7.0	8.1	8.0	19.2	19.3	105.1
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

unit: km^2

Table 5.3 (b) Total Land Classification Areas in Each County for Pixel-Based Classification Maps

1987 PBC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	492.1	18.4	81.0	188.6	101.5	28.3	201.0	1,111.0
Barren Land	1.8	0.4	1.5	1.6	0.9	0.2	1.8	8.3
Agriculture	62.2	36.9	52.7	426.7	289.6	57.0	110.2	1,035.3
Grassland	114.5	95.8	73.5	240.7	306.1	98.2	194.9	1,123.6
Forest	506.7	429.1	319.5	408.3	384.9	223.5	553.7	2,825.7
Water	37.6	15.5	10.8	13.3	12.0	24.5	25.3	139.1
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

1999 PBC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	543.5	21.4	100.0	219.2	114.3	45.6	232.7	1,276.7
Barren Land	0.6	0.1	0.1	3.1	2.2	1.0	1.3	8.4
Agriculture	63.7	33.5	41.9	402.0	274.1	66.8	106.3	988.4
Grassland	100.9	87.5	64.9	269.0	308.0	82.7	160.6	1,073.6
Forest	466.4	438.2	321.9	375.0	383.3	212.3	557.3	2,754.4
Water	39.8	15.5	10.1	11.0	13.2	23.2	28.8	141.6
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

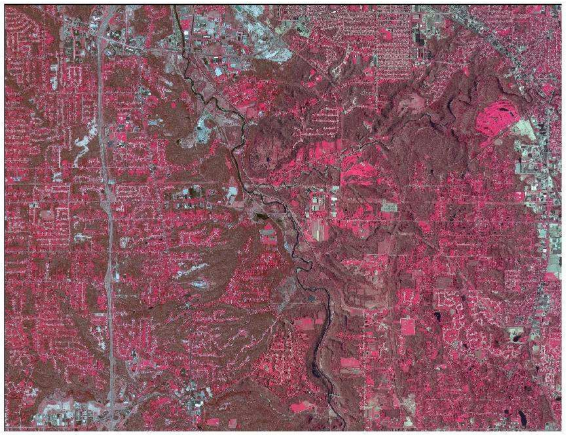
2006 PBC	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit	TOTAL
Urban	589.5	35.4	133.0	254.6	135.6	53.1	275.4	1,476.6
Barren Land	0.9	0.1	0.2	0.3	0.3	0.1	0.9	2.8
Agriculture	27.5	19.5	24.7	337.6	221.6	38.6	56.3	725.8
Grassland	93.2	89.7	60.3	246.9	299.5	92.5	160.7	1,042.8
Forest	465.6	432.8	309.2	427.9	425.8	224.0	566.6	2,852.0
Water	38.2	18.5	11.6	11.9	12.3	23.3	27.1	142.9
TOTAL	1,214.9	596.1	539.0	1,279.3	1,095.1	431.7	1,087.0	6,243.0

Unit: km^2

(1) Urban Areas

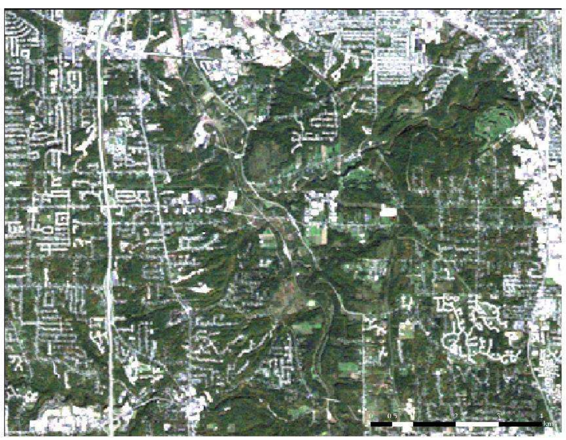
All urban classified areas in each year show similar characteristics in their concentrations around both Cleveland and Akron (see Figure 5.1). Through 1987 to 2006, gradual urban expansion around CVNP can be seen on both methodology maps. At a scale of around 1: 250,000 and less, both the OOC and PBC maps look quite similar. However, on closer examination there are many differences in their results.

First, the reduction of single disconnected pixels on the OOC maps is considered one of the biggest differences in two methodologies. Figure 5.2 shows an example of urban areas from the study area. The PBC map shows more disconnected pixels (a single pixel) in its urban areas, while the OOC shows less small urban objects on the image. This difference can be recognized in both Tables 5.2 and 5.3. In all cases the urban areas derived from the OOC method shows bigger areas than urban areas derived from the PBC method. The reduction of unconnected single pixels can be recognized especially in commercial or industrial areas where the OOC method usually created bigger objects, usually because of the larger impervious space. On the contrary, the PBC identifies more lower-density residential areas than the OOC. This is probably because the majority of suburban areas outside Cleveland and Akron Cities are covered by trees. The OOC assigned these areas mostly as forest or grassland, because objects in these residential areas contained large areas of vegetation reflection. The PBC shows better classification results in lower-density residential areas (see Figure 5.2), but, at the same

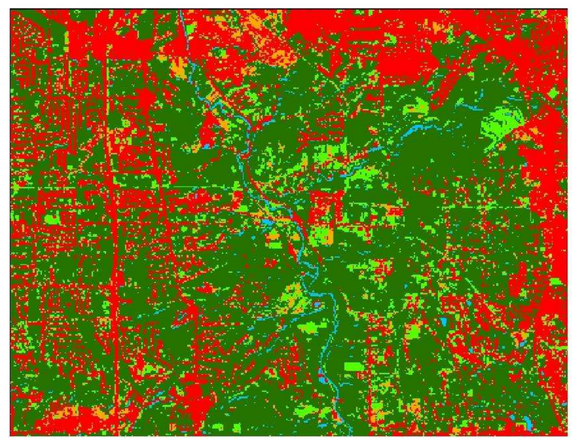


The 2006 Digital Color Infrared Orthophotography

The 2006 Object-Oriented Classification



The 2006 LANDSAT TM True Color Image



The 2006 Pixel-Based Classification

Figure 5.2 Comparison between Object-Oriented and Pixel-Based Classification Maps in suburban Area time, there are still too many single misclassification pixels that can be seen in residential areas.

The OOC method identifies freeways (roads >= 30 m wide) very well. The result clarified the advantage of the OOC method which recognizes shapes on classified maps. Many parts of freeways on the PBC are classified as agricultural areas because of the similarity in reflectance from medians and ditches to agricultural areas. As an example, significant portions of Route 480 and Route 271 were classified as agricultural areas on the PBC map in 1987 (Figure 5.1 (a)). The majority of agricultural objects in 1987 look very similar to urban areas. The PBC could not separate these agricultural areas and freeways very successfully. Freeways usually have narrower and longer objects in segmentation of the OOC maps. Using their characteristics, a specific rule set for the OOC maps was built for each year (e.g., for 1999 image, Length >= 900 m at Level 3 assigned as urban area) which significantly reduced the confusion between urban freeways and agricultural areas.

(2) Barren Land

Most of the misclassifications using the PBC method were related to mapping barren land. The reflectance from commercial and industrial areas and barren land showed similar high reflectance in all bands. As a result, some of commercial and industrial areas were recognized as barren land, and some barren land was recognized as urban. On the OOC maps, a rule set using relations with super-objects, which are higher (or bigger) objects, was utilized to solve this problem. Super-objects in a higher level of image objects were created first on the OOC maps. Then any smaller objects related to super-objects of barren land areas were assigned as barren land areas.

(3) Forest Areas

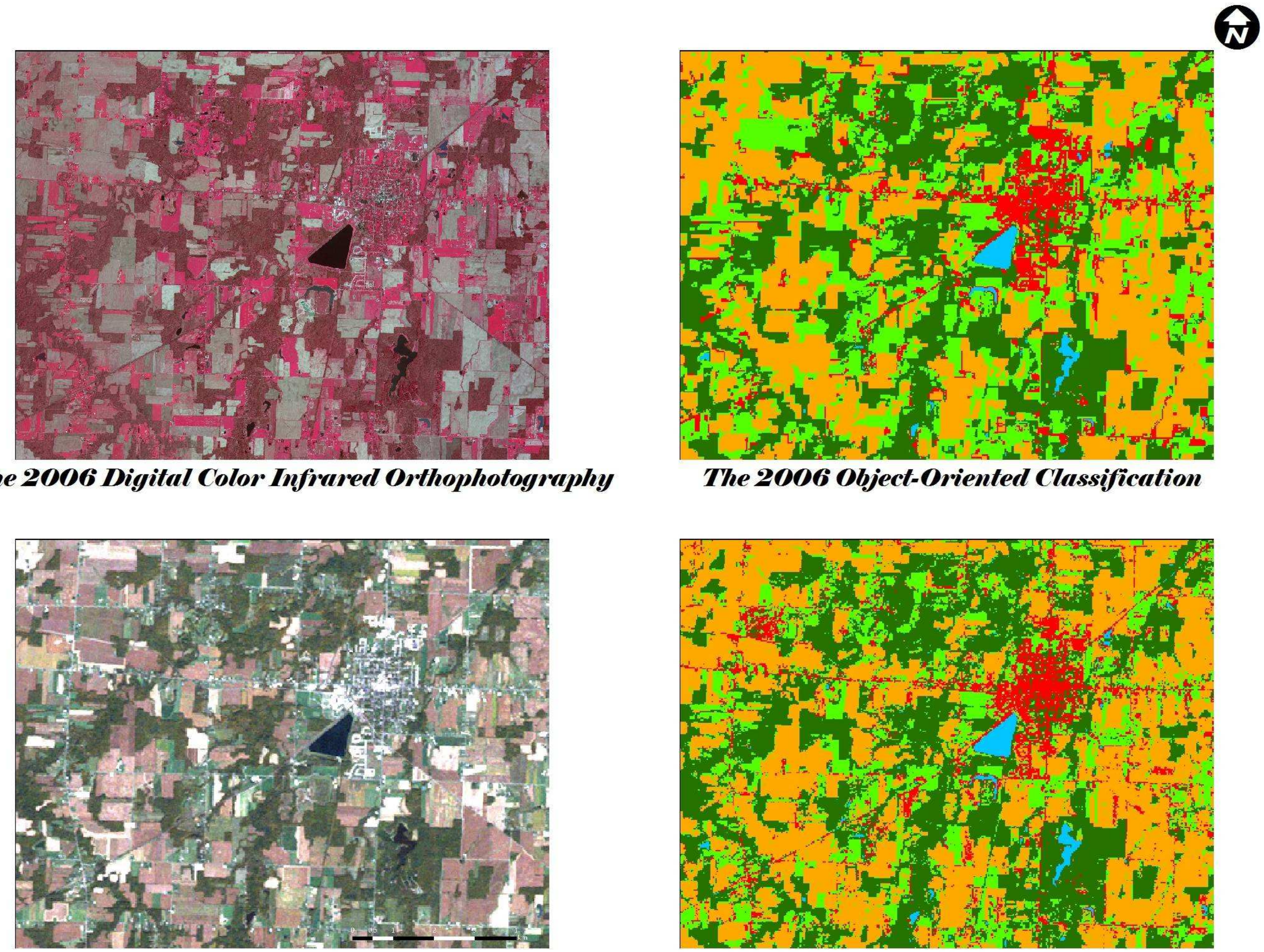
In forest areas, the differences between the OOC and PBC maps are quite similar to urban areas. The PBC maps have more disconnected single pixels in their forest classified areas. Most of these disconnected pixels are classified as either grassland or water. The areas classified as grassland can often be considered less dense forest where grassland (or shrubs) can be seen between trees. Areas misclassified as water are usually shaded areas enclosed by trees as shaded areas (shadows) have low spectral reflectance value like water. The OOC maps have more forest areas in single residential houses in suburban areas. This is because the rule set for the OOC maps is assigned to classify these objects between houses as forest areas.

(4) Water Areas

The results in water areas on the PBC and the OOC maps, especially lakes and ponds, are quite similar. Both classification methods classified larger water bodies well, but many rivers running through treed areas could not identified by the OOC. When objects were created, many rivers were identified as parts of other objects. Many rivers on the OOC needed to be classified manually. In general there were less rivers classified on the OOC maps because the scale parameters for objects were not small enough to recognize small rivers. As a result, the PBC maps have more water areas than the OOC maps. The PBC maps also have a lot of misclassified pixels as water in forest areas. When unsupervised classification clusters created, clusters for water areas included many of shadow areas in forests. As the result, there are a lot of unconnected water classified pixels seen in forest areas.

(5) Agricultural Areas

Agricultural areas occur extensively in the south potion of Lorain County and the west potion of Medina County. In these areas, the PBC maps identified farm roads (roads less than 30 m) better than the OOC maps did (Figure 5.3). These narrow roads are usually less than 15m (measured on GoogleEarth), but reflectance is similar to that in urban area. The OOC could not create objects for these pixels, but the PBC identified many of these single pixels as farm roads. In farm areas, both the OOC and PBC maps classified some land as urban. To reduce these misclassification, an arithmetic calculation of mean bands (e.g., Band3 - (Band2 + Band1) or Band 7/Band 5), texture, or shape rule-sets (area, length, rectangular fit, and more) were utilized to distinguish urban and agricultural areas. Tillage areas show brown color on the true color image (LANDSAT TM/ETM+ Band1 as blue, Band2 as green and Band 3 as red color). That means high reflectance from both Band 3 and Band 2. Using the arithmetic calculation, if Band 3 – (Band 2 + Band 1) shows positive value, then many of image objects were set to agricultural areas. Agricultural areas create bigger objects compared with other land feature objects. The advantage of identifying objects size and shape of the OOC can help identify



The 2006 Digital Color Infrared Orthophotography

The 2006 Object-Oriented Classification

The 2006 LANDSAT TM True Color Image

The 2006 Pixel-Based Classification

Figure 5.3 Comparison between Object-Oriented and Pixel-Based Classification Maps in Agricultural Area these differences in their image objects. As the result, the OOC maps showed better results in agricultural areas.

(6) Grassland

The difference in classifying grassland between the PBC and the OOC can be seen mostly in those areas surrounded by trees. As an example, on the 2006 PBC map, many unconnected pixels classified as grassland can be seen in forest areas. Grassland usually reflects higher in brightness and NDVI values. Inside forest, less density forests shows similar reflectance values like grassland. The PBC method detects these small differences in reflectance values from satellite images, but most of these pixels are not necessary to classify as grassland.

5.3 Accuracy Assessment by Error Matrix

Table 5.4 (a) and (b) displays all error matrices for the PBC and OOC maps including the overall accuracies and producer's and user's accuracies. The OOC maps have an average of 10.9 % higher in accuracies for all years. All error matrices were examined as follows.

Table 5.4 (a) Error Matrices for the Pixel-Based Classification Maps

1987 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	48	0	0	7	0	0	55	52.7%	87.3%
Barren Land	21	2	1	0	0	0	24	25.0%	8.3%
Agriculture	9	4	29	4	0	0	46	78.4%	63.0%
Grassland	3	0	5	41	3	0	52	69.5%	78.8%
Forest	8	2	2	7	80	1	100	94.1%	80.0%
Water	2	0	0	0	2	19	23	95.0%	82.6%
Total	91	8	37	59	85	20	300	Overall Accuracy	73.0%

1999 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	56	0	3	4	3	1	67	66.7%	83.6%
Barren Land	21	7	4	0	0	0	32	87.5%	21.9%
Agriculture	6	1	27	1	5	0	40	69.2%	67.5%
Grassland	0	0	5	30	11	0	46	81.1%	65.2%
Forest	1	0	0	1	92	0	94	82.1%	97.9%
Water	0	0	0	1	1	19	21	95.0%	90.5%
Total	84	8	39	37	112	20	300	Overall Accuracy	77.0%

2006 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	49	0	2	1	5	0	57	62.0%	86.0%
Barren Land	26	7	0	0	0	0	33	87.5%	21.2%
Agriculture	1	1	32	5	2	1	42	94.1%	76.2%
Grassland	0	0	0	38	8	0	46	80.9%	82.6%
Forest	0	0	0	3	92	2	97	83.6%	94.8%
Water	3	0	0	0	3	19	25	86.4%	76.0%
Total	79	8	34	47	110	22	300	Overall Accuraccy	79.0%

Figure 5.4 (b) Error Matrices for the Object-Oriented Classification Maps

1987 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	60	0	3	2	4	2	71	89.6%	84.5%
Barren Land	2	22	1	0	0	0	25	100.0%	88.0%
Agriculture	0	0	26	2	0	0	28	86.7%	92.9%
Grassland	0	0	0	37	3	1	41	75.5%	90.2%
Forest	5	0	0	8	95	2	110	92.2%	86.4%
Water	0	0	0	0	1	24	25	82.8%	96.0%
Total	67	22	30	49	103	29	300	Overall Accuracy	88.0%

1999 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	52	1	2	3	1	1	60	89.7%	86.7%
Barren Land	1	21	0	6	1	0	29	91.3%	72.4%
Agriculture	2	0	40	1	1	0	44	93.0%	90.9%
Grassland	1	0	1	47	1	0	50	71.2%	94.0%
Forest	2	0	0	9	84	1	96	93.3%	87.5%
Water	0	1	0	0	2	18	21	90.0%	85.7%
Total	58	23	43	66	90	20	300	Overall Accuracy	87.3%

2006 — Reference Data

Thematic Data	Urban	Barren Land	Agriculture	Grassland	Forest	Water	Total	Producer's Accuracy	User's Accuracy
Urban	49	0	3	3	0	0	55	84.5%	89.1%
Barren Land	3	19	3	2	0	0	27	100.0%	70.4%
Agriculture	2	0	41	2	4	0	49	85.4%	83.7%
Grassland	1	0	0	50	0	0	51	73.5%	98.0%
Forest	3	0	1	10	76	1	91	95.0%	83.5%
Water	0	0	0	1	0	26	27	96.3%	96.3%
Total	58	19	48	68	80	27	300	Overall Accuracy	87.0%

(1) Error Matrices for the Pixel-Based Classification Maps

The producer's accuracies for the 2006 PBC map are more than 80% except for the urban class (62.0%). The producer's accuracy for urban areas is lower due to misclassification of urban mostly as barren land. 26 pixels out of 79 classified areas as barren land were actually urban areas on reference data. Many of these urban areas classified as barren land are located in either commercial or industrial areas. The same situation could be said both on the 1999 and 1987 PBC maps. The misclassification of urban as barren land decreased all of the urban area producer's accuracies and user's accuracies in each year. The 1999 PBC map had a little higher producer's accuracy in urban the urban class, but it is still below 70% (66.7%). The percentage cannot be said high enough to rely on the data accuracy. The 1987 PBC map has the lowest accuracy in its urban area (52.7%). On the 1987 PBC map, actual urban areas on the reference data were assigned not only in barren land but also to agriculture and forest areas. These misclassifications can be seen visually on the 1987 PBC map (Figure 5.1 (a)).

Agricultural areas in 1999 and 1987 showed lower producer's accuracies (below 70%). The reason for this seems to be considered from unconnected single pixels in farm areas. On the other hand, forest areas show higher accuracies (more than 80% in each year) in their results. However, like agricultural areas, there are many unconnected single pixels classified as grassland, water, and other. These misclassified single pixels decreased the actual forest areas significantly. It is difficult for the pixel-based method to avoid these unconnected single pixels.

(2) Error Matrices for the Object-Oriented Classification Maps

The average of producer's accuracy for urban area is 87.9%, which is moderately high. Even though the producer's accuracy for urban area in 1987 is little bit lower than other two maps (84.5% (1987) versus 89.6% (2006) and 89.7% (1999)), it can be considered as an acceptable level. Another consideration for urban areas on the OOC maps is the low user's accuracy for urban areas. The reason for lower accuracy in 1987 is considered as a result of misclassification in residential areas. Mixed pixels with urban and forest areas in suburban areas confused the object-oriented method. The heterogeneity in suburban areas is very strong, and it is difficult for middle resolution satellites like LANDSAT TM/ETM+ data to separate residential houses and forest/grassland areas. As the result, the producer's accuracies for grasslands showed a fairly low percentage, too (75.5% for 2006, 71.2% for 1999, and 73.5% for 1987). These misclassifications also occurred in suburban areas in the study area or on the boundaries between forest and grassland. Most of misclassifications were assigned to forest each year. Considering these issues of misclassification of residential areas, the results of urban areas could be higher than that obtained. Other land surface classification shows high percentages both in producer's accuracy and user's accuracy.

(3) Statistical Comparison

Table 5.5 shows a descriptive statistic in the results of accuracy assessment for the OOC and PBC maps. Overall, the OOC showed better accuracies in their results. Both mean overall accuracy and producer's accuracy showed more than 10% difference as results. The user's accuracy of the OOC was 17% higher than the PBC. To see more detail, KAPPA statistics for each classification maps are shown on Table 5.6. KAPPA statistics for the OOC also showed better results than the PBC. All of the OOC maps showed more than 0.830 in their KAPPA statistics, meanwhile the average of the PBC KAPPA statistics is 10% lower than the OOC.

Table 5.5 Comparison between the Object-Oriented and Pixel-Based Classification Error Matrix

Classification	Mean Accuracy	Std. Deviation	Avg. Producer	Avg. User
Object-Oriented	87.9	2.974	88.3	87.6
Pixel-Based	76.3	3.055	77.3	70.2

Table 5.6 KAPPA Statistics

Year	OOC	PBC
2006	0.845	0.732
1999	0.841	0.704
1987	0.839	0.658

5.4. Summary

In conclusion the OOC maps showed better results for each year. In general the OOC showed better and bigger classified objects, while the PBC was good at detecting single houses or small objects like farm roads in some suburban areas and agricultural areas. However, on the other hand, there are many unconnected misclassified pixels all over the PBC maps. These small unconnected pixels will influence the total areas of each land classification category. From this point all analysis for urban changes and expansion patterns in this study area will look only at classification maps derived by the object-oriented methodology. Even though there were some small misclassifications on the OOC maps, they showed more acceptable accuracies (more than 85%) than the PBC.

CHAPTER 6

URBAN EXPANSION ANALYSIS

6.1 Introduction

In this chapter, patterns of land surface classification change are analyzed using ArcMap9.2, GIS software. Both the post-classification method and buffer zones analysis were applied to detect land surface classification changes around the CVNP from 1987 to 2006. As it is written in Chapter 4, satellite data, LANDSAT TM/ETM+ Path 19 and Row 31, did not cover the entire area of Geauga and Portage Counties. Therefore, results in these two counties only account for part of each county (page 30). After analyzing patterns of land surface classification change, population growth patterns comparing with increases of urban areas were examined using urban growth index.

6.2 Land Classification Pattern Analysis using GIS

6.2.1 The Post-Classification Results

Three land classification maps derived from the object-oriented classification method were utilized to analyze land surface classification changes in the study area. The individual land classification areas (in both km^2 and as a percentage) and relative land classification change (as a percentage) by county levels in 1987, 1999, and 2006 are summarized in Table 6.1.

Table 6.1 Land Surface Classification Change in the Study Area

Land Cover Class		Year						Total Change
		1987	%	1999	%	2006	%	1987 - 2006
Cuyahoga	urban	542.6	44.7%	617.5	50.8%	592.8	48.8%	9.2%
	barren land	0.5	0.0%	1.2	0.1%	0.0	0.0%	-98.0%
	agriculture	13.8	1.1%	7.8	0.6%	2.2	0.2%	-83.9%
	grassland	94.9	7.8%	126.9	10.4%	105.5	8.7%	11.2%
	forest	531.0	43.7%	431.7	35.5%	483.0	39.8%	-9.0%
	water	32.1	2.6%	29.8	2.5%	31.4	2.6%	-2.2%
Geauga	urban	16.6	2.8%	25.6	4.3%	31.2	5.2%	88.1%
	barren land	0.9	0.1%	1.2	0.2%	1.4	0.2%	57.0%
	agriculture	35.8	6.0%	17.5	2.9%	7.0	1.2%	-80.5%
	grassland	82.8	13.9%	111.8	18.8%	95.2	16.0%	15.0%
	forest	447.9	75.1%	429.6	72.1%	449.3	75.4%	0.3%
	water	12.1	2.0%	10.4	1.7%	12.0	2.0%	-1.0%
Lake	urban	108.5	20.1%	113.9	21.1%	123.5	22.9%	13.9%
	barren land	1.6	0.3%	0.5	0.1%	0.3	0.0%	-83.1%
	agriculture	29.8	5.5%	21.5	4.0%	17.8	3.3%	-40.5%
	grassland	54.8	10.2%	96.6	17.9%	70.7	13.1%	29.1%
	forest	337.7	62.7%	301.0	55.8%	319.7	59.3%	-5.3%
	water	6.6	1.2%	5.6	1.0%	7.0	1.3%	5.1%
Lorain	urban	186.6	14.6%	221.4	17.3%	240.4	18.8%	28.8%
	barren land	1.5	0.1%	0.0	0.0%	0.2	0.0%	-88.7%
	agriculture	470.1	36.7%	428.1	33.5%	297.7	23.3%	-36.7%
	grassland	209.6	16.4%	280.8	21.9%	320.9	25.1%	53.1%
	forest	400.6	31.3%	342.6	26.8%	412.0	32.2%	2.8%
	water	10.9	0.9%	6.3	0.5%	8.1	0.6%	-26.1%
Medina	urban	98.7	9.0%	117.8	10.8%	140.6	12.8%	42.4%
	barren land	1.0	0.1%	1.5	0.1%	1.7	0.2%	68.8%
	agriculture	340.4	31.1%	292.6	26.7%	172.5	15.8%	-49.3%
	grassland	263.5	24.1%	315.3	28.8%	342.6	31.3%	30.0%
	forest	383.8	35.0%	360.9	33.0%	402.7	36.8%	4.9%
	water	7.6	0.7%	7.0	0.6%	8.0	0.7%	5.1%
Portage	urban	32.0	7.4%	55.8	12.9%	55.4	12.8%	73.6%
	barren land	1.3	0.3%	4.7	1.1%	4.9	1.1%	288.3%
	agriculture	52.2	12.1%	45.2	10.5%	21.0	4.9%	-59.8%
	grassland	79.4	18.4%	104.5	24.2%	99.4	23.0%	25.2%
	forest	247.2	57.3%	204.1	47.3%	231.7	53.7%	-6.3%
	water	19.7	4.6%	17.5	4.1%	19.2	4.5%	-2.3%

Summit	urban	242.7	22.3%	302.3	27.8%	284.4	26.2%	17.2%
	barren land	2.8	0.3%	2.3	0.2%	1.4	0.1%	-49.5%
	agriculture	65.4	6.0%	35.2	3.2%	17.3	1.6%	-73.6%
	grassland	148.9	13.7%	188.5	17.3%	169.7	15.6%	14.0%
	forest	605.3	55.7%	540.1	49.7%	594.7	54.7%	-1.8%
	water	21.8	2.0%	18.6	1.7%	19.3	1.8%	-11.1%

unit: km^2

In total land classification changes from 1987 to 2006 all counties show a gradual increase in urban areas, while agricultural areas show the greatest decreases in every county (except barren land in Cuyahoga County). Forest areas in each county also show a decrease in their land areas, but they do not show a higher percentage than agricultural areas. In Cuyahoga County, 74.9 km^2 of land surface changed in urban areas from 1987 to 1999 is the largest area increase in urban areas, and Summit County shows the second largest urbanized area (59.6 km^2). Meanwhile Cuyahoga County lost 99.3 km^2 forest areas, which is the largest forest loss in the study area, and 65.2 km^2 in Summit County is the next greatest loss. Although land classification change percentages are highest in agricultural areas in Cuyahoga and Summit County, actual agricultural losses are quite low (5.5 km^2 and 17.9 km^2 respectively). However, in Lorain and Medina, where agricultural areas dominate land surfaces, the story is completely different. In these two counties, many urban areas have been converted from agricultural areas.

Decreases in water can be seen in most of counties, but it is considered as a result of changes of precipitation and seasonal differences. The study area is usually cold and snowy from January to March. Much of the snow has melted by the end of March through early April, but the region can sometimes get snow in early April also which can affect what is observed on the satellite imagery. For example the 1987 image was recorded on April 10, and at Chardon in Geauga County (at the headwaters of the Cuyahoga River) 6 inches of snow were recorded on April 5 just 5 days earlier. Suring snowfall the temperatures were in the range of 20-30ºF (*National Climatic Data Center/NOAA Satellite and Information Service*). The temperature increased to the mid-50s just a few days later, and much of snow had already melted by the time the image was acquired. As a result, that image showed increased water levels in the region.

Most urban growth occurred between 1987 and 1999 (average of all seven counties 29.7% from 1987 to 1999 and 6.7% from 1999 to 2006). From 1987 to 1999, all counties other than Lake County, indicated more than a 10% increase in the urban class. Geauga, Portage, and Summit Counties, which are located in east and south of CVNP showed more than a 20% increase in the urban class. Table 6.1 shows the total area of each class in each county, but it is difficult to know actual 'from-to' changes on the results from Table 6.1. Therefore, the post-classification analysis is more useful to see exact changes in their results quantitatively.

Three OOC maps were used to create the post-classification maps, which described land classification changes by 'from-to' pixel changes in three different periods, from 1987 to 1999, 1999 to 2006, and 1987 to 2006 (Table 6.2 (a), (b), and (c)). Each county has about 36 different classes showing the results of land cover conversions.

If a county does not have one land surface classification (e.g. barren land), it results in less classes in the post-classification result.) In Table 6.2 columns always show more current images, and rows show older-year images. Unchanged pixels are located along the diagonal of the matrix (from top-left to bottom-right), and any other values show changed pixels from earliest to latest years. For example, in Cuyahoga County, urban column on Table 6.2 (a) showed conversions from agriculture 5 km^2, grassland 27 km^2, forest 111 km^2, and water 2 km^2 to urban areas from 1987 to 1999.

Table6.2 (a) The Post-Classification Result from 1987 to 1999

Cuyahoga **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	472.2	0.4	1.0	23.5	44.1	1.4	542.6
barren land	0.1	0.3	0.0	0.0	0.0	0.0	0.5
agriculture	4.9	0.1	2.4	4.0	2.4	0.0	13.8
grassland	27.3	0.1	1.6	39.7	26.1	0.1	94.9
forest	110.7	0.3	2.7	59.4	356.6	1.3	531.0
water	2.3	0.0	0.0	0.3	2.5	27.0	32.1
Total 1999	617.5	1.2	7.8	126.9	431.7	29.8	1,214.9

Geauga **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	7.2	0.2	0.7	3.9	4.1	0.4	16.6
barren land	0.2	0.4	0.1	0.1	0.0	0.0	0.9
agriculture	2.6	0.1	4.1	18.5	10.4	0.1	35.8
grassland	3.4	0.0	5.2	45.2	28.8	0.1	82.8
forest	11.4	0.3	7.0	43.7	384.1	1.4	447.9
water	0.8	0.1	0.4	0.4	2.2	8.4	12.1
Total 1999	25.6	1.2	17.5	111.8	429.6	10.4	596.1

Lake **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	71.9	0.5	3.1	13.7	19.1	0.7	109.0
barren land	0.2	0.0	0.0	1.3	0.1	0.0	1.6
agriculture	5.3	0.0	6.8	11.6	6.0	0.1	29.8
grassland	6.6	0.0	3.2	28.1	16.9	0.0	54.8
forest	29.0	0.5	8.3	41.6	257.5	0.8	337.7
water	1.0	0.0	0.1	0.2	1.4	3.9	6.6
Total 1999	113.9	1.0	21.5	96.6	301.0	5.6	539.5

Lorain **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	113.8	0.0	17.8	29.3	24.4	1.2	186.6
barren land	0.8	0.0	0.3	0.3	0.0	0.0	1.5
agriculture	36.7	0.0	305.5	103.3	24.1	0.4	470.1
grassland	27.4	0.0	74.2	88.1	19.7	0.2	209.6
forest	41.6	0.0	30.1	59.1	269.2	0.7	400.6
water	1.1	0.0	0.3	0.6	5.2	3.8	10.9
Total 1999	221.4	0.0	428.1	280.8	342.6	6.3	1,279.3

Medina **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	43.8	0.3	11.9	26.2	15.4	1.1	98.7
barren land	0.2	0.5	0.1	0.1	0.0	0.1	1.0
agriculture	26.3	0.4	170.1	108.4	34.7	0.5	340.4
grassland	22.0	0.1	78.5	124.0	38.6	0.3	263.5
forest	24.9	0.2	31.6	56.0	270.3	0.8	383.8
water	0.7	0.0	0.3	0.6	1.9	4.2	7.6
Total 1999	117.8	1.5	292.6	315.3	360.9	7.0	1,095.1

Portage **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	18.5	0.7	1.8	5.6	4.5	0.9	32.0
barren land	0.5	0.4	0.2	0.1	0.1	0.0	1.3
agriculture	6.6	1.2	17.2	18.8	8.0	0.3	52.2
grassland	8.6	0.4	14.1	40.8	15.2	0.3	79.4
forest	20.3	1.8	11.5	38.5	172.9	2.2	247.2
water	1.3	0.2	0.4	0.6	3.4	13.8	19.7
Total 1999	55.8	4.7	45.2	104.5	204.1	17.5	431.7

Summit **1999**
1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	178.5	0.6	3.1	22.8	36.6	1.1	242.7
barren land	0.4	1.0	0.2	0.8	0.5	0.0	2.8
agriculture	15.1	0.1	11.1	24.5	14.5	0.2	65.4
grassland	26.0	0.3	8.8	69.0	44.6	0.2	148.9
forest	80.6	0.2	11.7	70.7	439.9	2.3	605.3
water	1.8	0.1	0.4	0.7	4.0	14.8	21.8
Total 1999	302.3	2.3	35.2	188.5	540.1	18.6	1,087.0

unit: km2

Table6.2 (b) The Post-Classification Result from 1999 to 2006

Cuyahoga 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	527.9	0.0	0.5	35.6	50.9	2.5	617.5
barren land	0.5	0.0	0.0	0.5	0.1	0.0	1.2
agriculture	3.1	0.0	0.7	2.2	1.7	0.1	7.8
grassland	24.7	0.0	0.7	48.3	53.1	0.2	126.9
forest	35.6	0.0	0.2	18.7	375.9	1.3	431.7
water	0.9	0.0	0.0	0.2	1.3	27.3	29.8
Total 2006	592.8	0.0	2.2	105.5	483.0	31.4	1,214.9

Geauga 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	14.2	0.0	0.6	5.0	4.8	1.0	25.6
barren land	0.0	1.0	0.0	0.0	0.1	0.0	1.2
agriculture	2.2	0.1	2.8	6.8	5.2	0.4	17.5
grassland	8.5	0.1	2.3	62.9	37.7	0.2	111.8
forest	6.1	0.1	1.2	20.4	400.3	1.4	429.6
water	0.1	0.0	0.0	0.1	1.2	9.0	10.4
Total 2006	31.2	1.4	7.0	95.2	449.3	12.0	596.1

Lake 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	89.3	0.1	3.0	9.1	11.4	1.0	113.9
barren land	0.0	0.0	0.0	0.3	0.1	0.0	0.5
agriculture	3.9	0.1	9.5	4.9	3.1	0.1	21.5
grassland	14.1	0.0	3.2	44.1	34.9	0.2	96.6
forest	15.8	0.0	2.0	12.2	269.4	1.5	301.0
water	0.4	0.0	0.0	0.1	0.9	4.1	5.6
Total 2006	123.5	0.3	17.8	70.7	319.7	7.0	539.0

Lorain 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	146.8	0.1	7.7	46.0	19.5	1.3	221.4
barren land	0.0	0.0	0.0	0.0	0.0	0.0	0.0
agriculture	42.8	0.1	241.7	116.1	26.8	0.6	428.1
grassland	33.2	0.0	45.9	136.4	64.9	0.3	280.8
forest	17.1	0.0	2.4	22.2	299.9	1.0	342.6
water	0.5	0.0	0.0	0.1	0.9	4.8	6.3
Total 2006	240.4	0.2	297.7	320.9	412.0	8.1	1,279.3

Medina 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	68.3	0.2	3.9	28.9	15.2	1.2	117.8
barren land	0.2	1.0	0.0	0.2	0.1	0.0	1.5
agriculture	27.8	0.1	127.3	106.5	30.6	0.3	292.6
grassland	30.6	0.1	38.8	177.3	68.1	0.5	315.3
forest	13.5	0.1	2.5	29.5	314.5	0.7	360.9
water	0.2	0.1	0.0	0.2	1.2	5.2	7.0
Total 2006	140.6	1.7	172.5	342.6	429.7	8.0	1,095.1

Portage 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	32.1	0.8	1.2	10.6	9.7	1.4	55.8
barren land	0.5	2.1	0.2	1.1	0.6	0.3	4.7
agriculture	4.6	1.0	13.9	17.6	7.6	0.4	45.2
grassland	9.5	0.4	4.6	57.0	32.5	0.4	104.5
forest	8.3	0.5	1.2	13.0	179.4	1.7	204.1
water	0.3	0.1	0.0	0.1	1.9	15.1	17.5
Total 2006	55.4	4.9	21.0	99.4	231.7	19.2	431.7

Summit 1999 / **2006**

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1999
urban	223.5	0.1	1.8	31.3	43.7	1.9	302.3
barren land	0.4	0.7	0.0	0.9	0.2	0.0	2.3
agriculture	5.5	0.0	8.7	12.8	7.9	0.2	35.2
grassland	25.4	0.3	4.7	92.5	65.4	0.3	188.5
forest	29.2	0.3	2.0	32.0	474.6	1.9	540.1
water	0.4	0.0	0.0	0.2	2.9	15.0	18.6
Total 2006	284.4	1.4	17.3	169.7	594.7	19.3	1,087.0

unit: km2

Table6.2 (c) The Post-Classification Result from 1987 to 2006

Cuyahoga **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	456.9	0.0	0.4	26.0	57.3	2.1	542.6
barren land	0.1	0.0	0.0	0.4	0.0	0.0	0.5
agriculture	5.6	0.0	0.9	3.7	3.5	0.1	13.8
grassland	22.6	0.0	0.3	31.7	40.2	0.1	94.9
forest	106.0	0.0	0.6	43.4	379.2	1.8	531.0
water	1.5	0.0	0.0	0.4	2.8	27.4	32.1
Total 2006	592.8	0.0	2.2	105.5	483.0	31.4	1,214.9

Geauga **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	7.9	0.3	0.3	2.7	4.9	0.5	16.6
barren land	0.3	0.5	0.0	0.0	0.1	0.0	0.9
agriculture	3.3	0.1	1.8	18.4	12.0	0.2	35.8
grassland	4.6	0.1	2.7	37.2	38.1	0.1	82.8
forest	15.1	0.4	2.1	36.8	391.8	1.8	447.9
water	0.1	0.0	0.0	0.2	2.4	9.4	12.1
Total 2006	31.2	1.4	7.0	95.2	449.3	12.0	596.1

Lake **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	73.3	0.1	2.0	9.7	22.4	0.9	108.5
barren land	0.2	0.0	0.0	1.2	0.1	0.0	1.6
agriculture	5.0	0.1	6.1	10.3	8.3	0.1	29.8
grassland	7.9	0.0	2.3	20.3	24.2	0.1	54.8
forest	36.5	0.1	7.2	29.0	263.3	1.5	337.7
water	0.6	0.0	0.0	0.2	1.5	4.3	6.6
Total 2006	123.5	0.3	17.8	70.7	319.7	7.0	539.0

Lorain **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	110.8	0.0	9.8	31.4	33.2	1.4	186.6
barren land	0.6	0.0	0.3	0.6	0.0	0.0	1.5
agriculture	56.1	0.1	228.7	143.4	40.8	1.0	470.1
grassland	26.7	0.0	47.4	94.6	40.6	0.2	209.6
forest	45.6	0.1	11.4	50.5	291.8	1.2	400.6
water	0.6	0.0	0.1	0.4	5.5	4.3	10.9
Total 2006	240.4	0.2	297.7	320.9	412.0	8.1	1,279.3

Medina **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	45.8	0.4	5.4	23.9	21.9	1.4	98.7
barren land	0.3	0.4	0.0	0.2	0.0	0.0	1.0
agriculture	38.7	0.5	113.0	138.0	49.4	0.7	340.4
grassland	26.8	0.0	43.7	127.6	65.0	0.4	263.5
forest	28.8	0.2	10.3	52.6	290.9	0.9	383.8
water	0.2	0.1	0.0	0.4	2.3	4.6	7.6
Total 2006	140.6	1.7	172.5	342.6	429.7	8.0	1,095.1

Portage **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	17.8	0.7	0.7	5.1	6.7	0.9	32.0
barren land	0.6	0.3	0.1	0.2	0.1	0.0	1.3
agriculture	6.9	1.6	9.9	22.0	11.3	0.5	52.2
grassland	8.3	0.5	6.4	37.4	26.4	0.3	79.4
forest	21.5	1.6	3.9	34.1	183.5	2.6	247.2
water	0.3	0.2	0.0	0.6	3.6	14.9	19.7
Total 2006	55.4	4.9	21.0	99.4	231.7	19.2	431.7

Summit **2006**

1987

from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	171.1	0.3	1.7	21.9	46.5	1.3	242.7
barren land	0.3	1.0	0.1	1.2	0.2	0.0	2.8
agriculture	15.1	0.0	6.6	25.3	18.2	0.3	65.4
grassland	22.7	0.0	4.6	58.3	63.0	0.2	148.9
forest	74.7	0.1	4.2	62.4	461.8	2.1	605.3
water	0.6	0.0	0.1	0.7	5.0	15.4	21.8
Total 2006	284.4	1.4	17.3	169.7	594.7	19.3	1,087.0

unit: km2

(1) Cuyahoga County

In Cuyahoga County, a total of 145 km^2 of the land surface was changed to urban areas from 1987 to 1999. 76.6 % of this urban area was originally forest, which is high compared with other land surfaces. These urban areas from forest are concentrated mostly near the edges of Cuyahoga County. From 1999 to 2006, 36 km^2 of forest areas turned to urban areas. These urban expansions can be seen because of an expansion of the Cleveland Hopkins International Airport and more residential areas around the edge of Cuyahoga County. However, there are many misclassifications around Cleveland Heights recognized at the same time. Figure 6.1 shows the result of the post-classification map in Cuyahoga County.

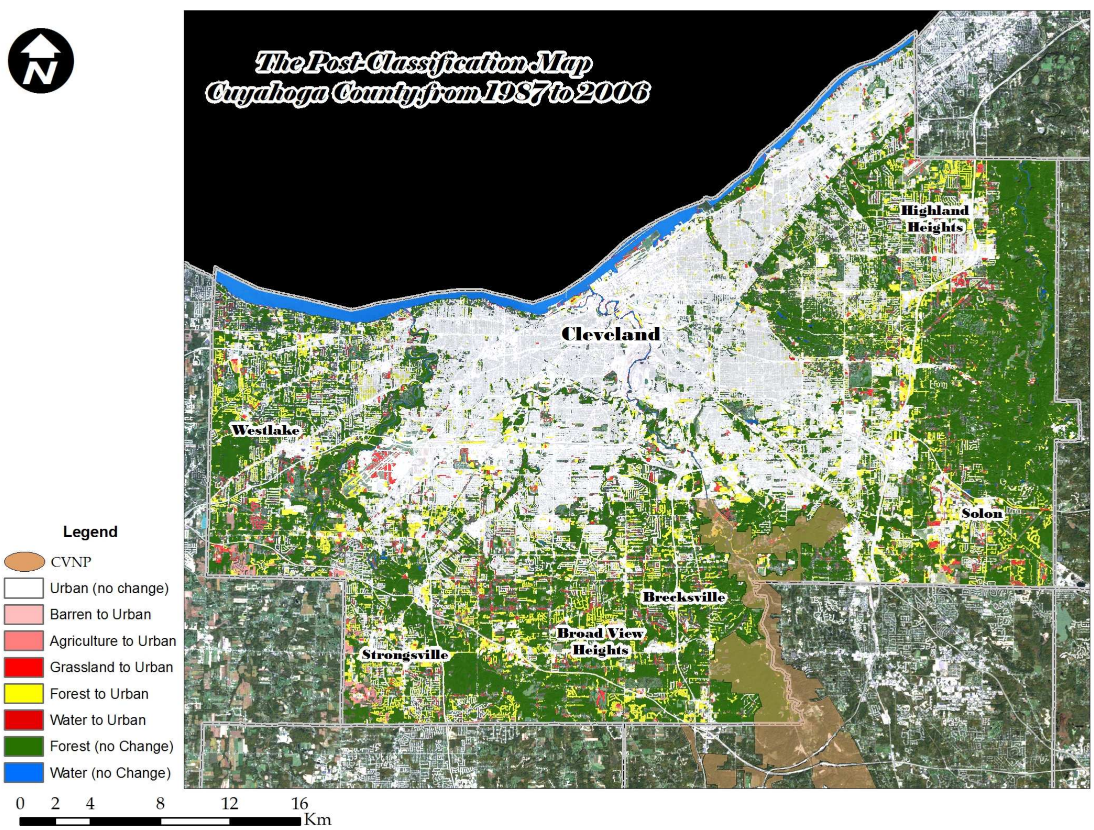


Figure 6.1 Post-Classification Map in Cuyahoga County from 1987 to 2006

On Figure 6.1, the urban expansion around Cleveland can be seen clearly represented by the color yellow. Some of urbanized areas by either Lorain or Medina County changed from agricultural areas, but more forest areas transformed to urban areas. In Cuyahoga County, urban areas spread widely to the west side of CVNP, around Strongsville, Broadview Heights, and Brecksville. The west and east side of Cleveland, Westlake and Highland Heights, also has a high concentration of urbanized areas over the past 20 years.

On Table 6.2 (c), many of forest areas changed to urban areas, but, on the other hand, there are many pixels changed from urban to forest areas (total 57.3 km^2 from 1987 to 2006) during the same period. A lot of these changes can be seen beside residential roads or edges around big forest patches, and these pixels are considered to come from difference in forest closure sizes between April and October. Many trees in the study area are deciduous trees, and these trees reduced reflectance from impervious surface on each classification image.

(2) Summit County

In Summit County, most converted urban areas were originally forest accounting for 66% of new urban areas from 1987 to 2006. The post-classification map of Summit County shows urban areas to have spread from the south to east sides of CVNP (Figure 6.2). The west side of CVNP shows more urbanized areas converted from agricultural uses or from grasslands.

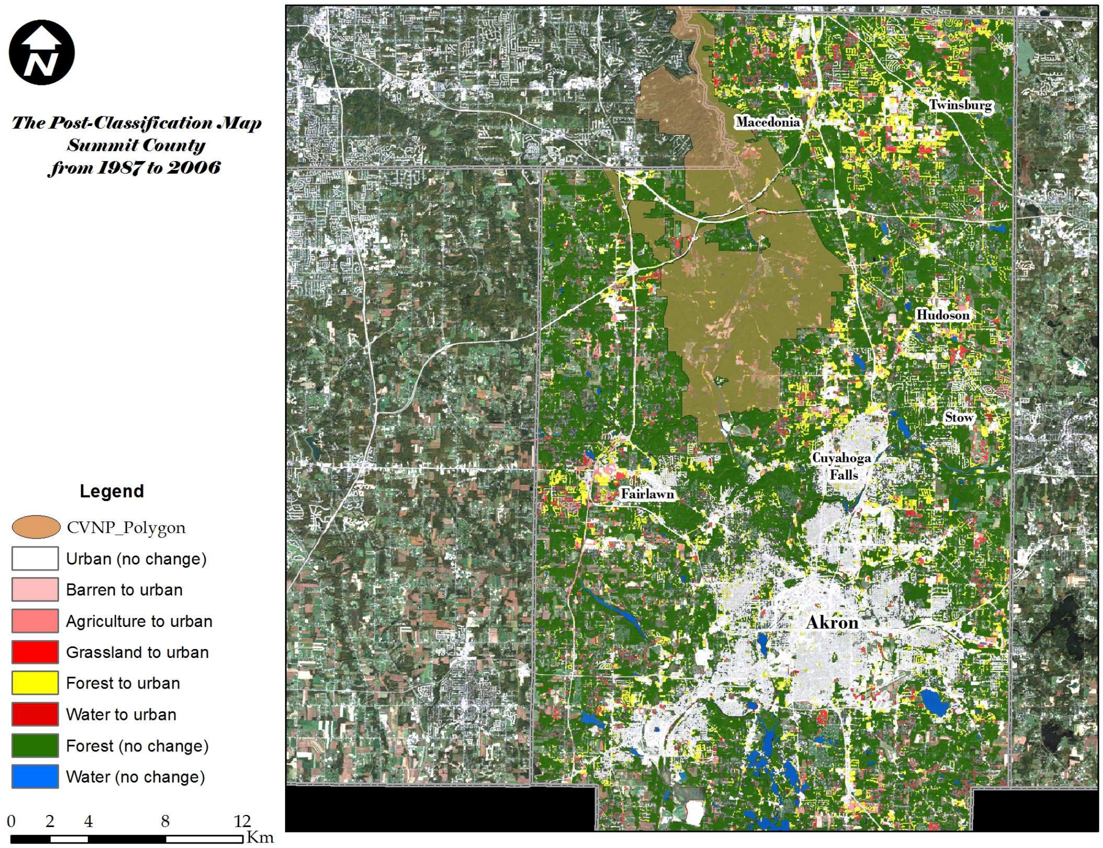


Figure 6.2 Post-Classification Map in Summit County from 1987 to 2006

Converted urban from forest can mostly be seen around Fairlawn and Cuyahoga Falls, both of which are located southwest and southeast of CVNP. The map shows that that several places changed from forest to urban in the center of Cuyahoga Falls, but the town was already developed in 1987, therefore there is likely some misclassification around the center of Cuyahoga Falls. Many developments can be seen around the edge of Cuyahoga Falls, especially closer to CVNP. Around Fairlawn, many of the new developments changed from agricultural areas. In Summit County, the biggest new urbanized areas occurred between Macedonia and Twinsburg and between Stow and

Twinsburg. Converted forest to urban can be easily seen by the yellow color surrounding the Cuyahoga Valley.

(3) Lorain County

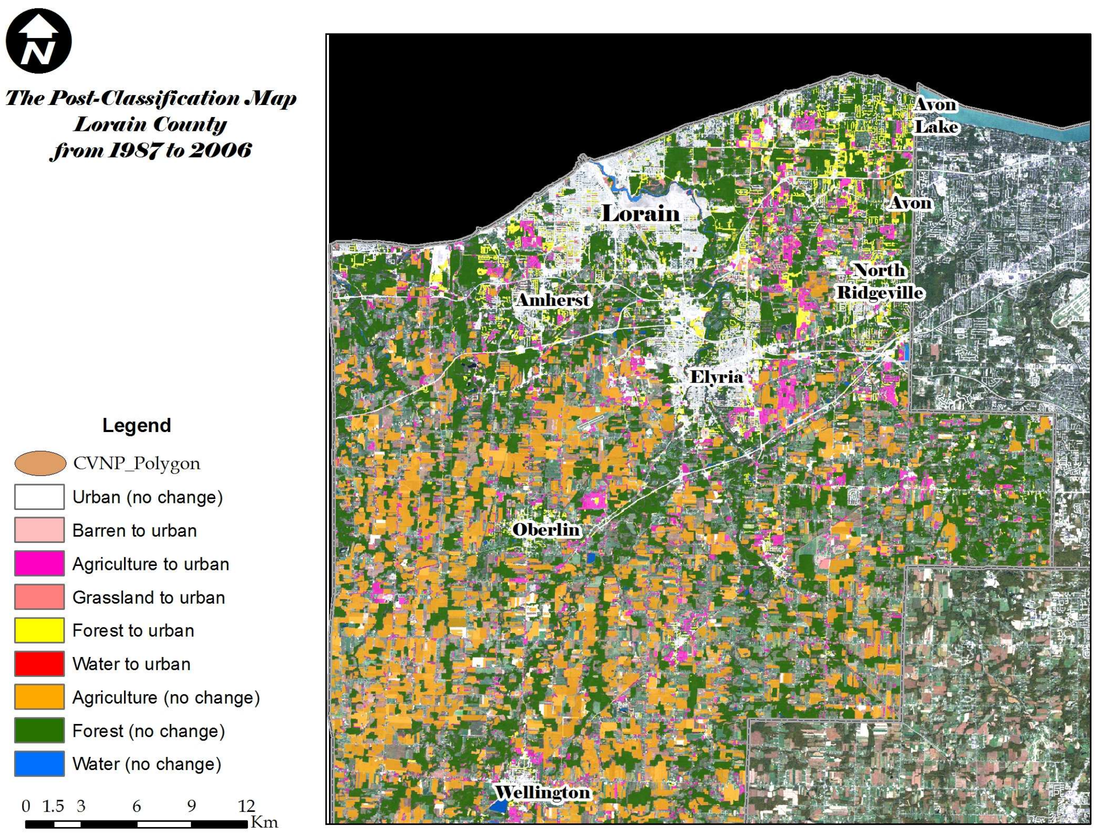


Figure 6.3 Post-Classification Map in Lorain County from 1987 to 2006

Most urban areas in Lorain County are concentrated by Lake Erie and Cuyahoga County (Figure 6.3). The city of Lorain is located at the mouth of the Black River, and Elyria is located south of the river. These two cities are the largest in the county, and have not grown to the same extent as cities in Cuyahoga or Summit Counties. The difference of urbanization in Lorain County compared with other counties is that most new urban has been converted from agriculture (pink areas on Figure 6.3). Near the border with Cuyahoga County, there used to be more forest areas near Avon, but many of these have been converted to urban. From Table 6.2 (c), 56.2 km^2 of agricultural areas were converted to urban, which is more than forest for the county (45 km^2). Also, 26.7 km^2 of grassland changed to urban areas.

(4) Medina County

Land classification change in Medina County is similar to Lorain County. Agricultural areas are mostly to the west of Medina City. According to the post-classification result, approximately 50% of agricultural land was lost from 1987 to 2006. However, land classification of agricultural areas is mixed with grassland areas sometimes, so the number cannot be said accurate. As the result on Table 6.2 (c), 138 km^2 of agricultural areas in 1987 turned to grassland in 2006. This is considered because cultivation areas covered by crops in 2006. The same situation can be said in Lorain County. Many agricultural areas and grasslands are mixed with cultivation areas and croplands, and therefore their land surfaces are different by seasons.

Most urban areas in Medina County are located around Medina, Brunswick, and Wadsworth cities, which are close to Akron (see Figure 6.4). There are less urbanized areas in west side of the county.

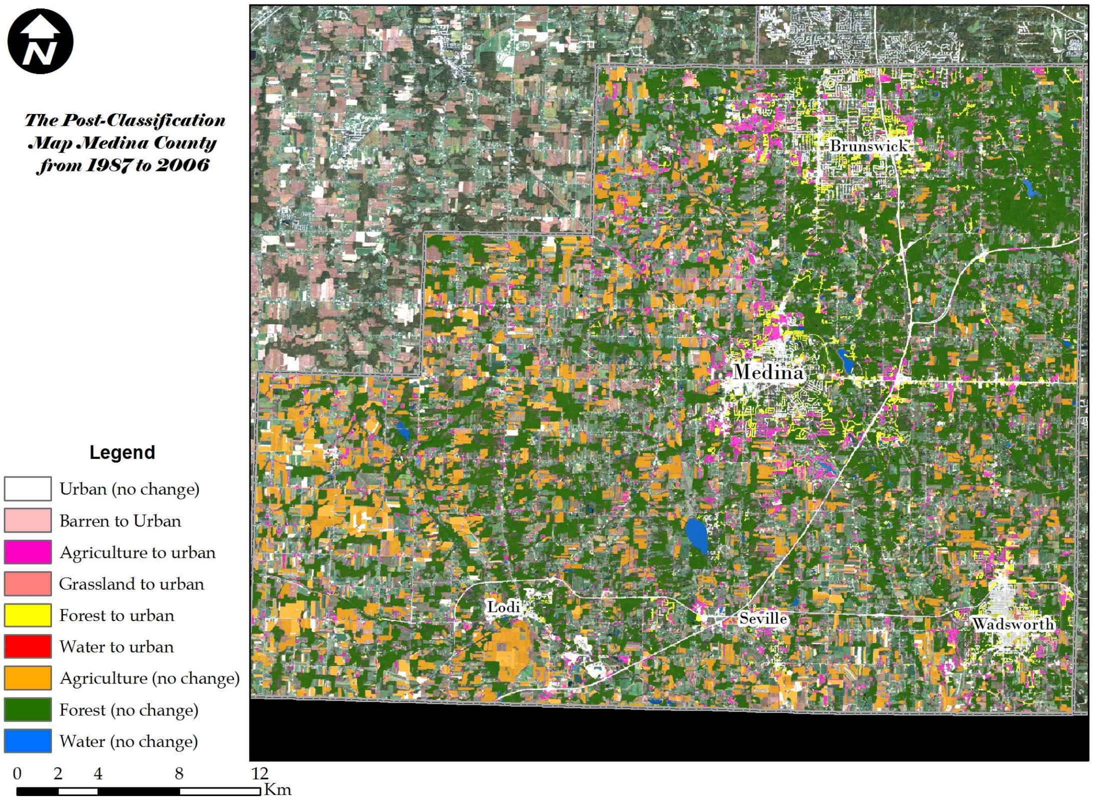


Figure 6.4 Post-Classification Map in Medina County from 1987 to 2006

(5) Portage County

Figure 6.5 shows the post-classification map in Portage County from 1987 to 2006. LANSAT TM/ETM+ Path 19 and Row 31 covers approximately only 35% of land surface in the county. Many converted forest to urban areas are located in the west side of the county. Streetsboro and Aurora especially show a widespread increase of urban areas since 1987. There are many large areas that were converted to urban in Streetsboro, and they are used mostly for commercial purposes. In downtown Kent, yellow areas show urban areas changed from forest, but these areas are considered as misclassification in 1987.

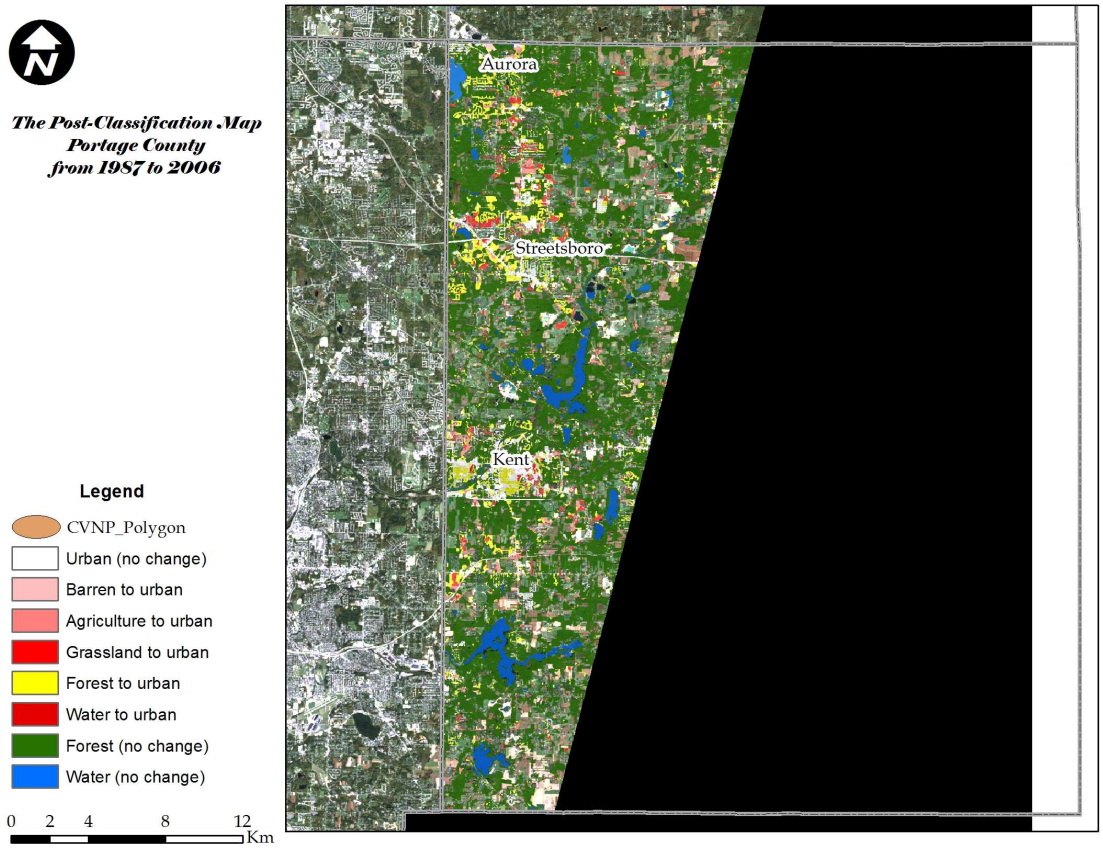


Figure 6.5 Post-Classification Map in Portage County from 1987 to 2006

(6) Geauga County

Figure 6.6 shows the post-classification map in Geauga County, and it shows approximately 56% of land surface in the county. Geauga County is the least developed county in the Cleveland and Akron Metropolitan Area in the past, but it is the fastest growing county among of these seven counties. From 1987 to 2006, the biggest construction in the county seems to be the completion of U.S. Route Highway 422 from Lake Ladue Reservoir to Solon. There are some residential developments in Bainbridge by U.S. Route Highway 422, but the post-classification map does not detect this change

Figure 6.6 Post-Classification Map in Geauga County from 1987 to 2006

well. The OOC map in 2006 did not classified urban areas well in Bainbridge, therefore it is a reason why there are less land surface area results in changes from forest to urban. Many residential areas in Geauga County are surrounded by trees (less density in residential areas), so there are more misclassifications considered on the OOC maps. Considering these misclassifications that are not recognized as urban in 2006, urban areas in Geauga County should be higher than the current result.

(7) Lake County

Figure 6.7 shows the post-classification map in Lake County. Similar to Lorain and other counties, many urban areas are located by Cleveland. Since 1987 East Lake and Willoughby have not changed very much. Most converted forest to urban can be seen around Mentor and Painesville. In Mentor there are many new commercial areas recognized in south of State Route 2 (Lakeland Freeway), and a lot of residential areas spread and expanded between Sate Route 2 to Lake Erie.

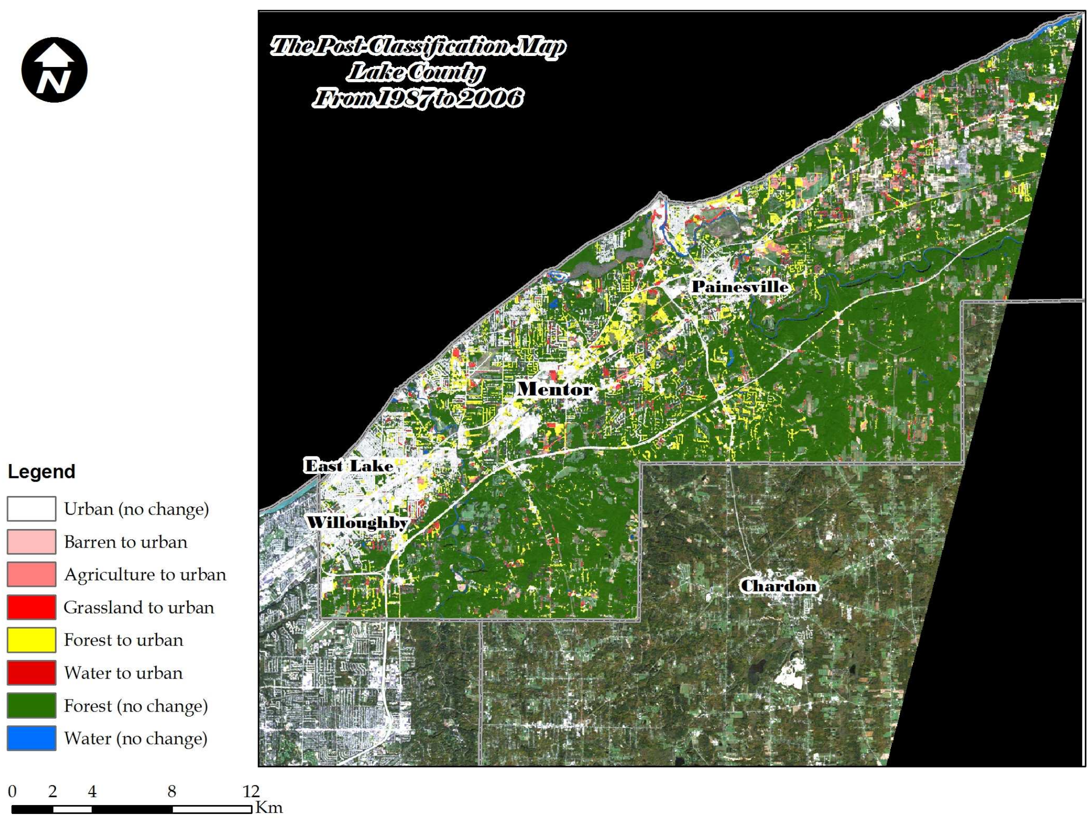


Figure 6.7 Post-Classification Map in Lake County from 1987 to 2006

6.2.2 Buffer Zones Analysis around Cuyahoga Valley National Park

Post-classification statistics are useful to show ‘from-to’ pixel changes in the study area by counties. However, here buffer analysis is useful to quantify spatial data within certain distances. In combination with the post-classification maps, the buffer analysis was able to analyze urban expansion around CVNP in detail. Five distance buffers (1 mile, 3 mile, 5 mile, 10 mile, and 15 mile) from the National Park boundary were created using GIS (Figure 6.8), and the results of multi-buffer analysis from 1987 to 2006 were summarized in Table 6.3.

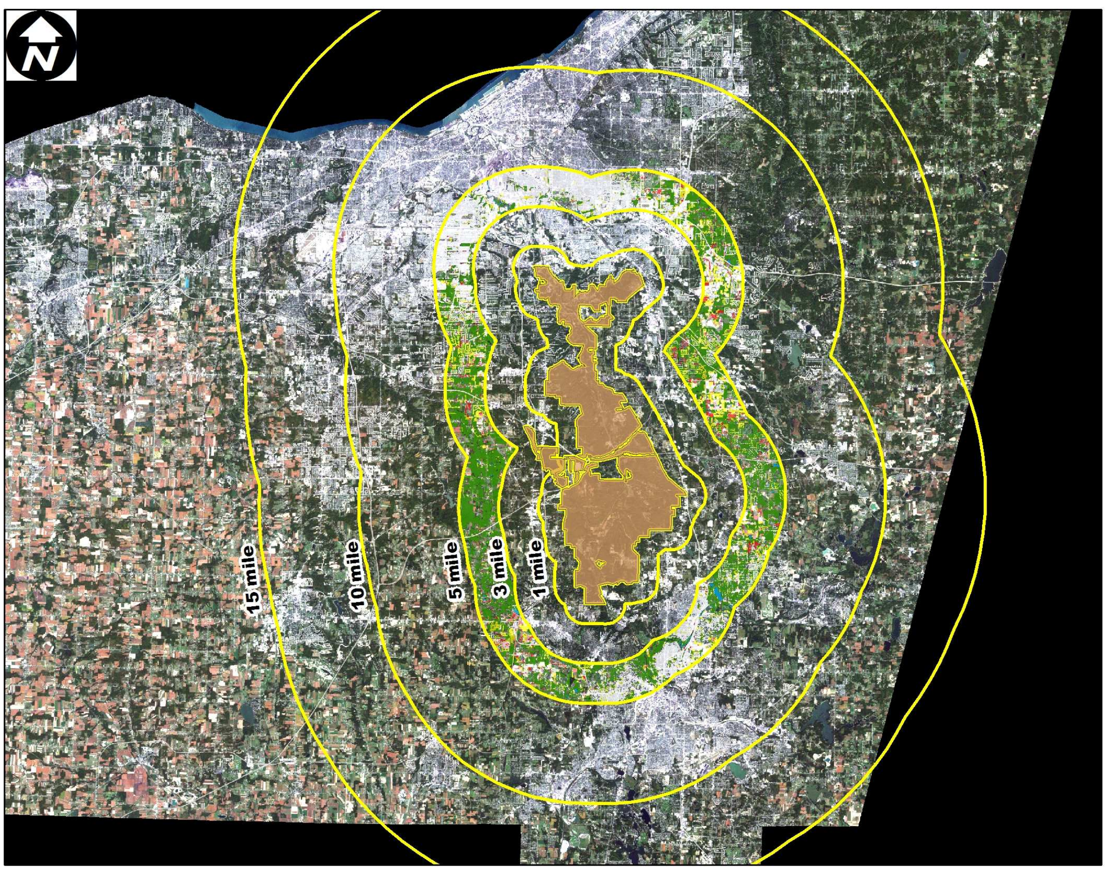


Figure 6.8 Multi Buffer Zones around Cuyahoga Valley National Park

Table 6.3 Buffer Zones Analysis Results from 1987 to 2006

inside — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	1.5	0.0	0.1	0.9	1.1	0.1	3.9
barren land	0.0	0.0	0.0	0.0	0.0	0.0	0.0
agriculture	0.2	0.0	0.6	0.9	1.2	0.0	3.0
grassland	0.7	0.0	0.5	6.0	4.2	0.0	11.5
forest	1.7	0.0	0.5	6.1	102.1	0.7	111.2
water	0.1	0.0	0.0	0.1	1.3	1.4	3.0
Total 2006	4.3	0.1	1.9	14.0	109.9	2.3	132.6

1mile — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	21.6	0.0	0.1	2.0	4.3	0.2	28.1
barren land	0.0	0.0	0.0	0.0	0.0	0.0	0.0
agriculture	1.1	0.0	0.3	2.0	1.4	0.0	4.8
grassland	3.4	0.0	0.2	5.3	9.6	0.1	18.5
forest	13.6	0.0	0.1	9.2	77.9	0.2	101.1
water	0.1	0.0	0.0	0.1	0.3	0.3	0.7
Total 2006	39.7	0.0	0.7	18.6	93.5	0.8	153.2

3mile — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	79.3	0.0	0.2	6.1	13.4	0.3	99.3
barren land	0.1	0.0	0.0	0.0	0.1	0.0	0.2
agriculture	3.4	0.0	0.1	3.5	3.1	0.0	10.2
grassland	5.4	0.0	0.0	9.2	14.0	0.1	28.6
forest	31.3	0.0	0.2	13.1	117.9	0.3	162.9
water	0.2	0.0	0.0	0.1	0.7	1.2	2.0
Total 2006	119.7	0.0	0.5	32.0	149.2	1.9	303.2

5mile — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	105.9	0.0	0.2	7.1	16.1	0.4	129.6
barren land	0.1	0.0	0.0	0.5	0.0	0.0	0.6
agriculture	4.2	0.0	1.0	5.5	4.1	0.0	14.9
grassland	8.3	0.0	0.5	16.5	17.6	0.0	42.9
forest	32.9	0.0	0.6	16.7	117.6	0.3	168.2
water	0.2	0.0	0.0	0.1	1.0	1.8	3.1
Total 2006	151.6	0.1	2.3	46.4	156.5	2.6	359.5

10mile — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	300.3	0.2	1.1	22.0	43.1	1.9	368.5
barren land	0.4	0.0	0.0	0.2	0.0	0.0	0.6
agriculture	13.2	0.3	9.5	30.9	17.7	0.4	72.0
grassland	22.2	0.0	4.5	59.7	54.7	0.3	141.4
forest	78.1	0.3	2.9	57.5	405.1	2.2	546.0
water	1.1	0.1	0.0	0.7	3.7	18.5	24.2
Total 2006	415.3	0.9	18.1	171.0	524.3	23.2	1,152.8

15mile — **2006**

1987 from/to	urban	barren land	agriculture	grassland	forest	water	Total 1987
urban	159.2	0.7	2.1	25.7	41.2	2.0	231.0
barren land	0.5	1.3	0.2	1.1	0.2	0.1	3.4
agriculture	24.7	1.3	26.7	57.8	27.9	0.7	139.1
grassland	25.9	0.5	14.6	88.8	76.7	0.4	206.9
forest	66.4	1.4	6.8	71.5	486.1	3.5	635.7
water	0.8	0.1	0.0	0.7	6.0	29.4	37.0
Total 2006	277.6	5.3	50.5	245.6	638.0	36.1	1,253.1

unit: Km^2

Table 6.4 Land Changes in Buffer Zones

LULC	inside		1 mile		3 mile	
	Area	%	Area	%	Area	%
urban	0.5	0.4%	11.6	7.6%	20.4	6.7%
barren land	0.1	0.1%	0.0	0.0%	-0.2	-0.1%
agriculture	-1.1	-0.9%	-4.1	-2.7%	-9.6	-3.2%
grassland	2.6	2.0%	0.0	0.0%	3.4	1.1%
forest	-1.3	-1.0%	-7.6	-5.0%	-13.7	-4.5%
water	-0.7	-0.5%	0.1	0.0%	-0.2	-0.1%
LULC	5 mile		10 mile		15 mile	
	Area	%	Area	%	Area	%
urban	22.0	6.1%	46.8	4.1%	46.6	3.7%
barren land	-0.6	-0.2%	0.4	0.0%	1.9	0.2%
agriculture	-12.6	-3.5%	-53.9	-4.7%	-88.7	-7.1%
grassland	3.5	1.0%	29.5	2.6%	38.7	3.1%
forest	-11.8	-3.3%	-21.7	-1.9%	2.3	0.2%
water	-0.6	-0.2%	-1.0	-0.1%	-0.9	-0.1%

From Table 6.3, there is virtually no new urbanization detected inside the National Park since 1987. Approximately 0.5 km^2 of urban areas was created inside the park, but 1 mile buffer zone shows the highest increase in urban areas as a percentage. The percentages gradually decrease as further away from the CVNP boundary. Table 6.4 shows actual area changes and changes of percentages compared with areas in 1987. The actual urban area in 1 mile buffer zone shows the smallest overall total urban area compared with other buffer zones, but by percentage change, the 1 mile buffer zone has the highest increase in urban area. The closer to the park boundary, the higher percentages in urban area changes can be seen on Table 6.4. In the mile buffer zone, approximately 60% of land surface is still covered by forest, but the percentage of forest may decrease in the future if gradual urban expansion from Cleveland and Akron continues at the same rate discussed in this thesis.

6.3 Population Growth Analysis in Cleveland and Akron Metropolitan

Urban expansion from Cleveland and Akron has been occurring continuously and expanding in the direction of the CVNP from 1987 to 2006. Now let's take a look at population changes in cities/townships in the study area. Summary for population changes from 1990 to 2006 in each county are described in Table 6.5. Cuyahoga County shows a huge population decrease since 1990. The decrease can be seen from Cleveland and its adjacent cities. Population in Summit and Lorain Counties expanded more than 30,000 people, and these two counties include fast growing cities by Cuyahoga County. Population data for each county division is provided in appendix A.

Table 6.5 Summary for Population Changes from 1990 to 2006

Year	Cuyahoga	Geauga	Lake	Lorain	Medina	Portage	Summit
1990	1,412,140	81,129	215,499	271,126	122,354	142,585	514,990
2000	1,393,978	90,895	227,511	284,664	151,095	152,061	542,899
2006	1,314,241	95,676	232,892	301,993	169,353	155,012	545,931
Population Change	-97,899	14,547	17,393	30,867	46,999	12,427	30,941

In Cuyahoga County, 38 out of 58 cities/townships have had decreases in their population by 2006. Since 1990 Cleveland had 61,303 people migrate from the city, a trend reflected in adjacent cites, too. However, Cleveland is still the second populous city in the entire of Ohio next to Columbus in 2000 (478,403 people) according to U.S. Census Bureau. Figure 6.9 illustrates the population distribution in Cleveland and Akron Metropolitan Areas and Figure 6.10 illustrated population changes from 1990 to 2006.

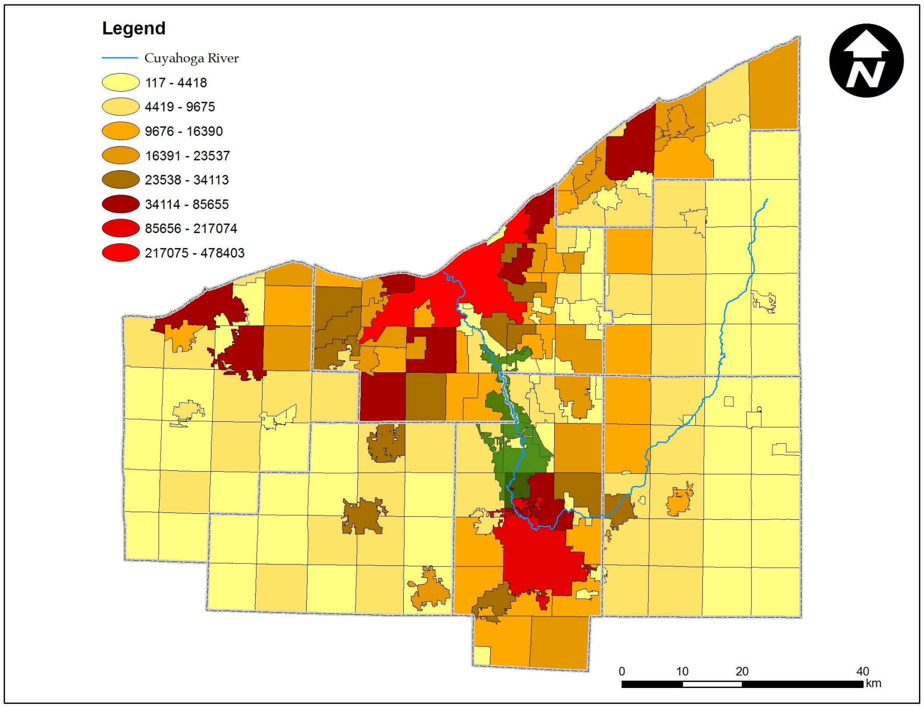


Figure 6.9 Population Distribution in Cleveland and Akron Metropolitan Area in 2000

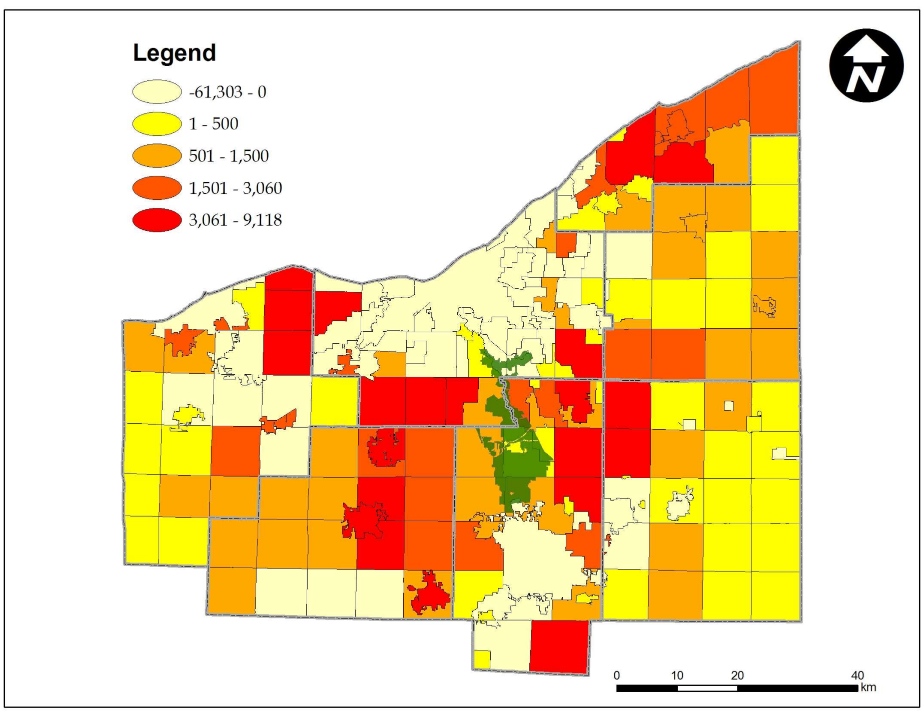


Figure 6.10 Population Changes from 1990 to 2006

In 2000, many people still lived in the adjacent cities to Cleveland - Lakewood, East Cleveland, Cleveland Heights, and University Heights. However, since 1990, approximately more than 60% of districts' population in Cuyahoga County had decreased, meanwhile many cities around the edge of Cuyahoga County have been growing in their population. From 1990 to 2006, Cleveland City lost totally 27,213 people and was expected to lose about 34,090 by 2006. The four largest adjacent cities, Cleveland Heights (-4,096 people), East Cleveland (-5,879 people), Shaker Heights (-1,426 people), and Lakewood (-3,072 people) also showed huge numbers of decrease in their population. On the other hand, the suburban cities of Cuyahoga County, Strongsville (8,550 people/24.2%), North Royalton (5,451 people/23.5%), Solon (3,254 people/17.5%), and Broadview Heights (3,748 people/30.7%), showed high population increases from 1990 to 2000. Broadview Heights especially, showed the highest percentage increase among of these (30.7%), and the city continued to expand 1,596 more people from 2000 to 2006 (Figure 6.10).

In Geauga County, the majority of census divisions showed increases in their population, and both Auburn (1,860 people/56.4%) and Bainbridge (1,222 people/12.6%) showed the highest increases (more than 1,200) from 1900 to 2000 compared with other townships. In Lake County, Concord, Mentor, and Painesville increased more by more than 2,000 from 1990 to 2000, and most of the districts in the county showed continuous growth in their population. Lorain County showed a similar trend like Lake County. The closer to Cleveland, the more population growth could be seen. Avon city showed the highest increase (4,109) in the county and estimated 5,009 more people would come to the city until 2006. In Medina County, both Brunswick and Medina showed large increases in their population (5,158 and 5,908 respectively).

The east side of CVNP showed the high concentration of population increases since 1990. In Portage County, there were three cities, Aurora, Streetsboro, and Tallmadge, showing an increase of more than 1,500 people, and all of them would increase continuously until 2006. In the north portion of Summit County, Twinsburg represented the highest increase (7,400) in population, and Hudson (5,311), Stow (4,437), Sagamore Hills (2,837), and Macedonia (1,715) also recorded increases in their population. Clearly population increases can be seen more around CVNP, especially east and west side of the park presented high concentration of growing cities/townships.

6.4 Urban Expansion Analysis around Cuyahoga Valley National Park

Finally, the relationship between population growth and urban expansion is examined using population census data and the post-classification data from 1987 to 2006. The analysis is undertaken taken at the census subdivision level (city/township), using Census 2000 TIGER/Line shapefiles (United States Census Bureau, 2006), and population numbers collected from the U.S. Census Bureau population census data. I chose only growing cities/townships which satisfy the following conditions,

Cities or townships which are

1) located inside 15 mile buffer zones;

2) more than 1,000 increase in their population since 1990; and

3) Primary road, interstate highway, U.S. and State Highway, or Secondary roads - State Route (SR) 82, 303, and 91interest the Census Blocks.

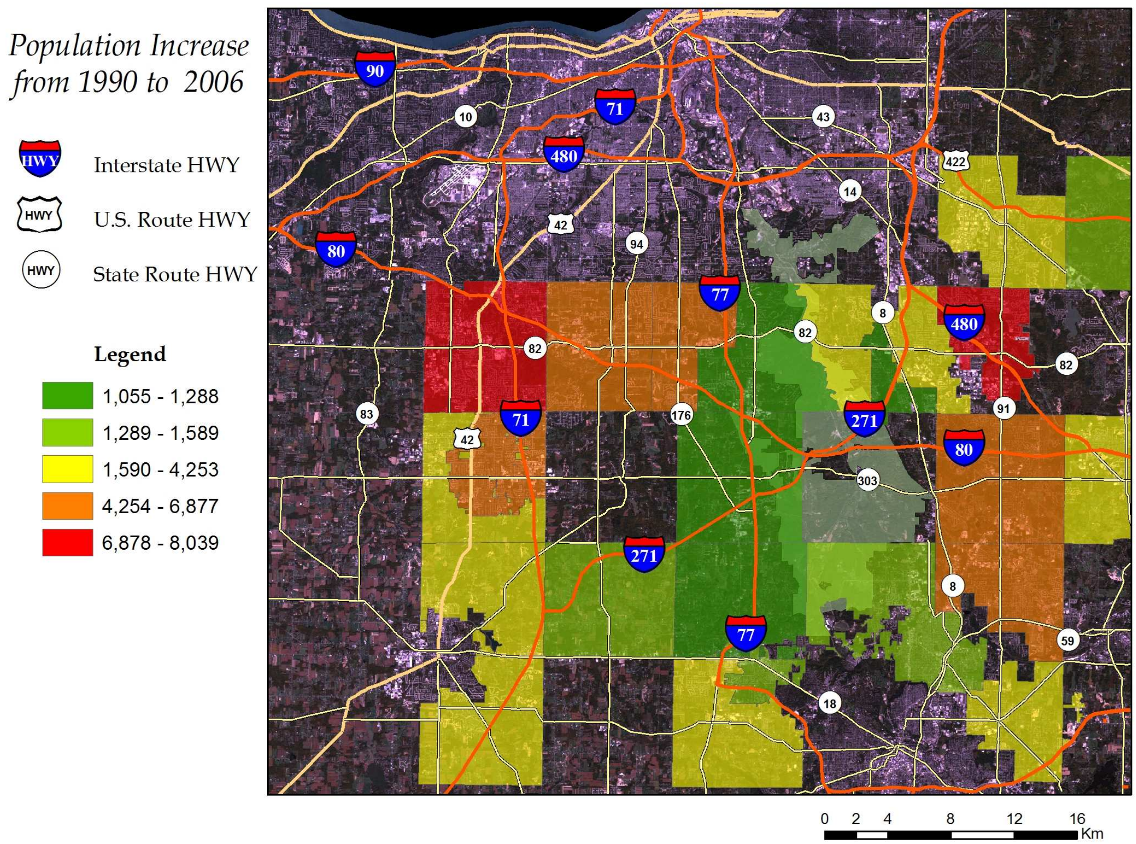


Figure 6.11 Population Increase in Fast-Growing Cities/Townships in the Study Area

The reason I choose these conditions are that much of the urbanization is happening by CVNP, which is between Cleveland and Akron, and these are connected by SR-82, 303, or 91. Figure 6.11 shows the selected cities/townships with main highways in Northeast Ohio region. Using only these fast-growing cities/townships, urban growth indices, which are the ratio of urban increase to population increase, were calculated

(Table 6.7), and the relationship between urban increase and population growth was plotted on Figure 6.12. The graph shows moderately high positive relationship (correlation coefficient: 0.7967 ($p < .01$)) between urbanized areas and population growth. The coefficient of determination for a simple Pearson correlation value of 0.7967 is equal to 0.635, indicating that 63.5% of the variance is accounted for its relationship between population growth and urban increase. From these results, Twinsburg and Strongsville show similar increases in their populations (approximately 8,000), but their urban area increases are very different. Urban area in Twinsburg increased 8.3 km^2 against 14.1 km^2 in Strongsville. North Royalton, Streetsboro and Solon showed similar increases in their urban areas (10.3km^2, 9.9km^2, and 10.2 km^2 respectively), but population in North Royalton increased 6,268 against 4,253 in Streetsboro and 3,709 in Solon. In Strongsville and in Streetsboro, some business districts were built in the city (e.g. Wal-Mart or Westfield SouthPark Center, a shopping mall). The difference between these cities can identify in their urban indices. The urban index of North Royalton is 1.54 against 2.23 in Streetsboro and 1.60 in Strongsville. Urban index seems to be influenced by mostly by increase of commercial properties or infrastructures. For example, in Cuyahoga Falls, there were large commercial and residential developments by north of Chapel Hill Mall. Compared with its population increases, large increase of urban areas raised their urban indices. In Richfield, there were large constructions around the junction of I-77 and I-271 and the junction of Ohio Turnpike (I-80) and SR-21 undertaken between 1987 and 2006. These large constructions created more urban area in these cities and might encourage more people to live there in the future.

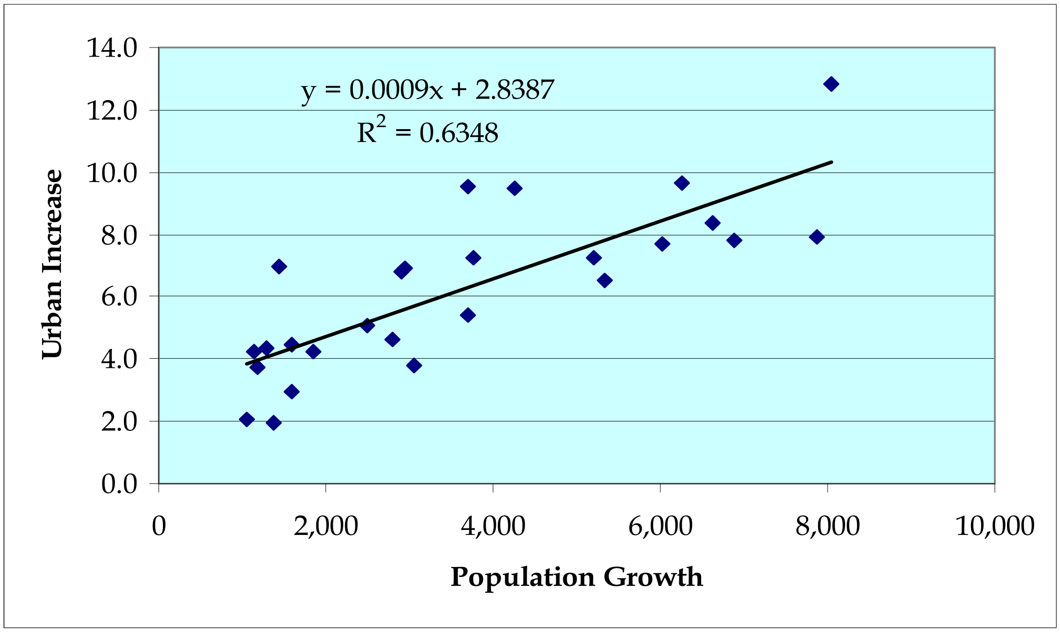


Figure 6.12 Relationship between Urban Increase and Population Growth

Table 6.7 Urban Growth Index

NAME	Total Area	Population Growth	Urban Increase	Urban Growth Index
Aurora	62	5,210	7.3	1.40
Bainbridge	67	1,589	4.5	2.81
Bath	58	1,184	3.7	3.15
Brecksville	51	1,288	4.3	3.37
Broadview Heights	34	5,344	6.5	1.22
Brunswick	33	6,877	7.8	1.14
Brunswick Hills	32	2,795	4.6	1.65
Copley	54	2,955	6.9	2.33
Cuyahoga Falls	66	1,448	7.0	4.82
Fairlawn	11	1,380	1.9	1.40
Granger	61	1,585	2.9	1.86
Hinckley	70	1,848	4.3	2.31
Hudson	67	6,026	7.7	1.27
Macedonia	25	2,909	6.8	2.33
Medina	47	3,704	5.4	1.47
Montville	54	3,764	7.2	1.92
North Royalton	55	6,268	9.6	1.54
Northfield Center	14	1,055	2.1	1.95
Richfield	66	1,145	4.2	3.70
Sagamore Hills	29	3,060	3.8	1.23
Solon	53	3,709	9.5	2.57
Stow	45	6,633	8.3	1.26
Streetsboro	63	4,253	9.5	2.23
Strongsville	64	8,039	12.8	1.60
Tallmadge	1	2,500	5.1	2.04
Twinsburg	32	7,878	7.9	1.00

**Urban Growth Index = 1,000*(Urban Increase/Population Growth)*

6.5 Summary

Urban expansion pattern in the study area was successfully analyzed by the post-classification method, buffer zones analysis, and population growth analysis using GIS. Urban growth was recognized concentrated around the Cuyahoga Valley, and population growth analysis in city/township level helped to understand which cities/townships has been increased in their population. However, there are some disadvantages of the post-classification which is a necessity of high accuracy in each land classification map. By increasing each accuracy, numbers of urban area change will be more reliable.

CHAPTER 7

DISCUSSION

7.1 Introduction

Urban expansion pattern around CVNP was recognized by using the post-classification maps and buffer zone analysis, and population changes were analyzed using population census data, which showed great population increases around CVNP. In contrast, the interior of the Cuyahoga Valley has been protected, and almost no urbanization has been seen in the last few decades. Using remote sensing and GIS data, the contrast between the non-growth inside the park and growth outside the park is very obvious. This study demonstrates that there is an advantage to using spatial analysis using both GIS and remote sensing to understand the urban expansion patterns around CVNP from 1987 to 2006. It is still difficult to determine specific changes using satellite data because of misclassification issues. Therefore to better understand actual land surface changes and know if there were any influences inside the Cuyahoga Valley in the past years, field observations and knowledge from experts helps. In order to verify the results of remote sensing investigations, several field observations were undertaken in and around CVNP on several dates (Table 7.1). Figure 7.1 shows field observation locations inside and outside

Table 7.1 Date of Field Observations

Year	Date
2007	March 09
	March 29
	May 06
	June 09
	July 14
	September 22
	September 30
	October 21
2008	March 30
	April 03
	April 24

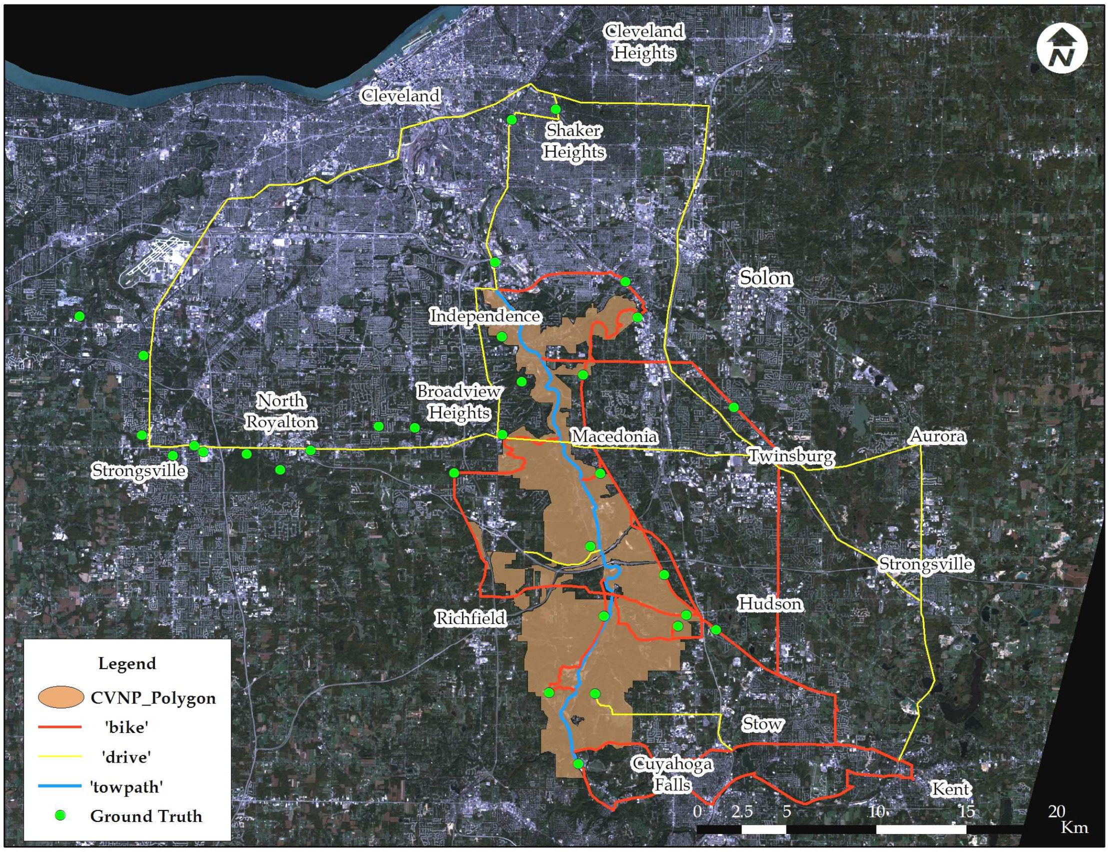


Figure 7.1 Locations of Field Observation Points inside and outside Cuyahoga Valley National Park

CVNP. In this chapter, current conditions inside and outside the Cuyahoga Valley are discussed based on results of satellite data analysis, field observations, and interviews with a biologist at Metroparks serving Summit County and an ecologist at Cuyahoga Valley National Park.

7.2 Urbanized Area outside Cuyahoga Valley National Park

From satellite data analysis, urban expansion was concentrated close to the CVNP. Many of the suburban cities and townships that lie on or near main interstates and state routes showed the largest increases in their population since 1990. Some of the largest population increases are concentrated between Strongsville in Cuyahoga County

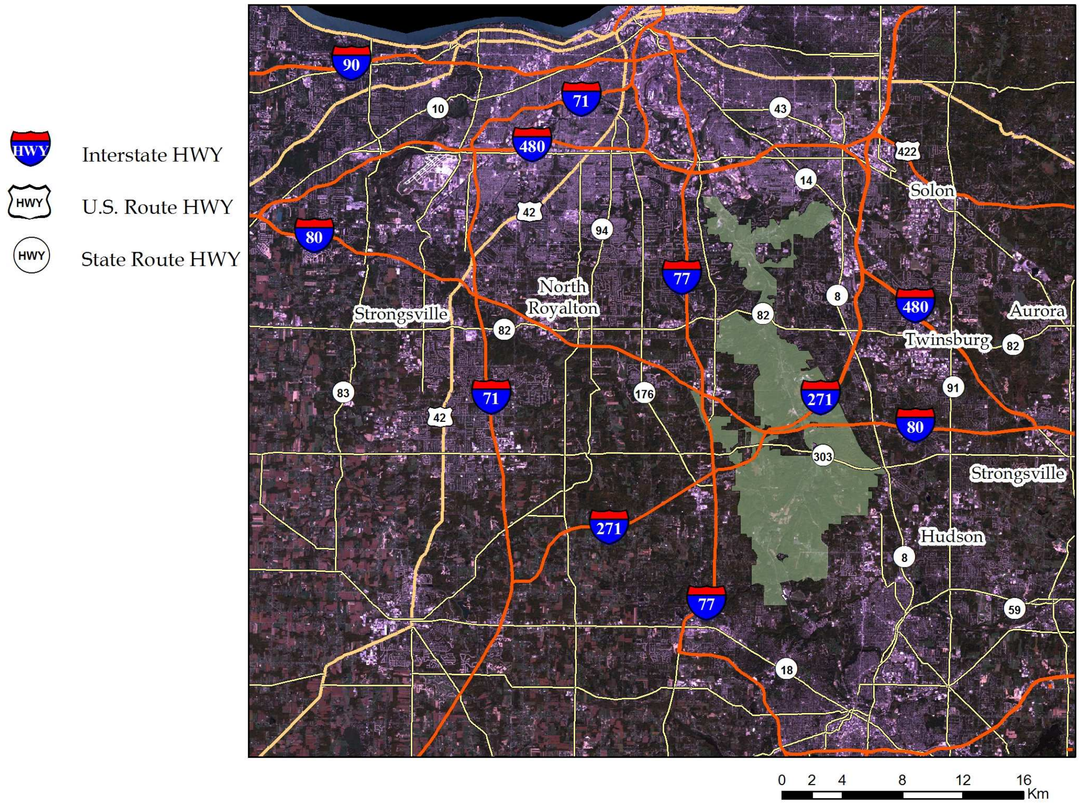


Figure 7.2 Roads Map in the Study Area

and Aurora in Portage County around SR-82, and between Stow in Summit County and Solon in Cuyahoga County around SR-91 (Figure 7.2). To verify new urban areas along with these state routes, field observation points were randomly selected in some of fast-growing cities/townships. At the same time, to check decay inside Cleveland, a few field observation points were chosen around downtown Cleveland.

7.2.1 State Route 82

Based on the urban expansion analysis and population change in the Cleveland and Akron Metropolitan Area, many of the expanding townships and cities are located

(a) State Routes 82 in Twinsburg

(b) Residential Houses in Sagamore Hills

(c) Brecksville Shopping Center

(d) Westfield SouthPark Center

(e) Shopping Mall in Strongsville

(f) Residential Houses in Strongsville

Figure 7.3 Pictures around State Route 82

beside SR-82. The assumption is that they grew rapidly because of the proximity to major interstate highway junctions (Figure 7.2). From SR-82, people can get to major junctions on I-71, I-77, I-80, I-271, and I-480 directly which lead to almost everywhere inside and outside Northeast Ohio. Most areas are dominated by new residential developments, shopping malls, restaurants, and other service industries.

On the east side of CVNP, from Aurora to Twinsburg, few new residential areas can be seen on SR-82 (Figure 7.3 (a)), but there are many of new housing developments close to SR-82. More service industries and business districts are located by I-480 in Twinsburg. There are more residential houses located between I-271 and CVNP. Some of houses are built right next to CVNP. Figure 7.3 (b) shows new houses (after 1999) right next to CVNP.

After driving through CVNP to west, Brecksville Shopping Center (Figure 7.3 (c)) is located next to Chippewa Creek Drive, and it is crowded with people during the day and evening. The expansion of Brecksville Shopping Center can be seen on satellite images as occurring sometime during 1999 to 2006. On the west side of CVNP a huge expansion of residential areas can be seen from 1986 to 1999. There are also two big shopping malls on SR-82 by I-80 and I-71. Westfield SouthPark Center in Strongsville, is the biggest shopping mall in the region and contains 261 stores (Figure 7.3 (d)). The mall parking lot is usually packed with cars every weekend and in the evenings. Next to Westfield SouthPark Center, a second shopping center includes restaurants and fast food stores (Figure 7.3 (e)). Westfield SouthPark Center opened in 1996, a timeframe when the population in Strongsville increased from 35,308 in 1990 to 43,858 in 2000 (*U.S. Census Bureau, 2006*). This area has the largest increase in population in the study area

(a) RTA Train in Cleveland

(b) Morning Traffic on I-480

Figure 7.4 Pictures of Transportation

during this timeframe. This also showed one of the largest increases in area of the urban class seen on the land classification maps (see Chapter 6). Even though, the population has grown, and the urban class has expanded, the overall population density in these new growth areas is relatively low. For example, the population density of Strongsville is (687 per km^2) compared with cities around Cleveland (more than 1,500 per km^2) – Cleveland Heights (2,375 per km^2), East Cleveland (3,385 per km^2), Lakewood (3,267 per km^2), University Heights (2,980 per km^2), Maple Heights (1,947 per km^2), and Parma Heights (1,993 per km^2) (all data from 2000 Population Census). Figure 7.3 (f) shows spacious residential areas in Strongsville.

Most of these new residential houses near SR-82 are located by the edge of Cuyahoga County. Cleveland has a transportation system called RTA (Greater Cleveland Regional Transit Authority), but infrastructure is not well developed around SR-82 (Figure 7.4). Thus there is a high automobile dependence, and heavy commuter traffic can be seen in every morning and evening times on week days. On the weekends, many people go to Westfield SouthPark Center for shopping, and traffic gets heavy on SR-82. Also using SR-82, people can enter to the CVNP through Chippewa Creek Drive, drive to Station Road Bridge parking lots by the Ohio & Erie Towpath Trail, or take a scenic drive to River view Road.

7.2.2 State Route 303 and 91

SR-303 is also directly connected to the center of CVNP at Peninsula. Traffic on this road is quite heavy perhaps because it connects Hudson, which grew significantly between 1990 and 2006 (5,311 increase), to the valley. Along, and near, SR-303, there are more new housing developments compared with other areas in the region. Also, around the intersection of SR-303 and SR-91, there are many new commercial and business districts, with new residential areas both north and south of the intersection. To the west of the CVNP on SR-303 near Brunswick and Hinckley, there is less development than on the east of the CVNP even though population has been increasing since 1990 (24% in Brunswick and 32% in Hinckley since 1990).

7.2.3 Cleveland

In Cleveland, south of Shaker Heights, many old houses, abandoned manufacturing ground or buildings can be seen (see Figure 7.4). Inside Cleveland city, several construction sites and developments can be seen. For example, the area known as the Flats, the place used for manufacturing purposes, is now used for more entertainment

(a) Abandoned Building in Cleveland

(b) Old House in Cleveland

Figure 7.5 Pictures of Old Structures in Cleveland

or multipurpose uses. These old remnants of industrial manufacturing are keys to improving the city's environment in the future, and are necessary to create a vibrant town to bring back people to Cleveland or surrounding areas.

7.3 Restorations and Recreation inside Cuyahoga Valley National Park

Compared with the areas outside the Cuyahoga Valley, the park itself has been well protected and has even improved since the industrial era. For example, vegetation restoration has taken place in old agricultural and industrial areas. One of the biggest restoration projects is by I-80, I-271, and SR-303, where a sports and entertainment stadium, (the Coliseum at Richfield) used to be located. The Coliseum was built in 1974, closed in 1994, and was finally demolished in 1999. The site was remediated to woodland meadow (*Independence Excavating*). Another example is the Jaite Paper Mill site along the Cuyahoga River Valley. The mill produced up to 8 tons of paper daily (*National Park Service*) and closed in 1984. The site is now under restoration by Cuyahoga Valley National Park (Figure 7.6(a)).

(a) Jaite Paper Mill

(b) Ohio & Erie Canalway Lock 26

(c) Hale Farm & Village

Figure 7.6 Pictures inside Cuyahoga Valley National Park

Among the many historical places in the valley are 44 locks along the Ohio & Erie Canalway that lifted canal boats 395 feet in elevation between Cleveland and Akron (*National Park Service*) (Figure 7.6 (b)). Several of these are highlighted as sites of historical significance that tourists can visit. In addition there are several farms that have been preserved as agricultural and historical sites (Figure 7.6 (c)) or restored to woodland or vegetation areas. There is also currently a land acquisition program undertaken by Cleveland Metroparks, Metroparks serving Summit County, National Park Services, as well as by other nonprofit organizations.

(a) Bike Store in Peninsula

(b) Cuyahoga Valley Scenic Railroad

(c) Blossom Music Center

(d) Boston Mills Ski Resort

Figure 7.7 Pictures of Recreational Activities inside Cuyahoga Valley National Park

Many park visitors come to CVNP for different recreational purposes such as biking, walking, and running on the Towpath Trail (Figure 7.7 (a)), taking the Cuyahoga Valley Scenic train (Figure 7.7 (b)), watching concerts at the Blossom Music Center from spring through the late Summer (Figure 7.7 (c)), and skiing and snowboarding at the two ski resorts in winter (Figure7.7 (d)) as well as cross-country skiing all over the park.

7.4 Invisible Threats to Cuyahoga Valley National Park

Superficially the park environment has improved until now, but there are many invisible environmental threats to the park. First, the spread of invasive plant species is a problem. These exotic plants tend to decrease the number and variety of native plants inside the park (*National Park Service*). These plants were brought from other countries and regions for agricultural or gardening purposes, and they spread rapidly. Some of these invasive species already existed when CVNP established, but because of the increased urbanization and traffic into the valley the spread of new species is inevitable being spread by wind, birds, white tail deer, and even cars or people. If people bring exotic plants to their gardens or yards, seeds from these plants may spread toward the Cuyahoga Valley. Not all of exotic species are invasive, some of them are devastating to native species (*National Park Service*). They can change the ecosystem of parts of the park, and sensitive and native species may become extinct in the future. Table 7.2 a list of invasive plants from Cuyahoga Valley National Park (*National Park Service*). Among of these invasive plants, for example, is Japanese honeysuckle which may influence ash tree seedlings and eliminate songbird habitats. Garlic mustard is also everywhere in the park, and threatens Two-leaved Toothwort, which is the habitat of the West Virginia White Butterfly (*leapbil.org*). Forman (1995) noted that human activity commonly increases the rates of invasion, population fluctuation, and extinction of plant communities.

Table 7.2 List of Invasive Plants in CVNP

Common Name	Scientific Name
Garlic mustard	*Alliaria petiolata*
Japanese Barberry	*Berberis Thunbergii*
Autumn olive	*Elaeagnus umbellata*
Common privet	*Ligustrum vulgare*
Japanese honeysuckle	*Lonicera japonica*
Amur honeysuckle	*Lonicera maackii*
Morrow honeysuckle	*Lonicera morrowii*
Tartarian honeysuckle	*Lonicera tatarica*
Purple loosestrife	*Lythrum salicaria*
Reed canary grass	*Phalaris arundinacea*
Common reed	*Phragmites australis*
Japanese knotweed	*Polygonum cuspidatum*
Glossy buckthorn	*Rhamnus frangula*
European buckthorn	*Rhamnus cathartica*
Multiflora rose	*Rosa multiflora*
Narrow-leaved cattail	*Typha angustifolia*

A second threat is the increased probability of more, or more extreme, floods in the Cuyahoga Valley due to increasing urban areas (impervious surfaces) around CVNP. Historically, flooding is not an unusual phenomenon in the valley. However, these impervious surfaces do not absorb water resulting in increased overland flow and large volumes of water arriving rapidly into the streams, an observation noted in the Cuyahoga Valley (*Skerl et al., 2005*). A higher volume of water causes more erosion and sedimentation downstream. This situation may also degrade water quality. Cuyahoga Valley National Park ecologist, Kevin Skerl, noted in the Akron Beacon Journal (November 4, 2007) the serious issue of an increase in flooding which may cause more damage to the park environment in the future. As showing on Figure 7.8, highlighted watersheds (Brandywine Creek, Chippewa Creek, Furnace Run, Sagamore Creek, Tinkers Creek, and Yellow Creek) lead all runoff water into the Cuyahoga River inside

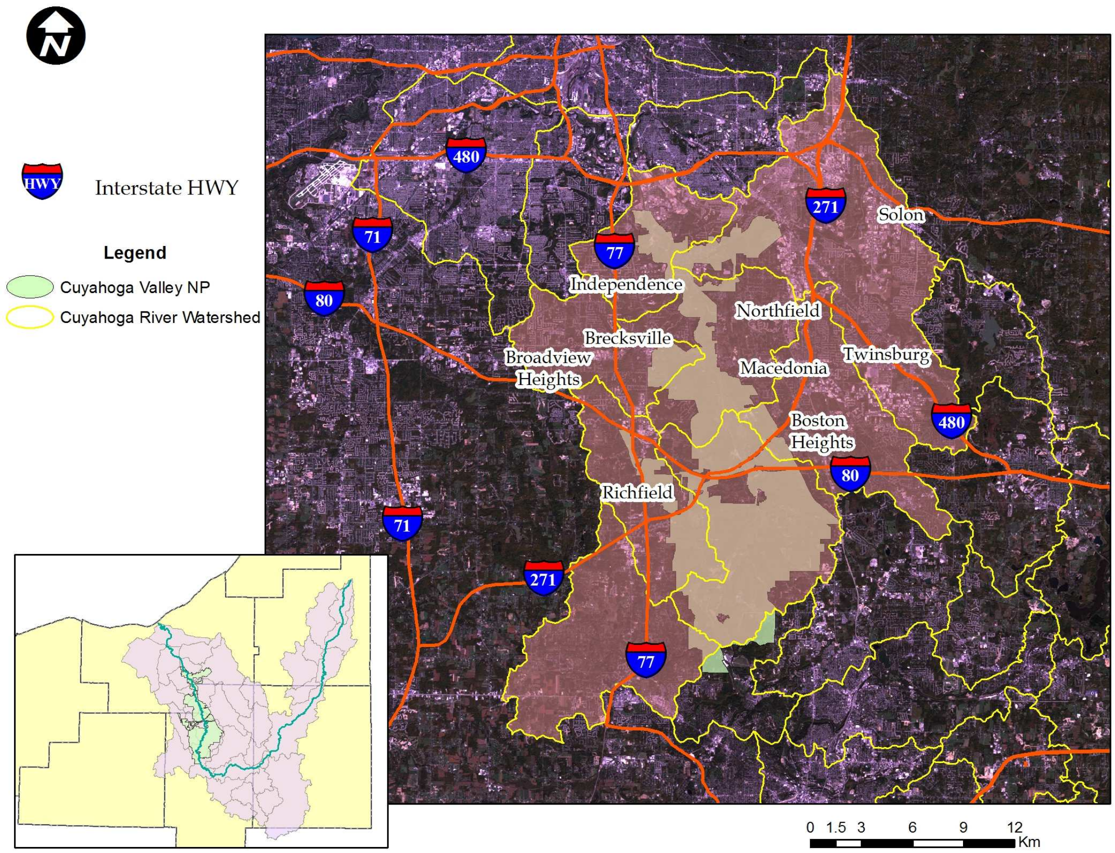


Figure 7.8 Cuyahoga River Watershed

the national park. Increase of impervious surfaces inside these watersheds may cause serious damage to the park environment and threat human life also. Land surface changes can also erode stream shapes, alter floodplains, increase polluted runoff, increase stream temperatures, and degrade aquatic life (*Cuyahoga River Community Planning Organization*).

7.5 Summary

Field observations and interviews from experts in the park environment helped identify actual land surface changes inside and outside CVNP and identify threats due to urban growth. From satellite remote sensing analysis, it is impossible to detect the condition of properties, actual land-use, or the popularity of places. Therefore field observations add a new element to the study, and expertise from the CVNP ranger and ecologist at Summit County Metroparks helped explore issues inside and outside the park.

CHAPTER 8

CONCLUSION

8.1 Conclusion

In summary, urban expansion between Cleveland and Akron has gradually expanded close to Cuyahoga Valley National Park. The Cuyahoga Valley has progressively gained back its environment due to the efforts of various groups, however, there is increasing pressure from urban growth outside the park.

Twenty years of this urban growth pattern were analyzed using LANDSAT TM/ETM+ satellite data and GIS data. By comparing two classification methods, the pixel-based and object-oriented classification, showed their advantage and disadvantages of creating land surface classification maps. The object-oriented classification maps showed overall better results compared with the pixel-based classification method. However, improvement of the results of the object-oriented classification is still necessary to acquire a higher accuracy in analyzing urban expansion patterns. The characteristics of two classification methods are quite different, but the object-oriented classification seems to have more flexibility than the pixel-based classification (supervised and unsupervised). Especially, its ability to analyze different object levels (image object hierarchy) give us more opportunities to classify objects precisely. At the same time, however, the flexibility of the object-oriented classification may result in longer processes especially if analysts don't have experience using the method.

Moreover, the post-classification method, buffer zones analysis, and population growth analyses using GIS proved their usefulness in confirming land surface patterns quantitatively and statistically. These methodologies identified locations of land surface changes and showed how land surfaces have changes around CVNP in the past. However, again, it is important to build more accurate classification maps to obtain better results. To improve the results, for example, it would be better to use two satellite datasets in different seasons (e.g. spring and summer) or use higher resolution datasets, like SPOT (20m resolution) or panchromatic data (15m resolution) from LANDSAT ETM+. It will be necessary to know the characteristics of the object-oriented classification how the classification method can apply to middle-resolution of satellite data set.

To better analyze human impacts on the Cuyahoga Valley National Park, field work inside the park or cooperation with experts is important, because, like the outside the park, heterogeneity is quite complicated. Many places inside the Cuyahoga valley were abused historically, yet many of these are now restored. Many of invasive species look like healthy vegetation but they are gradually moving out the native species. More detailed analysis of water quality and run-off will address the causality of more or less flooding and water quality issues

Even though there are many issues remaining in the National Park, overall, this study contributes in assessing urban expansion patterns around Cuyahoga Valley National Park, and identifying vulnerable places inside the park. To measure and understand human impacts on CVNP, it is necessary to observe the condition of the Cuyahoga River or the park environment over a longer period of time. However, both GIS and remote sensing analysis successfully analyzed urban expansion patterns in the study area, and hopefully this study will provide information for the park management or urban planning around the Cuyahoga Valley in the future.

References

Aronoff S. 2005. Remote Sensing for GIS Managers. *ESRI Press.*

Anderson JR, Hardy E, Roach J, and Witmer R. 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *Geological Survey Profession Paper* 964.

Beach D. 1998. The Greater Cleveland Environment Book Caring for home and bioregion. *EcoCity Cleveland*.

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

Campbell JB. 2002. Introduction to Remote Sensing 3rd Edition. *The Guilford Press NY*.

Castellana L, D'Addabbo A, and Pasquariello G. 2007. A composed supervised/unsupervised approach to improve change detection from remote sensing. *Pattern Recognition Letters 28*: 405-413

Christopherson RW. 2002. Geosystems Fourth Edition. *Prentice-Hall, Inc*.

Clapham Jr. WB. 2003. Continuum-based classification of remotely sensed imagery to describe urban sprawl on a watershed scale. *Remote Sensing of Environment* 86: 322-340

Cockrell R. 1992. A Green Shrouded Miracle the Administrative History of Cuyahoga Valley National Recreation Area, Ohio. *National Park Service*.

Congalton RG and Green K. 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis Publishers.

Cuyahoga River Community Planning Organization. *http://www.cuyahogariverrap.org/index.html*

Cuyahoga Valley Historical Museum and Cuyahoga Valley National Park Association. 2004. Image of America Cuyahoga Valley. *Arcadia Publishing*.

Ecocity Cleveland. *http://www.ecocitycleveland.org/*

ESRI. GIS and Mapping Software. *http://www.esri.com/index.html*

Floyd MF, Jang H, and Noe FP. 1997. The relationship between environmental concern and acceptability of environmental impacts among visitors to two U.S. National Park settings. *Journal of Environmental Management 51*: 391-412

Forman RTT. 1995. LAND MOSAICS The Ecology of Landscapes and Regions. *Cambridge University Press*

Forman RTT and Devlinger RD. 2000. The ecological road-effect zone of a Massachusetts (U.S.A.) suburban highway. *Conservation Biology 14*: 36-46

Forman RTT, Sperling D, Bissonette JA, Clevenger AP, Cutshall CD, Dale VH, Fahrig L, France R, Goldman CR, Heanue K, Jones JA, Swanson FJ, Turrentine T, and Winter TC. 2003. Road Ecology. *Science and Solutions Island Press*.

Franklin SE. 2001. Remote Sensing for Sustainable Forest Management. CRC Press LLC.

Gillham O and MacLean AS. 2002. The Limitless City: A Primer on the Urban Sprawl Debate. Island Press.

Grabski ML. 2005. Images of America Cleveland Flats. *Arcadia Publishing*.

Gregory M, Franklin SE, Ellsworth L. 2005. Remote Sensing for Large-area Habitat Mapping. *Progress in Physical Geography* 29: 449-474

Independence Excavating. www.indexc.com/Projects/Coliseum-Demolition

Hasse JE and Lathrop RG. 2003. Land resource impact indicators of urban. *Applied Geography 23*: 159-175

Hawbaker TJ, Radeloff VC, Hammer RB, and Clayton MK. 2004. Road density and landscape pattern in relation to housing density, land ownership, land cover, and soils. *Landscape Ecology 20*: 609-625

Hay GJ, Castilla G, Wulder M, and Ruiz JR. 2005. An automated object-based approach for the multiscale image segmentation of forest scenes. *International journal of Applied Earth Observation and Geoinformation* 7: 339-359

Hay GJ and Castilla G. 2006. Object-Based image Analysis Strengths, Weaknesses, Opportunities and Threats (Swot). OBIA, 2006: 1st International Conference on Object-based Image Analysis.

Hoersch B. Braun G, and Schmidt U. 2002. Relation between landform and vegetation in alpine regions of Wallis, Switzerland. A multiscale remote sensing and GIS approach. *Computers, Environment and Urban Systems* 26: 113-139

Hong SK, Kim S, Cho KH, Kim JE, Kang S, and Lee D. 2004. Ecotope mapping for landscape ecological assessment of habitat and ecosystem. *Ecological Research* 19: 131-139

Independence Excavating Earth now Moon Later. *http://www.indexc.com/Projects/Coliseum-Demolition*

Im J and Jensen JR. 2005. A change detection model based on neighborhood correlation image analysis and decision tree classification. *Remote Sensing of Environment 99*: 326-340

Jackson MY and Newton MK. 1996. More Cuyahoga Valley Tales. *The Cuyahoga Valley Association.*

Jacquin A, Misakova L, and Gay M. 2008. A hybrid object-based classification approach for mapping urban sprawl in periurban environment. *Landscape and Urban Planning* 84: 152-165

Jat MK, Garg PK, and Khare D. 2008. Monitoring and modeling of urban sprawl using remote sensing and GIS techniuques. *International Journal of Applied Earth Observation and Geoinformation* 10: 26-43

James S and Jackson MY. 1985. Cuyahoga Valley Tales. *The Cuyahoga Valley Association*.

Jensen JR. 1998. Introductory Digital Image Processing A Remote Sensing Perspective 2nd Edition. *Upper Saddle River, NJ: Prentice Hall*.

Ji W, Ma J, Twibell RW, and Underhill K. 2006. Characterizing Urban Sprawl using Multi-stage Remote Sensing Images and Landscape Metrics. *Computers, Environment and Urban Systems* 30: 861-879

Jiang P. 1995. Using GIS to develop a tourist resort in the Cuyahoga Valley National Recreation Area: an example based on day use site selection. *Kent State University Masters Theses Department of Geography*.

Kim SS, Lee CK, and Klensky DB. 2003. The influence of push and pull factors at Korean national parks. *Tourism Management* 24: 169-180

Kline JD. 2000. Comparing states with and without growth management analysis based on indicators with policy implications comment. *Land Use Policy* 17: 349-355

Kuemmerle T. Radeloff VC. Perzanowski K, and Hostert P. 2006. Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. *Remote Sensing of Environment 103*: 449-464

Leung YF and Marion J. 1999. Assessing trial conditions in protected areas: application of a problem – assessment method in Great Smoky Mountains National Park, USA. *Environmental Conservation* 24 (4): 270-279

Lunetta Rs, Johnson DM, Lyon JG, and Crotwell J. 2004. Impacts of imagery temporal frequency on land-cover change detection monitoring. Remote Sensing of Environment 89: 444-454

Maantay J and Ziegler J. 2006. GIS for the Urban Environment. *ESRI Press Readlands, California*.

Marion JL and Farrell TA. 2002. Management practices that concentrate visitor activities: camping impact management at Isle Royale National Park, USA. *Journal of Environmental Management 66*: 201-212

Martinuzzi S, William AG, and Gonzalez OMR. 2007. Land development, land use, and urban sprawl in Puerto Rico integrating remote sensing and population census data. *Landscape and Urban Planning* 79: 288-297

McGarigal K and Marks BJ. 1995. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure. *USDA For. Serv. Gen. Tech. Rep. PNW-351*

Miller CP and Wheeler RA. 1997. CLEVELAND A Concise History, 1796 – 1996 Second Edition. *Indiana University Press Bloomington and Indianapolis*.

Narumalani S, Mishra DR, and Rothwell RG. 2004. Change detection and landscape metrics for inferring anthropogenic processes in the greater EFMO area. *Remote Sensing of Environment 91*: 478-489

National Park Service. US Department of Interior. Cuyahoga Valley National Park. *http://www.nps.gov/cuva/*

Navulur K. 2007. Multispectral Image Analysis Using the Object-Oriented Paradigm. *CRC Press. Taylor & Francis Group, LLC*.

Nelson AC. 1999. Comparing states with and without growth management analysis based on indicators with policy implications. *Land Use Policy* 16: 121-127

Nepal SK and Nepal SA. 2004. Visitor Impacts on Trails in the Sagarmatha (Mt. Everest) National Park, Nepal. *AMIBO: A Journal of the Human Environment* 33.6: 334-340

Nordberg ML and Evertson J. 2005. Vegetation index differencing and linear regression for change detection in a Swedish mountain range using Landsat TM and ETM+ imagery. *Land Degradation & Development 16*: 139-149

Novak AB and Wang YQ. 2004. Effects of Suburban Sprawl on Rhode Island's Forest: A LANDSAT View from 1972 to 1999. *Northeastern Naturalist 11(1)*: 67-74

O'Connor A, Zerger A, and Itami B. 2005. Geo-temporal tracking and analysis of tourist movement. *Mathmatics and computers in simulation* 69: 135-150

Ode A and Fry G. 2006. A model for quantifying and predicting urban pressure on woodland. *Landscape and Urban Planning 77*: 17-27

Payn TW, Hill RB, Hock BK, Skinner MF, Thorn AJ, and Rijkse WC. 1999. Potential for the use of GIS and spatial analysis techniques as tool for monitoring changes in forest productivity as tool for monitoring changes in forest productivity and nutrition, a New Zealand example. *Forest Ecology and Management* 122: 187-196

Peretz JH, Tonn BE, Reed GD, and Robles LAD. 2005. Using Scenarios to assess the impact of air pollution in the Great Smoky Mountains National Park. *Public works management & Policy* 10: 170-185

Platt CV. 2006. Cuyahoga Valley National Park Handbook. The Kent State University Press.

Platt RV and Rapoza L. 2008. An Evaluation of an Object-Oriented Paradigm for Land Use/Land Cover Classification. *The Professional Geographer Forum and Journal of the Association of American Geographers* 60: 87-100

Richards JA and Jia X. 2006. Remote Sensing Digital Image Analysis An Introduction Fourth Edition. Springer

Schmidt KS and Skidmore AK. 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment 85*: 92-108

Schowengerdt RA. 2007. Remote Sensing Models and Methods for Image Processing Third Edition. Academic Press, Elsevier

Shalaby A and Tateishi R. 2007. Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the northwestern coastal zone of Egypt. *Applied Geography 27*: 28-41

Skerl KL, Winstel J, and Ross TE. 2005. Development pressures prompt integration of science and planning to enhance stormwater management in the Cuyahoga Valley. *Integrated Science for Resource Management and Planning 53*

Song C, Woodcock CE, Seto KC, Lenney MP, and Macomber SA. 2001. Classification and Change Detection using Landsat TM Data: When and How to Correct Atmospheric Effects? *Remote Sensing of Environment* 75: 230-244

Soudani K, François C, Maire Gl, Dantec CL, and Dufrĕne E. 2006. Comparative Analysis of IKONOS, SPOT, and ETM+ Data for Leaf Area Index Estimation in Temperate Coniferous and Deciduous Forest Stands. *Remote Sensing of Environment 102*: 161-175

Southworth J, Nagendra H, Carlson LA, and Tucker C. 2004. Assessing the impact of Celaque National Park on forest fragmentation in western Honduras. Applied Geography 24: 303-322

Store R and Kansgas J. 2001. Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modeling. *Landscape and Urban Planning* 55: 79-93

Tappeiner U, Tasser E, Tappeiner G. 1998. Modeling vegetation patterns using natural and anthropogenic influence factors: preliminary experience with a GIS based model applied to an Alpine area. *Ecological Modeling* 113: 225-237

United States Census Bureau. 2007. *http://www.census.gov/*

Welch R, Madden M, and Jordan T. 2002. Photogrammetric and GIS techniques for the development of vegetation databases of mountainous areas: Great Smoky Mountains National Park. *Photogrammetry and Remote Sensing* 57: 53-68

Wiersma YF, Nudds TD, and Rivard DH. 2004. Models to distinguish effects of landscape patterns and human population pressure associated with species loss in Canadian National Parks. *Landscape Ecology 19*: 773-786

Wilson Eh, Hurd JD, Circo Dl, Prisloe Mp, and Arnold C. 2003. Development of a geospatial model to quantify describe and map urban growth. *Remote Sensing of Environment 86*: 275-285

Wong DWS and Lee J. 2005. Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS. *Wiley Jon Wiley & Sons. Inc.*

Wulder MA, LeDrew EF, Franklin SE, Lavigne MB. 1998. Aerial Image Texture Information in the Estimation of Northern Deciduous and Mixed Wood Forest Leaf Area Index (LAI). *Remote sensing for Environment* 64: 64-76

Wulder MA and Franklin SE. 2003. Remote Sensing of Forest Environments Concepts and Case Studies. Kluwer Academic Publishers.

Wulder MA, Hall RJ, Coops HN, Franklin SE. 2004. High Spatial Resolution Remotely Sensed Data for Ecosystem Characterization. *Bioscience* 54: 511-521

Wulder MA, and Franklin SE. 2007. Understanding Forest Disturbance and Spatial Pattern Remote Sensing and GIS Approaches. Taylor & Francis

Yuan F, Sawaya KE, Loeffelholz BC, and Bauer ME. 2005. Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Remote Sensing of Environment 98: 317-328

APPENDIX A

The table shows population number by cities or township in 7 counties, Northeast Ohio.

The data is acquired from U.S. Census Bureau.

Table Summary of Population Changes in cities/townships from 1990 to 2006

Cuyahoga County	Population Census			Population Growth	
	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Bay Village	17,000	16,087	14,976	-913	-1,111
Beachwood	10,677	12,186	11,350	1,509	-836
Bedford	14,822	14,214	13,320	-608	-894
Bedford Heights	12,131	11,375	10,663	-756	-712
Bentleyville	674	947	914	273	-33
Berea	19,051	18,970	18,139	-81	-831
Bratenahl	1,356	1,337	1,293	-19	-44
Brecksville	11,818	13,382	13,106	1,564	-276
Broadview Heights	12,219	15,967	17,563	3,748	1,596
Brook Park	22,865	21,218	19,699	-1,647	-1,519
Brooklyn	11,706	11,586	10,692	-120	-894
Brooklyn Heights	1,450	1,558	1,484	108	-74
Chagrin Falls	4,348	4,024	3,739	-324	-285
Cleveland	505,616	478,403	444,313	-27,213	-34,090
Cleveland Heights	54,052	49,958	47,097	-4,094	-2,861
Cuyahoga Heights	682	599	682	-83	83
East Cleveland	33,096	27,217	25,213	-5,879	-2,004
Euclid	54,875	52,717	48,717	-2,158	-4,000
Fairview Park	18,028	17,572	16,212	-456	-1,360
Garfield Heights	31,739	30,734	28,518	-1,005	-2,216
Gates Mills	2,508	2,493	2,330	-15	-163
Glenwillow	455	449	591	-6	142
Highland Heights	6,249	8,082	8,620	1,833	538
Highland Hills	1,618	1,618	1,413	0	-205
Hunting Valley	648	735	704	87	-31
Independence	6,500	7,109	6,789	609	-320
Lakewood	59,718	56,646	52,194	-3,072	-4,452
Linndale	159	117	91	-42	-26

Lyndhurst	15,982	15,279	14,195	-703	-1,084
Maple Heights	27,089	26,156	24,293	-933	-1,863
Mayfield	3,462	3,435	3,191	-27	-244
Mayfield Heights	19,847	19,386	18,110	-461	-1,276
Middleburg Heights	14,702	15,542	15,237	840	-305
Moreland Hills	3,354	3,298	3,142	-56	-156
Newburgh Heights	2,310	2,389	2,197	79	-192
North Olmsted	34,204	34,113	32,126	-91	-1,987
North Randall	977	906	850	-71	-56
North Royalton	23,197	28,648	29,465	5,451	817
Oakwood	3,392	3,667	3,630	275	-37
Olmsted	32,126	34,113	32,126	1,987	-1,987
Olmsted Falls	6,741	7,962	8,333	1,221	371
Orange	2,810	3,236	3,319	426	83
Parma	87,876	85,655	80,009	-2,221	-5,646
Parma Heights	21,448	21,659	20,293	211	-1,366
Pepper Pike	6,185	6,040	5,738	-145	-302
Richmond Heights	9,611	10,944	10,372	1,333	-572
Rocky River	20,410	20,735	19,377	325	-1,358
Seven Hills	12,339	12,080	11,925	-259	-155
Shaker Heights	30,831	29,405	27,245	-1,426	-2,160
Solon	18,548	21,802	22,257	3,254	455
South Euclid	23,866	23,537	21,791	-329	-1,746
Strongsville	35,308	43,858	43,347	8,550	-511
University Heights	14,790	14,146	13,015	-644	-1,131
Valley View	2,137	2,179	2,064	42	-115
Walton Hills	2,371	2,400	2,321	29	-79
Warrensville Heights	15,745	15,109	13,967	-636	-1,142
Westlake	27,018	31,719	31,025	4,701	-694
Woodmere	834	828	769	-6	-59
Geauga County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Auburn	3,298	5,158	5,997	1,860	839
Bainbridge	9,694	10,916	11,283	1,222	367
Burton	4,187	4,358	4,521	171	163
Chardon	4,037	4,763	4,941	726	178
Chardon	4,446	5,156	5,284	710	128
Chester	11,049	10,968	11,048	-81	80
Claridon	3,016	3,173	3,355	157	182
Hambden	3,311	4,024	4,615	713	591
Hunting Valley	799	735	704	-64	-31
Huntsburg	2,642	3,297	3,637	655	340

Middlefield	4,111	4,418	4,674	307	256
Middlefield	1,898	2,233	2,414	335	181
Montville	1,682	1,984	2,161	302	177
Munson	5,775	6,450	6,751	675	301
Newbury	5,611	5,805	5,980	194	175
Parkman	3,083	3,546	3,927	463	381
Russell	5,614	5,529	5,631	-85	102
South Russell	3,402	4,022	3,986	620	-36
Thompson	2,219	2,383	2,552	164	169
Troy	1,903	2,567	2,775	664	208
Lake County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Concord	12,432	15,282	16,321	2,850	1,039
Eastlake	21,161	20,255	19,669	-906	-586
Kirtland	5,881	6,670	7,309	789	639
Kirtland Hills	628	597	765	-31	168
Lakeline	210	165	162	-45	-3
Leroy	2,581	3,122	3,766	541	644
Madison	17,954	18,428	19,874	474	1,446
Mentor	47,358	50,278	51,593	2,920	1,315
Mentor-on-the-Lake	8,271	8,127	8,293	-144	166
Painesville	16,493	18,562	19,087	2,069	525
Painesville	15,699	17,503	17,933	1,804	430
Perry	6,780	8,240	9,068	1,460	828
Timberlake	833	775	742	-58	-33
Waite Hill	454	446	538	-8	92
Wickliffe	14,558	13,484	13,097	-1,074	-387
Willoughby	20,510	22,621	22,356	2,111	-265
Willoughby Hills	8,427	8,595	8,449	168	-146
Willowick	15,269	14,361	14,361	-908	0
Lorain County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Amherst	10,332	11,797	11,841	1,465	44
Amherst	7,060	7,598	7,695	538	97
Avon	7,337	11,446	16,455	4,109	5,009
Avon Lake	15,066	18,145	22,117	3,079	3,972
Brighton	812	942	1,009	130	67
Brownhelm	7,060	7,782	8,069	722	287
Camden	1,522	1,530	1,573	8	43
Carlisle	7,554	7,339	7,238	-215	-101
Columbia	6,594	6,912	7,015	318	103
Eaton	8,821	9,675	5,861	854	-3,814
Elyria	3,699	3,520	3,371	-179	-149
Elyria	56,746	55,953	55,745	-793	-208

Grafton	3,344	2,302	5,869	-1,042	3,567
Grafton	3,052	2,722	2,931	-330	209
Henrietta	1,795	1,873	1,894	78	21
Huntington	1,172	1,282	1,451	110	169
Lagrange	4,644	5,972	6,209	1,328	237
Lorain	71,245	68,652	70,592	-2,593	1,940
New Russia	2,470	2,357	2,403	-113	46
North Ridgeville	21,564	22,338	27,197	774	4,859
Oberlin	8,191	8,195	8,239	4	44
Penfield	1,312	1,690	1,859	378	169
Pittsfield	1,546	1,549	1,629	3	80
Rochester	627	752	904	125	152
Sheffield	1,943	2,949	3,465	1,006	516
Sheffield	3,751	4,117	4,170	366	53
Sheffield Lake	9,825	9,371	9,085	-454	-286
Wellington	5,386	5,904	6,107	518	203
Medina County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Brunswick	28,230	33,388	35,107	5,158	1,719
Brunswick Hills	4,340	5,469	7,135	1,129	1,666
Chatham	1,799	2,158	2,649	359	491
Granger	2,932	3,928	4,517	996	589
Guilford	4,773	5,447	3,674	674	-1,773
Harrisville	4,776	4,914	2,400	138	-2,514
Hinckley	5,845	6,753	7,693	908	940
Homer	1,196	1,461	1,931	265	470
Lafayette	4,804	5,476	5,386	672	-90
Litchfield	2,506	3,250	3,845	744	595
Liverpool	3,713	4,329	5,027	616	698
Medina	19,231	25,139	26,350	5,908	1,211
Medina	4,864	7,783	8,568	2,919	785
Montville	3,371	5,410	7,135	2,039	1,725
Sharon	3,234	4,244	5,009	1,010	765
Spencer	1,786	2,429	2,325	643	-104
Wadsworth	15,718	18,437	20,155	2,719	1,718
Wadsworth	3,375	3,996	4,417	621	421
Westfield	3,394	4,172	3,089	778	-1,083
York	2,479	2,912	3,660	433	748
Portage County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Atwater	2,663	2,762	2,875	99	113
Aurora	9,192	13,556	14,402	4,364	846
Brady Lake	490	513	497	23	-16
Brimfield	8,389	7,963	7,868	-426	-95

Charlestown	1,903	2,003	2,109	100	106
Deerfield	2,764	3,211	3,255	447	44
Edinburg	1,978	2,344	2,468	366	124
Franklin	6,478	5,276	4,986	-1,202	-290
Freedom	2,530	2,751	2,860	221	109
Garrettsville	2,014	2,262	2,203	248	-59
Hiram	1,888	2,296	2,407	408	111
Hiram	1,330	1,242	1,187	-88	-55
Kent	28,835	27,906	27,946	-929	40
Mantua	4,418	4,661	4,724	243	63
Mantua	1,178	1,046	1,016	-132	-30
Mogadore	4,008	3,893	3,946	-115	53
Nelson	2,778	2,985	3,104	207	119
Palmyra	2,531	2,785	2,897	254	112
Paris	1,785	1,827	1,947	42	120
Randolph	4,970	5,504	5,575	534	71
Ravenna	8,961	9,270	9,167	309	-103
Ravenna	12,069	11,771	11,422	-298	-349
Rootstown	6,612	7,212	7,200	600	-12
Shalersville	5,270	5,976	6,030	706	54
Streetsboro	9,932	12,311	14,185	2,379	1,874
Suffield	6,312	6,383	6,349	71	-34
Sugar Bush Knolls	211	227	223	16	-4
Tallmadge	14,870	16,390	17,370	1,520	980
Windham	1,955	2,060	2,187	105	127
Windham	2,943	2,806	2,723	-137	-83
Summit County	POP1900	POP2000	POP2006	1900 to 2000	2000 to 2006
Akron	223,019	217,074	209,704	-5,945	-7,370
Barberton	27,623	27,899	27,063	276	-836
Bath	9,015	9,635	10,199	620	564
Boston	1,879	1,664	2,044	-215	380
Boston Heights	733	1,186	1,223	453	37
Clinton	1,175	1,337	1,404	162	67
Copley	11,130	13,641	14,085	2,511	444
Coventry	11,295	10,900	10,938	-395	38
Cuyahoga Falls	48,950	49,374	50,398	424	1,024
Fairlawn	5,779	7,307	7,159	1,528	-148
Franklin	14,910	14,530	14,530	-380	0
Green	19,179	22,817	23,532	3,638	715
Hudson	17,128	22,439	23,154	5,311	715
Lakemore	2,684	2,561	2,749	-123	188
Macedonia	7,509	9,224	10,418	1,715	1,194

Mogadore	4,008	3,893	3,946	-115	53
Munroe Falls	5,359	5,314	5,260	-45	-54
Northfield	3,624	3,827	3,715	203	-112
Northfield Center	3,982	4,931	5,037	949	106
Norton	11,477	11,523	11,549	46	26
Reminderville	2,163	2,347	2,507	184	160
Richfield	5,010	5,424	6,155	414	731
Sagamore Hills	6,503	9,340	9,563	2,837	223
Silver Lake	3,052	3,019	3,148	-33	129
Springfield	14,773	15,168	15,418	395	250
Stow	27,702	32,139	34,335	4,437	2,196
Tallmadge	14,870	16,390	17,370	1,520	980
Twinsburg	9,606	17,006	17,484	7,400	478
Twinsburg	1,896	2,153	2,577	257	424