“A Spatio-Temporal Analysis of Land Use and Land Cover Change and Sinkhole Development in Opequon Creek Watershed, West Virginia: 1984-2009”

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by

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Chapter 1: Rationale and Objectives

1.1 INTRODUCTION

While there have been many studies dealing with urban growth impacts on watershed hydrology and geomorphology, very few have analyzed the spatial character and composition of such growth using remote sensing and geographic information system technology, especially in sensitive watersheds typified by karst. Karst watersheds, those typified by sinkholes, sinking streams and blind valleys, are more sensitive to environmental change than typical watersheds because soils are thin and water has relatively short residence times in underlying aquifers. This research addresses a portion of the Opequon Creek Watershed (Figure 1), an urbanizing karst subwatershed of the Potomac River in Berkeley County, West Virginia. Analysis is especially urgent as this watershed is experiencing highly elevated urban growth (34% in just the past 5 years) because of its proximity to both Washington, D.C. and Hagerstown, Maryland. In fact, the watershed is now considered to be part of the Greater Baltimore-Washington, DC, metropolitan area.
Sinkholes in particular, are a common landform in this region, and hundreds of sinkholes have been identified here and in nearby counties. Many researchers have noted that in urbanizing areas, the ground surface can become unstable and collapse, resulting in sinkhole development (e.g., Kastning and Kastning, 1997). In addition, due to the increased volume and rate at which surface water runs off impermeable urban structures such as roofs, sidewalks, streets, and parking lots, other effects are identified, such as erosion, sedimentation, sinkholes, sinkhole flooding and groundwater contamination (e.g., Kastning and Kastning, 1997; Doerfliger et al., 1997).

New sinkholes have been identified in the study area and the hazardous nature of such landscape change is socially and academically important to understand. Not much
has been done to examine sinkhole frequency and distribution temporally, as it relates to urban growth, in urbanizing Berkeley County. Likewise, there exists no wide-ranging land use planning initiative in the panhandle of West Virginia aimed at addressing these issues in a sensitive karst watershed. This is particularly important to address since the watershed crosses political and jurisdictional boundaries, and thus it is important that a better understanding of the nature and character of urban growth is achieved in order to derive management plans and land use planning tools that can combat these fragmented land use patterns and irregular urban growth.

The main focus of this research therefore, is to quantify land use and land cover in the urbanizing Opequon Creek sub-watershed via a temporal change detection analysis of remotely-sensed imagery, as well as to explore the link between urban growth and the development of sinkholes over the last 20 years. Secondary emphasis is on developing and evaluating object-oriented image analysis as an automated methodology for sinkhole inventory in karstic regions, using easily-attainable and inexpensive aerial photography and satellite imagery.

Specifically the project objectives are:

1. To classify and analyze land use and land cover change, including sinkholes, in a urbanizing karst subwatershed (Opequon Creek Watershed); and

2. To evaluate the potential for use of image-object analysis for sinkhole inventory at the watershed level

3. Using results derived from objective A and B, to evaluate and assess the potential for traditional land use planning measures that may mitigate urban-related impacts in karst watersheds in general and Opequon Creek Watershed in particular.
These will address understanding land use and land cover change over the past 25 years, including sinkhole development, whether image-object analysis suitable for sinkhole inventory at the watershed scale, and what potential land use planning tools can be used in the Opequon Creek Watershed.

1.2 WHY USE IMAGE-OBJECT ANALYSIS?

The use of object-oriented imaging software allows for inexpensive quantitative analysis of sinkholes and automated classification of land use and land cover at the watershed scale. While alternative and more accurate technologies exist to map sinkholes at various scales, such as LiDAR (Light Detection and Ranging) and ALSM (Airborne Laser Swath Mapping), these methods are prohibitively expensive for municipalities and small watershed organizations that are primarily concerned with sinkhole development or land use and land cover change impacts. LiDAR imagery (Figure 2) can cost as much as $2000/acre, which is not practical for large-area studies or smaller studies initiated by small, cash-strapped towns.

Figure 2: LiDAR Bare-Earth Imagery of Sinkholes (Carter et. al., 2001)
The development of an accurate, cost-effective method for large-area sinkhole inventory (object-oriented analysis) offers enormous potential for watershed stakeholders and municipalities in these economically uncertain times.

It is also my contention that since sinkholes are readily identifiable features in a landscape (by their shape and negative depression attributes), they can be identified in digital images both by their spectral reflectance (characteristic vegetation, soil moisture), and their shape (e.g. Figure 3) using object-oriented image analysis software. The methods used here, if proven accurate, can significantly contribute to the inventory of karst geohazards globally.

Figure 3: Aerial Photograph of West Virginia Sinkhole Plain (Jones, 1997)

Dissemination of the results allows both local watershed participants and regional organizations to co-operate in efforts to manage these sensitive areas. It is hoped that key watershed stakeholders, such as municipalities, farmers, residents and businesses may benefit via recognition of detrimental land use practices and work together to achieve
more functional watershed management. Lastly, not much work has been done using digital imagery for sinkhole analysis.

1.3 ORGANIZATION OF DISSERTATION

Chapter 2 gives various background aspects of the study area including geology, physiographic provinces, soils, drainage, hydrology and climate. It is intended that this chapter frame the study area and present ancillary information for a backdrop against which the study is conducted.

Chapter 3 examines the literature for land use and land cover changes in karst watersheds that result from increasing urban pressures and development at the watershed level. Impacts from these changes are analyzed to understand changes taking place in these watersheds.

Chapter 4 explains the use of remote-sensing and image-object-based approaches to landscape analysis, as well as detailing the nature of land use and land cover change in Opequon Creek Watershed in particular during the last twenty-five years. The datasets and some of the methods of analysis are also presented in this chapter. Then spatial analysis of classifications is conducted to examine correlations between variables and land uses and land covers, as well as quantifying the nature and character of sinkhole development.

Chapter 5 details the object-oriented analysis used in the study and presents statistical analysis used during accuracy assessment to verify validity of results. Also presented here are the results from the comparison of several methods of landscape
analysis undertaken in a control area to determine suitability of Definiens Professional for
landscape inventory in karst watersheds compared to traditional methods.

Chapter 6 reviews potential for traditional land use planning tools and measures
for their ability to curb and mitigate sprawling development patterns in Opequon Creek
Watershed may be contributing to sinkhole development.

Chapter 7 summarizes and discusses the results of the dissertation and suggests
future work in this area.
Chapter 2: Study Area: Opequon Creek Watershed

Population increase has become a global concern as impacts are felt by cities, states, and federal governments (Fuhs, 1999). The United States Census Bureau estimates population in the United States increased by 13.2% between 1990 and 2000 (US Census Bureau, 2000). At the same time the United Nations estimated that in the last decade the global population has increased at an even greater rate (Fuhs, 1999).

Population increase in Opequon Creek Watershed has become a recent problem (Table 1) as people move into West Virginia from Washington, D.C. and Hagerstown, Maryland.

### POPULATION DATA FOR BERKELEY COUNTY, WV

<table>
<thead>
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<th>Date</th>
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Table 1: Population Data for Berkeley County, West Virginia (Source: US Census Bureau 2009)
Human-induced impacts are manifesting themselves through increasing urban pressures that impact watersheds, like deforestation, water table drawdown, disappearing farmland, sinkhole development, and contamination of groundwater from agricultural and urban runoff (Williams, 1993). These effects are even more numerous in karst watersheds, those typified by sinking streams, caves, and sinkholes (Williams, 1993). These watersheds are particularly sensitive due to thin soils, slow recharge and direct conduits moving surface waters to underlying aquifers (Daoxian, 1987).

These watersheds are an important source of drinking and commercial water, agriculture, and habitat for humans and wildlife (Daoxian, 1987). Therefore, sensitive areas such as these need to be understood and protected in order to assure viable sources of human and wildlife needs. High density development negatively impacts these areas by changing hydrology and morphology of the land and contaminating both soil and water resources (Daoxian, 1987).

This research attempts to quantify and assess the impacts of increasing urbanization at the watershed scale, as well as suggesting possible solutions, such as traditional planning tools that may have the potential to mitigate urbanizing impacts. Some of these tools include transfer of development rights, purchase of development rights, conservation easements, urban growth boundaries, and smart growth initiatives. This research suggests that land use and watershed planning may offer the potential to mitigate and reverse some of the negative impacts of urbanization experienced in local and regional watersheds in sensitive regions via a reduction or relocation of development.
According to Williams (1993), watersheds are particularly vulnerable to human impacts because of multiple land uses and various political and municipal jurisdictions. In the United States 25% of the drinking water is obtained from groundwater of karst watersheds (Davis et al., 2001). These watersheds are very sensitive to human intrusions because of increases in impervious surfaces, rerouting of hydrology, and sedimentation from construction, which are all found with increasing urbanization (Doerfliger et al., 1997).

Human-induced impacts in these sensitive areas are driven by changing hydrology that comes with development in the watershed. Hydrologic changes can be caused by roof tops, streets, buildings, pavement and other impervious surfaces (Doerfliger et al., 1997). Doerfliger et al. (1997) goes on to say that “other human-induced impacts include sinkhole development, which is usually a result of these hydrologic changes, water table drawdown, pollutant transport, groundwater contamination, and sedimentation of waters”. Hydrologic contamination then results from bad water systems, anthropogenic accidents, and runoff.

According to Canaan Valley Institute Booklet “Protecting Our Water: Berkeley County, West Virginia”, increasing population pressures in the county have led to increasing drawdown of aquifers and affected the quantity of available waters. In 2002, two springs that supply some of the water for the Berkeley County Public Service Water District were flowing at less than 50% normal flow and the Potomac River had reached record lows. Contributing to the problem, Berkeley County added approximately 1000 new housing units per year during the 1990’s (Berkeley County Source Water
Assessment and Protection Committee Booklet, 2004). Likewise, the “Karst Survey and Preliminary Groundwater Supply Assessment” conducted by Specialized Engineering of Ranson, WV for site development of a subdivision in Berkeley County, concluded that water demand in the county is the dominant component affecting spring flows in the watershed. The increasing development continues to cause demand for water that outpace the ability of the karst rocks to provide recharge.

Opequon Creek Watershed in West Virginia lies approximately 100 kilometers from both Washington, D.C. and Hagerstown, Maryland and has experienced increased urban growth and a corresponding population boom over the last 30 years. Opequon Creek, a tributary of the Potomac River drains a large section of the region and flows over predominantly karst terrain (Figure 4).

![Figure 4: Karst areas (yellow) of the United States (Source: United States Geological Survey National Karst Map)](image)

This research is limited to the Martinsburg area of Berkeley County in West Virginia (Figure 5) due to the large size of the entire watershed. Likewise, a study at the
sub-watershed scale enables more detailed spatial and temporal examination of land use and land cover change and sinkhole development. Therefore, the abrupt southern boundary represents this division.

The Opequon Creek watershed provides an excellent case study due to exponential growth of population in the eastern panhandle of West Virginia, especially in Martinsburg (Figure 6) and Inwood, coupled with the virtual lack of statewide or regional regulatory structures and comprehensive watershed management plans.

West Virginia has large areas of karst topography (Figure 7) providing a prime test site to examine the impacts of urban growth taking place in these sensitive environments, as well as establishing a locale for examination of a semi-automated sinkhole inventory method using object-oriented image analysis.

Figure 5: Digital Orthophotograph Mosaics of Study Area (Source: West Virginia Geological Survey State Address and Mapping Board Aerial Photographs, 2003)
Figure 6: Martinsburg Topographic Map (Source: United States Geological Survey Topographic Series, 1995)

Figure 7: Map of Surficial Karst in Study Area (Source: Cardwell, 1968)
2.1 STUDY AREA DEMOGRAPHICS

The eastern panhandle counties of Jefferson and Berkeley have exhibited increasing growth rates in the last few censuses (US Census Bureau 2009). While relatively small in size (less than 20,000) Martinsburg has experienced over 30% population growth during the last decade, making it atypical of the state and region (US Census Bureau, 2000). Berkeley County now has one of the highest population densities (236/square mile in 2000) in West Virginia (Figure 8), which has contributed to numerous geohazards, such as landslides and sinkholes (West Virginia Blue Book, 2000).

Figure 8: Map of West Virginia Population Density by County
(Source: WV Blue Book, 2000)
According to the West Virginia Geological Survey Website (www.wvgs.wvnet.edu), Berkeley County is the second oldest county in West Virginia. The Counties in West Virginia Blue Book (2001) states that it was formed in 1772 from Frederick County, Virginia. Berkeley County is 523 km² and has a population of 102,044, which represents a 34.4% change since the 2000 census (75,905), according to the U.S. Census Bureau, 2000. The county seat is in Martinsburg which has around 20,000 inhabitants (U.S. Census Bureau, 2009).

2.2 STUDY AREA GEOLOGY

West Virginia has two different geologically distinct areas: Appalachian Plateau and the Valley and Ridge, separated by the Allegheny Front (Lessing, 1976). The western part of West Virginia is mainly flat rocks with coal, while the east is folded and faulted from earlier tectonics, with virtually no coal. Lessing (1976) goes on to add that the oldest rocks in the state are found in the extreme east and get older as you move westward (Figure 9). These oldest rocks are from the late Precambrian (Catoctin Formation) (Cardwell, 1968).

Lessing (1976) further states that, “there are no significant Mesozoic or Cenozoic rocks in the state…”. Most of the eastern part of Berkeley County and western Jefferson County, where the study is undertaken, is underlain by Ordovician and Cambrian age (425-600 m.y.) limestones and shales (Grimsley, 1916; Cardwell, 1968). The limestone areas have slopes and ridges that range from mild to steep, with the ridges being dissected by valleys, depressions, and sinkholes (Grimsley, 1916).
The physiography in the eastern panhandle counties of Berkeley, Jefferson, and Morgan is divided near Martinsburg (Grimsley, 1916). The western part of these counties has mountains, while Berkeley and Jefferson sit in a limestone valley (the Great Valley), so elevations change from 260 feet at Harpers Ferry to 2300 feet on Cacapon Mountain (Grimsley, 1916). The area where these two regions meet (Figure 10) is where this research is conducted.
Figure 10: Map of Physiographic Provinces of Appalachia (Source: Cardwell, 1975)

According to Grimsley (1916), the mountains in the east have been extensively folded and faulted, with a northeast to southwest trend of high angle dips (Figure 11). The structural geology is made more complex by large folds that overlap more minor, local folds (Grimsley, 1916).
The Appalachian region extends from the eastern Blue Ridge to the Ohio Valley, south into Alabama, and north to New York (Grimsley, 1916). The rocks in this region are almost all sedimentary rocks that were laid down on the eastern shore of a Paleozoic Interior Sea (Grimsley, 1916). These deposits were later folded during several mountain-building events that took place and the surface changed by subsequent geologic events (Cardwell, 1975). In the eastern panhandle of West Virginia near the study area there are 3 physiographic subdivisions: Blue Ridge, Great Valley and the Allegheny Ridge and Valley Province (Figure 12).
2.3 VALLEY AND RIDGE PROVINCE

The Valley and Ridge Province is made of folded and faulted rocks that are from late Precambrian to early Mississippian in age (Lessing, 1976; Cardwell, 1968). The Great Valley (Figure 13) is 20 miles west of the Blue Ridge Mountains. This flat area is made of folded and faulted Cambrian and Ordovician limestone and dolomite, with the Martinsburg shale of the study area being the only Ordovician shale (Lessing, 1976). Between the valley and the Allegheny Front are rocks from late Ordovician to early Mississippian age. The valleys are mostly made of easily eroded shale and siltstone, while the mountain ridges are tougher sandstone and limestone (Lessing, 1996).
There are also three major thrust sheets that have displaced the surface and subsurface rocks for 30 to 50 miles (Grimsley, 1916).

2.4 APPALACHIAN PLATEAU PROVINCE

The Appalachian Plateau Province is in the western part of West Virginia where the rocks are largely flat. The rocks here range in age from late Ordovician to Permian (Lessing, 1996). Most of the Appalachian Plateau is made of Pennsylvanian and Permian rocks (Cardwell, 1975). The rocks in the northern part of the Plateau are younger than those in the south. According to Lessing (1996), the boundary between the northern and
southern sections is complex and is marked by changes in topography, stratigraphy, and structure.

2.5 STRUCTURAL GEOLOGY FEATURES

The two major structural features in the study area are the Ferrel Ridge Anticline and the Massanutten Syncline. Ferrel Ridge is an anticlinal fold that brings the Oriskany sandstone to the surface, along with a couple of limestones and the Marcellus and Hamilton shales (Grimsley, 1916; Dean and Kulander, 1987). Erosion has since removed the top of the folds bringing the Willis Creek Limestones and shales to the surface. In this area the strata dip around 15-25 degrees (Grimsley, 1916). The other major structural feature is the Massanutten Syncline (Grimsley, 1916; Dean and Kulander, 1987), which makes a trough where Opequon Creek flows through the study area.

There are also a lot of small folds and faults that impact water flow, which can affect sinkhole development. For example, east from Martinsburg, structures include Blairton Anticline, Files Crossroad Fault, Fish Hatchery Fault, Winebrenner’s Anticline, Blizzard Syncline and the Kerneysville Fault (Grimsley, 1916; Cardwell, 1968). Southwest of Martinsburg are the Airport Anticline, Martinsburg Anticline, Rosemont Fault and the Exit 23 Anticline (Grimsley, 1916; Cardwell, 1968).

Northwest of Martinsburg are the Old Mill Anticline, Massanutten Syncline, Falling Waters Anticline, Rumsey Syncline, Georgetown Anticline and the North Mountain Fault (Grimsley, 1916; Cardwell, 1968). All of these structural features lie within a 6-9 mile radius of Martinsburg. These all help determine groundwater
mechanics and surface flow within the area, and as such are contributors to sinkhole development.

2.6 STUDY AREA STRATIGRAPHY

Ordovician and Cambrian age limestones and dolomites (Figure 14) are represented in the study area by several units (Cardwell, 1968).

![Exposed Ordovician Rockdale Run Limestone in Berkeley County](image)

Figure 14: Exposed Ordovician Rockdale Run Limestone in Berkeley County

The upper part of the Ordovician in Berkeley County (Figure 15) is typified by the Martinsburg shale (Om), which is in the eastern part of the county and study area (Cardwell, 1968). This formation is predominantly gray to dark shales, yellowish in the upper portions, with thin limestone and sandstone interbeds, particularly in the lower portion, with a thickness of 1500-2000 feet (Cardwell et al., 1968).
According to local geologic sections (Figure 16), the Martinsburg shale formation ranges from 500-1450 foot thick but is about 1400 ft thick throughout most of the study area (Grimsley, 1916).

Grimsley (1916) also states, the main outcropping of the Martinsburg shale (Figure 17) can be found in the eastern part of the county, from the Potomac, southwest to Virginia. Anticlines and folds in the shale bring limestones to the surface where they lead to sinkhole development upon karstification and urban pressures (Dean and Kulander, 1987; Grimsley, 1916). East and west of the shales are large areas of limestones.
Figure 17: Map of Martinsburg Shale and Rockdale Run Limestone Outcropping inside Study Area (Source: Dean & Kulander, 1987)

The shales are highly fractured, which contributes to migration of waters into Goose Creek, which then flows into the Opequon Creek and Potomac River (Grimsley, 1916). The topography in these shale areas are usually round hills, with steep slopes (Grimsley, 1916). Beneath the Martinsburg shales are beds of Ordovician limestones (Dean and Kulander, 1987). Rocks east of the Ferrel Ridge anticline dipping toward the Massanutten Syncline include the Beekmantown, Trenton, and Black River Groups (Grimsley, 1916; Dean and Kulander, 1987). These rocks were correlated by Grimsley (1916) as the Chambersburg and Shenandoah Groups in early Jefferson, Berkeley, and Morgan County Geologic Reports. East of the Opequon Creek, limestones include the St. Paul, Trenton, Black River and Beekmantown Groups (Cardwell, 1968; Dean and Kulander, 1987).
The Chambersburg Limestone (Oc) is dark-gray to blue-black aphanitic (microscopically fine-grained) limestones and argillaceous (clayey) (Dean and Kulander, 1987). This rock is about 500 feet thick (Cardwell, 1968). The Chambersburg limestone is the first rocks at the surface outside of Martinsburg. Outcrops are also found in the eastern part of Berkeley County and southwestern Jefferson County (Dean and Kulander, 1987). According to Grimsley (1916) it also outcrops on both sides of the fold east of Opequon Creek. A local section shows the thickness of the Chambersburg at Opequon Creek near Beddington to be about 515 ft thick (Grimsley, 1916).

The next oldest rock is the New Market (Onm) and Row Park (Orp) Limestones. According to Caldwell (1968) “the New Market limestone is dove-gray in color and has aphanitic texture. It is between 40-250 feet thick, and is made up of fine-grained limestone”. The New Market member is exposed both East and West of the Chambersburg Limestone (Page and Donaldson, 1964). The Row Park Limestone only outcrops in the northern parts of the county (Dean and Kulander, 1987). It is made up of gray limestone with chert nodules and dolomite (Grimsley, 1916; Cardwell, 1968). This member is between 0-100 feet thick in outcrop (Page and Donaldson, 1964). The next oldest limestones are part of the Beekmantown Group: Pinesburg Station Dolomite, Rockdale Run Formation, Stonehenge Limestone, and the Stoufferstown Member (Cardwell, 1968; Dean and Kulander, 1987).

Only small sections of the Pinesburg Station Dolomite (Obps) are exposed in the watershed near Opequon Creek (Cardwell, 1968). This rock lies beneath the Row Park Limestone and is between 0-500 ft thick (Cardwell, 1968). According to Cardwell
(1968), this rock is fine-to-medium crystalline, brown-to-light gray dolomite, containing chert.

The Rockdale Run Formation (Obr) is between 2400-2700 feet thick and is bluish-to-light-gray and brown, thick-bedded dolomite and limestone, containing gray chert (Cardwell, 1968). Beneath this rock is the Stonehenge Limestone (Obs), which is about 800 feet thick and consists of gray, thin-bedded to massive limestone, with small black chert nodules and beds of conglomerate (Cardwell, 1968). Large areas of this rock come to the surface in the eastern parts of the county and west of Martinsburg (Cardwell, 1968).

The next oldest rocks move into Cambrian, including the Conococheague and Elbrook Formations. Under the Stonehenge limestone is the Conococheague Formation (Cc), which is about 2200 feet thick and consists of algal and mechanically deposited limestone, with interbeds of aphanitic limestone and dolomite (Cardwell, 1968). Page and Donaldson (1964) go on to say that the upper 300-400 ft of this formation is mainly aphanitic limestone. This formation comes to the surface in the eastern part of the county.

The last major limestone in the study area is the Elbrook Formation (Ce). According to Dean and Kulander (1987), this formation has a thickness of 2000 feet with the top 1000 feet exposed. The rock is thin-bedded, blue-gray limestone and shale, with some limestone and minor dolomites (Dean and Kulander, 1987). This formation is not of much concern to the study since it only comes to the surface in the extreme western and eastern portions of the county.
2.7 STUDY AREA SOILS

The eastern part of the county is considered to be in the Great Valley, with the rest of the county having narrow valleys and steep mountains (Bell, 2003). There are 11 soil series in the county including: Buchanan-Poorhouse, Calvin, Dekalb-Hazelton, Downsville, Duffield-Ryder-Nollville, Hagerstown-Funkstown, Monongahela-Pope-Tygart-Philo, Pectonville-Blackthorn-Caneyville, Swanpond-Opequon-Carbo, Urban Lands, and Weikert-Berks-Clearbrook (Bell, 2003). Of these there are several soil series in the Opequon Creek area near Martinsburg in the study area that may impact sinkhole development (Figure 18). These include:

1. **Urban Land Series**- soil that has been extensively changed due to development in the Martinsburg area. Urban land series make up almost 5% of the general soils map in Berkeley County. This soil type is mainly used for industrial, commercial and residential development (Bell, 2003).

2. **Hagerstown-Funkstown Series**- These are deep, well-drained soils that are found west of Martinsburg on the uplands that are dissected by drainage areas (Bell, 2003). Plenty of limestone outcroppings are found in this soil unit. Two-thirds of this series has been clear-cut and is being used for crops, or development (Bell, 2003).

3. **Weikert-Berks-Clearbrook Series**- This soil develops in level-to-steep slopes that are moderately-well drained, which usually occurs from shale parent material, and is mostly forested, with smaller areas cleared for crops (Bell, 2003).
4. **Swanpond-Opequon-Carbo Series** - This soil is found on low, sloping uplands. Sinkholes and limestone outcroppings are common in this unit (Bell, 2003). Most areas of this series have been cleared for hay with a few areas left for development and hardwood forests, while extensive quarrying of the limestone in this unit has taken place (Bell, 2003).

![Figure 18: Map of study area soils (Source: Bell, 2003)](image)

2.8 **DRAINAGE**

According to Bell (2003), “a drainage basin is the land area where precipitation will drain”. Based on this, West Virginia is divided into 6 major drainage basins: Potomac, Monongahela, Kanawha & New, Ohio, and the Guyandotte/Tug/Big
Sandy (Jones, 1997). The Potomac and the James empty into the Atlantic Ocean, while the other basins drain into the Ohio River and the Gulf of Mexico (Bell, 2003).

As discussed, Berkeley County and the study area are found in the Northern Appalachian Ridge and Valley province with the major morphology being parallel ridges and valleys with southwest-northwest orientations (Bell, 2003). Berkeley County is drained by the Potomac River system (Figure 19) and its tributaries, including Opequon Creek (Jones, 1997).

Figure 19: Map of Major River Basins of West Virginia (Source: Jones, 1997)

The average total annual precipitation for the Opequon Creek Watershed (Figure 20) is about 38 inches per year (Jones, 1997). The Shenandoah Valley section of the county is drained by Opequon Creek and its tributaries: Dry Run, Evans Run, Hoke Run,
Middle Creek, Mill Creek, Sylvan Run, and Tuscarora Creek. Where areas are underlain by limestone, depressions and sinkholes are common, while areas with shales are usually dissected by streams (Bell, 2003).

![Map of West Virginia showing precipitation distribution](image)

**Figure 20:** Map of Distribution of Average Annual Precipitation in West Virginia (Source: Jones, 1997)

### 2.9 CLIMATE

In the winter in Berkeley County the average temperature is 32° F, with the average daily minimum being 23° (Bell, 2003). During the summer the average temperature is 73°F, with the average daily maximum being 85° (Table 2). The total annual precipitation is almost 38 inches, with over most of this between April and
September (Jones, 1997; Bell, 2003). The average seasonal snowfall is 25 inches, with the average mid-afternoon relative humidity at 54% (Bell, 2003).

**TEMPERATURE AND PRECIPITATION DATA FOR STUDY AREA**

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*Table 2: Temperature and Precipitation Data for Study Area 1961-1990* (Bell, 2003)
2.10 OPEQUON CREEK WATERSHED BASIN

The Potomac River is the main drainage feature for the region and forms a boundary between West Virginia and Maryland, just north of Berkeley County. East of Beddington, Opequon Creek (Figure 21) enters the Potomac River. Opequon Creek’s source is on the east slope of Little North Mountain west of Winchester, Virginia (Bell, 2003). It flows southeast from Winchester to Bartonsville, then northeast past Wadesville into Berkeley County (Bell, 2003).

The distance from source to mouth is 65 miles through limestone valleys (Bell, 2003). The headwaters flow through slopes of 18-22 feet per mile near Winchester, but then drop to 3-5 feet per mile for the rest of its path (Bell, 2003).

Figure 21: Photograph of Opequon Creek near Inwood, West Virginia
2.11 KARST SPRINGS OF STUDY AREA

In addition to surface waters, such as Opequon Creek, there are many emerging and disappearing springs of karst and non-karst origin in Berkeley and Jefferson counties that contribute to the hydrology of the watershed, as well as the development of sinkholes (Bell, 2003). These springs are used as sources of municipal water in the county and have plenty of historical uses (McColloch, 1986). For example, Berkeley Springs (Figure 22), in adjacent Morgan County, became a spa during the 18th Century due to the mineral and medicinal properties of the spring (McColloch, 1986).

Figure 22: Bathhouse and Springs at Berkeley Springs, WV (Source: McColloch, 1986)
“Springs of West Virginia” (McColloch, 1986) documents the location of almost 1200 springs in 49 of the 55 counties in West Virginia. Thousands of other springs exist in the state but usually have small discharges. For the Opequon Creek study area, McColloch (1986) finds 6-10 documented springs per quadrangle, with half of those originating on karst (Figure 23).

Figure 23: Number of documented West Virginia springs (Source: McColloch, 1986)

Springs are an important natural resource that add to discharge in karst regions and allow for many uses for public, industrial, and domestic water supply (McColloch,
The movement of waters through karst areas leads to relevant issues of contamination and impacts in the quality and quantity of water in the study area. Below are springs in the study area with flows of more than 100 gallons per minute (Figure 24).

**Figure 24: Map of Springs in Study Area with flowrates >100 Gallons Per Minute; Listed by Spring ID # (Source: McColloch, 1986)**

Lithology of the study area definitely affects the rates and availability of spring discharge (McColloch, 1986). Porosity and permeability of limestone differs from that of shales and coals. According to McColloch (1986), primary and secondary porosity in
limestone is developed by cracks, fractures, and faults along joints in the bedrock, as well as through direct conduit channeling of waters into the subsurface, leading to more springs in limestone than other rock types (Figure 25).

Figure 25: Number of Springs by rock type in Study Area (Source: McColloch, 1986)

Topography also regulates the location of the water table and spring levels, with the water table usually conforming to the contours of the ground surface (McColloch, 1986). According to Hobba (1976), large springs in West Virginia are common along anticlines, lineaments, faults, and fractures, which are found in abundance in the thick sequences of limestones in the study area.
Lastly, the occurrence and quantity of springs is heavily influenced by anthropogenic activities (McColloch, 1986). According to Ferrell (1984), the level of the water table has been lowered in areas of extensive pumping of ground water, or where recharge areas have been extensively paved or roofed. According to “Springs of West Virginia” (McColloch, 1986), there are a total of 53 springs in Berkeley County and 93 in Jefferson County (Tables 3 & 4).

<table>
<thead>
<tr>
<th>1) Johnsontown Spring</th>
<th>28) Cross Spring at Wellers Farm</th>
</tr>
</thead>
<tbody>
<tr>
<td>2) Falling Waters Spring</td>
<td>29) Griffith Spring</td>
</tr>
<tr>
<td>3) Will Ellis Farm Spring</td>
<td>30) Dailey Spring</td>
</tr>
<tr>
<td>4) Town Spring</td>
<td>31) Big Spring and Snodgrass Spring</td>
</tr>
<tr>
<td>5) Spring Mill Spring</td>
<td>32) Buck Hill Spring</td>
</tr>
<tr>
<td>6) Speck Farm Spring</td>
<td>33) Shade Spring</td>
</tr>
<tr>
<td>7) G. Taylor Spring</td>
<td>34) Van Meter Spring</td>
</tr>
<tr>
<td>8) Speck Spring</td>
<td>35) Shaw Spring</td>
</tr>
<tr>
<td>9) Harland Spring</td>
<td>36) McDonald Spring</td>
</tr>
<tr>
<td>10) Fort Hill Spring</td>
<td>37) Grey Spring</td>
</tr>
<tr>
<td>11) Boyd Rooney Farm Spring</td>
<td>38) Carter Spring</td>
</tr>
<tr>
<td>12) Tomahawk Spring</td>
<td>39) Douglas Miller Farm Spring</td>
</tr>
<tr>
<td>13) Dennis Farm Spring</td>
<td>40) Peerless Orchard Farm Spring</td>
</tr>
<tr>
<td>14) Porterfield Sulphur Spring</td>
<td>41) Spring (Name Unknown)</td>
</tr>
<tr>
<td>15) Spring (Name Unknown)</td>
<td>42) Spring (Name Unknown)</td>
</tr>
<tr>
<td>16) Porterfield Limestone Spring</td>
<td>43) Springvale Farm Spring</td>
</tr>
<tr>
<td>17) Kees Spring</td>
<td>44) Lee Whitacre Farm Spring</td>
</tr>
<tr>
<td>18) Jones Spring</td>
<td>45) Boyer Farm Spring</td>
</tr>
<tr>
<td>19) Kitchen Spring</td>
<td>46) Gum Spring</td>
</tr>
<tr>
<td>20) Swan Pond Spring</td>
<td>47) Spring (Name Unknown)</td>
</tr>
<tr>
<td>21) Kilmer Spring</td>
<td>48) Cool Spring</td>
</tr>
<tr>
<td>22) D.T. Burkhart Spring</td>
<td>49) Lefevre Spring</td>
</tr>
<tr>
<td>23) Neglar Spring</td>
<td>50) Lemons Spring</td>
</tr>
<tr>
<td>24) Martinsburg Water Supply Spring</td>
<td>51) Porter Farm Spring</td>
</tr>
<tr>
<td>25) Blairton Spring</td>
<td>52) Boiling Springs</td>
</tr>
<tr>
<td>26) Shanghai Sulphur Well Spring</td>
<td>53) Charles Crim Spring</td>
</tr>
<tr>
<td>27) Couchman Springs</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: 53 Karst Springs of Berkeley County, West Virginia (Source: McColloch, 1986)
<table>
<thead>
<tr>
<th></th>
<th>Table 4: 93 Karst Springs of Jefferson County, West Virginia (Source: McCulloch, 1986)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Maple Shade Farm Springs</td>
</tr>
<tr>
<td>2</td>
<td>Springdale Farm Spring</td>
</tr>
<tr>
<td>3</td>
<td>Spring Hill Farm Spring</td>
</tr>
<tr>
<td>4</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>5</td>
<td>Rock Spring</td>
</tr>
<tr>
<td>6</td>
<td>McQuilkin Farm Spring</td>
</tr>
<tr>
<td>7</td>
<td>Downs Farm Spring</td>
</tr>
<tr>
<td>8</td>
<td>J. Beaseley Spring</td>
</tr>
<tr>
<td>9</td>
<td>Morgan Spring</td>
</tr>
<tr>
<td>10</td>
<td>Falling Spring</td>
</tr>
<tr>
<td>11</td>
<td>Billmeyer Farm Spring</td>
</tr>
<tr>
<td>12</td>
<td>Southwood Spring</td>
</tr>
<tr>
<td>13</td>
<td>Van Meter Farm Spring</td>
</tr>
<tr>
<td>14</td>
<td>Elmwood Farm Spring</td>
</tr>
<tr>
<td>15</td>
<td>General Horace Gates Farm Spring</td>
</tr>
<tr>
<td>16</td>
<td>Rippling Spring</td>
</tr>
<tr>
<td>17</td>
<td>Marist College Camp Spring</td>
</tr>
<tr>
<td>18</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>19</td>
<td>Melvin Farm Spring</td>
</tr>
<tr>
<td>20</td>
<td>General Darkes Home Spring</td>
</tr>
<tr>
<td>21</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>22</td>
<td>Balch Spring</td>
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<tr>
<td>23</td>
<td>Grey Spring</td>
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<td>24</td>
<td>Springdale Farm Spring</td>
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<tr>
<td>25</td>
<td>Spring (Name Unknown)</td>
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<tr>
<td>26</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>27</td>
<td>Meyersdale Farm Spring</td>
</tr>
<tr>
<td>28</td>
<td>Owens Farm Springs</td>
</tr>
<tr>
<td>29</td>
<td>Harpers Ferry Spring</td>
</tr>
<tr>
<td>30</td>
<td>O.H. Meyer Farm Spring</td>
</tr>
<tr>
<td>31</td>
<td>Barr Spring</td>
</tr>
<tr>
<td>32</td>
<td>Flowing Springs</td>
</tr>
<tr>
<td>33</td>
<td>Flowing Springs</td>
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<tr>
<td>34</td>
<td>Klein Spring</td>
</tr>
<tr>
<td>35</td>
<td>Warner Spring</td>
</tr>
<tr>
<td>36</td>
<td>North Branch of Walker Spring</td>
</tr>
<tr>
<td>37</td>
<td>Aldridge Springs</td>
</tr>
<tr>
<td>38</td>
<td>Schlack Farm Spring</td>
</tr>
<tr>
<td>39</td>
<td>Washington Springs</td>
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<td>40</td>
<td>Opequon Spring</td>
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<tr>
<td>41</td>
<td>Turkey Run Spring</td>
</tr>
<tr>
<td>42</td>
<td>Walker and Vine Springs</td>
</tr>
<tr>
<td>43</td>
<td>Capper Farm Springs</td>
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<tr>
<td>44</td>
<td>Piedmont Farm Spring</td>
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<tr>
<td>45</td>
<td>Engle Springs</td>
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<tr>
<td>46</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>47</td>
<td>Marlow Farm Spring</td>
</tr>
<tr>
<td>48</td>
<td>Wysong Spring</td>
</tr>
<tr>
<td>49</td>
<td>Cammack Farm Spring</td>
</tr>
<tr>
<td>50</td>
<td>Stonefield Springs</td>
</tr>
<tr>
<td>51</td>
<td>Russel Farm Spring</td>
</tr>
<tr>
<td>52</td>
<td>Claymont Court Spring</td>
</tr>
<tr>
<td>53</td>
<td>Claymont Court Spring</td>
</tr>
<tr>
<td>54</td>
<td>Claymont Springs</td>
</tr>
<tr>
<td>55</td>
<td>Claymont Paige Spring</td>
</tr>
<tr>
<td>56</td>
<td>H.F. Byrd Spring</td>
</tr>
<tr>
<td>57</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>58</td>
<td>Dailey Farm Spring</td>
</tr>
<tr>
<td>59</td>
<td>Wilt Farm Spring</td>
</tr>
<tr>
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<td>Hostler Spring</td>
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<tr>
<td>61</td>
<td>Spring (Name Unknown)</td>
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<td>George Washington Cavern Spring</td>
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<tr>
<td>63</td>
<td>Wynkoop Farm Spring</td>
</tr>
<tr>
<td>64</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>65</td>
<td>Clipp Spring</td>
</tr>
<tr>
<td>66</td>
<td>White House Spring</td>
</tr>
<tr>
<td>67</td>
<td>Cool Spring on Young Farm</td>
</tr>
<tr>
<td>68</td>
<td>W.E. Johnson Springs</td>
</tr>
<tr>
<td>69</td>
<td>Mountain Mission Spring</td>
</tr>
<tr>
<td>70</td>
<td>Harrison Farm Spring</td>
</tr>
<tr>
<td>71</td>
<td>Fairfax Grant Farm Spring</td>
</tr>
<tr>
<td>72</td>
<td>Rock Spring on J.B. Huyett Farm</td>
</tr>
<tr>
<td>73</td>
<td>Keller and Lackey Farms Springs</td>
</tr>
<tr>
<td>74</td>
<td>Tom Painter Farm Spring</td>
</tr>
<tr>
<td>75</td>
<td>Baker Farm Spring</td>
</tr>
<tr>
<td>76</td>
<td>Head Spring on Bullskin Run</td>
</tr>
<tr>
<td>77</td>
<td>Locust Hill Farm Spring</td>
</tr>
<tr>
<td>78</td>
<td>Henry Baker Farm Spring</td>
</tr>
<tr>
<td>79</td>
<td>Joseph Bell Farm Spring</td>
</tr>
<tr>
<td>80</td>
<td>Shannon Hill Spring</td>
</tr>
<tr>
<td>81</td>
<td>Shannondale White Sulphur Spring</td>
</tr>
<tr>
<td>82</td>
<td>Shannondale Blue Sulphur Spring</td>
</tr>
<tr>
<td>83</td>
<td>Shannondale Red Sulphur Spring</td>
</tr>
<tr>
<td>84</td>
<td>Adams Farm Spring</td>
</tr>
<tr>
<td>85</td>
<td>Robert Smith Farm Spring</td>
</tr>
<tr>
<td>86</td>
<td>Lippett Springs on Olive Boy Farm</td>
</tr>
<tr>
<td>87</td>
<td>Spring (Name Unknown)</td>
</tr>
<tr>
<td>88</td>
<td>Dr. Frey Farm Springs</td>
</tr>
<tr>
<td>89</td>
<td>John Bayles Farm Spring</td>
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<td>90</td>
<td>Meyers Farm Spring</td>
</tr>
<tr>
<td>91</td>
<td>Maisie Ware Farm Spring</td>
</tr>
<tr>
<td>92</td>
<td>Dr. Langdon Farm Spring</td>
</tr>
<tr>
<td>93</td>
<td>Dr. Boyd Farm Spring</td>
</tr>
</tbody>
</table>
There are 25 springs in the study area with greater than 100 gallons per minute flow rates (Table 5). All of these springs are karst springs, originating on limestone (McColloch, 1986). The number of springs in the study area was determined by importing the TIFF image of the springs of Jefferson and Berkeley Counties from McColloch (1986) into ArcGIS 9.2. Then, an intersect function was performed that truncated the results to include only those springs inside the watershed boundary that occur on carbonates (Figure 26). These 25 springs emerge on karst topography and can be impacted by development and urbanization of these karst waters.

Currently the Martinsburg Water Supply Spring (southeast of Martinsburg), Kilmer Spring (northwest of Martinsburg), and Big Spring (south of Martinsburg) are used in conjunction with a deep well source for municipal water for Martinsburg (McColloch, 1986). The Martinsburg Water Supply Spring is a karst perennial spring with a discharge of 1370 gpm. Kilmer Spring is located one mile west-northwest of Martinsburg and has a discharge of 2900 gpm. Another major spring in the area is Big Spring, also used for the Martinsburg municipal water supply. This karst spring is perennial and is located 1 mile south of Martinsburg with a discharge of 1000 gpm (McColloch, 1986).
Figure 26: Map of Locations of Karst Springs in Study Area (Source: McColloch, 1986)
## KARST SPRINGS IN STUDY AREA

<table>
<thead>
<tr>
<th>COUNTY</th>
<th>SPRING NAME</th>
<th>GALLONS/ MINUTE</th>
<th>TOPOGRAPHIC POSITION</th>
<th>ROCK TYPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERKELEY</td>
<td>DENNIS FARM SPRING</td>
<td>3020</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>SWAN POND SPRING</td>
<td>100</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>KILMER SPRING</td>
<td>2900</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>D. T. BURKHART SPRING</td>
<td>320</td>
<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>MARTINSBURG WATER SUPPLY SPRING</td>
<td>1370</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>COUCHMAN SPRINGS</td>
<td>1130</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>DAILY SPRING</td>
<td>130</td>
<td>HILLSIDE</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>BIG SPRING AND SNODGRASS SPRING</td>
<td>1000</td>
<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>SHAW SPRING</td>
<td>2080</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>MCDONALD SPRING</td>
<td>1870</td>
<td>HILLSIDE</td>
<td>LIMESTONE</td>
</tr>
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<td></td>
<td>CARTER SPRING</td>
<td>720</td>
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<td>SPRINGVALE FARM SPRINGS</td>
<td>220</td>
<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>LEFEVRE SPRING</td>
<td>673</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>PORTER FARM SPRING</td>
<td>650</td>
<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>BOILING SPRINGS</td>
<td>3040</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td>JEFFERSON</td>
<td>GENERAL HORACE GATES SPRING</td>
<td>840</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>SPRING (NAME UNKNOWN)</td>
<td>680</td>
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<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>BALCH SPRING</td>
<td>450</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>GREY SPRING</td>
<td>1060</td>
<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
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<td>SPRINGDALE FARM SPRING</td>
<td>760</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
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<tr>
<td></td>
<td>OWENS FARM SPRINGS</td>
<td>750</td>
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<td>LIMESTONE</td>
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<tr>
<td></td>
<td>OPEQUON SPRING</td>
<td>6500</td>
<td>VALLEY</td>
<td>LIMESTONE</td>
</tr>
<tr>
<td></td>
<td>TURKEY RUN SPRING</td>
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<td>STREAM CHANNEL</td>
<td>LIMESTONE</td>
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<tr>
<td></td>
<td>CAPPER FARM SPRINGS</td>
<td>1020</td>
<td>HILLSIDE</td>
<td>LIMESTONE</td>
</tr>
</tbody>
</table>

Table 5: Karst Springs in Study Area with flowrates >100 GPM (Source: McColloch, 1986)
Chapter 3: Land Use and Land Cover Change in Karst

This chapter explores the land use and land cover changes taking place in karst watersheds as a result of sprawling development patterns and urban-related growth pressures, as well as the impacts that are manifesting as a result of those changes. The results from the analysis of changing land use and land cover in the Opequon Creek Watershed (see Chapter 4) shows that sinkholes have been developing at an increasing pace in the last 25 years as a result of urban growth and pressures brought about by infrastructure, development and water use. Therefore, a better understanding of these processes is necessary to develop mitigating strategies.

3.1 THE KARST PROBLEM

Human-induced impacts in karst areas come from changes in hydrology that are found with development in the watershed (Williams, 1993). According to Williams (1993), “karst landscapes are particularly vulnerable to human impacts due to lack of natural pollutant filtration in the thin soils characteristic of karst and short residence times of karst waters”.

There has been much research involving the impacts of urban growth on karst landscapes (Urich, 1991; Sauro et al., 1991; Day, 1991; White et al., 1984; Yang and Drum 2002). As this unregulated development, or urban sprawl, continues to progress into agricultural and forested lands, citizens, governments, and organizations around the country are looking for tools and solutions that can change this trend (Fuhs, 1999).
Sprawl is a problem nationally and at regional and local scales, such as in the current study area.

Conventional tools (see Chapter 6) that are used to combat sprawl in urbanizing areas include urban growth boundaries, transfer of development rights, growth management programs, agricultural zoning and land conservation initiatives (Weitz and Moore, 1998). However these tools by themselves have proven to be largely ineffective in areas lacking strong land use enabling legislation, such as West Virginia (Arrandale, 1997). This weakens the effectiveness of sprawl-related tools in combating the destruction of greenspace, loss of agricultural land, water quality degradation, and the resulting impacts of development in karst watersheds, such as sinkholes and landslides (Figure 27).

Figure 27: Photograph of Recent Landslide in Opequon Creek Watershed
As of the 2009 legislative session, there were several bills of enabling legislation being worked on that would provide the framework that would give management practices and land use plans more effectiveness in implementing wide-ranging plans.

Gaps in the research include a thorough geographic analysis of this type of growth spatially and temporally, not just the observable impacts, as well as a lack of reasonably inexpensive methods for sinkhole and karst watershed land use and land cover inventory. Many studies have shown that human development associated with urban buildup in karst areas leads to sinkhole development and contamination of waters that are vital to municipalities, industry, farmers, and residents (Urich, 1991; Sauro et al., 1991; Day, 1991; White et al., 1984; Yang and Drum 2002). At the same time, these studies have largely failed to identify the spatial relationship between irregular urban growth and negative impacts. Likewise, there have been relatively few temporal studies that can observe longer-term changes taking place in these watersheds. With no semi-automated methodology for sinkhole inventories at larger watershed and regional scales, field methods are time-consuming and expensive.

3.2 FRINGE IMPACTS AND WATERSHED SCIENCE

The largest problem in watershed management in the past has been the fragmented nature of administration and policy planning (Wang, 2001). There is usually no coordination between the agencies that may make up a watershed because of political boundaries (Wang, 2001). Therefore, it is difficult to plan and implement mitigation strategies that can cross these fragmented political jurisdictions. Wang (2001) contends that, “land use planning is often split both temporally and spatially, since land use
planning is produced for areas within a designated political boundary, only to serve the community which adopted the plan”. This overlooks the fact that watershed management must account for land use practices that affect water quality and quantity downstream, especially in karst regions.

In the United States, land use planning is implemented at the community level (municipal and county), which can lead to a bias in planning toward those interests of the community, and not the health and wellness of the watershed during land use planning decision-making (Wang, 2001). This fragmentation of watersheds into areas under different planning and political jurisdictions does not take into account that unlike planning, human activities cross political boundaries (Wang, 2001).

The relationship between water quality and land uses in a watershed shows that increasing population pressures results in increasing loads of harmful nutrients and pollutants, which can cause degradation of water quality and quantity (Smith, 1993). Therefore, direct correlation has been drawn between increasing urbanization and water quality impairment at the watershed level.

### 3.3 Population Pressures and Land Use Change

Another area of the literature deals with the various population pressures that increasing urbanization places on these sensitive karst watersheds. Within this section of the literature, land use changes related to population are identified as the reason for most of the changes within karst regions.

Urich (1991) examines rising population pressures in tropical karst regions of the Philippines, associated with intensifying rice production. The study determines that land
use has largely changed through conversion of marginal land into agricultural production to feed these people. This conversion leads to exploitation of karst resources and environmental degradation, such as soil erosion, sinkhole development, and loss of soil fertility (Urich, 1991). Population increase is the most important cultural ecology change associated with karst landscapes, because of the sensitive nature of these regions to anthropogenic development (Williams, 1993).

Urich (1991) further notes that population pressure has led to the expansion of slash and burn agriculture, a direct source of atmospheric carbon and environmental degradation. This type of agricultural practice also leads to clearing of soil and roots, which if left in place could prevent the development of sinkholes. Urich (1991) further states that the changes in traditional cultural ecology have led local residents to alter the cultural uses and practices of karst environments in the hope of developing their resource base. The result is often overuse of these lands, as well as both qualitative and quantitative changes in groundwater (Urich, 1991). According to Urich (1991), “spring flow in one karst region of the Philippines declined by 40% over the last 20 years as a result of urban pressures”.

This theme is expanded upon by Sauro et al. (1991) in a study of human development and resulting impacts on the Asiago Plains of Italy, a large karst watershed involved in rapid urbanization. Since World War II, almost 20% of the land surface in the plains area had been developed (Sauro et al., 1991), resulting in home building and agriculture that led to deforestation, the enlargement of cultivated areas and pastureland, and overuse of grazing areas, which in turn led to impacts manifested via polluted
groundwater, eroded soils, loss of soil fertility and sinkhole development (Sauro et al., 1991).

Furthering this body of evidence in a similar study of the tropical karstlands of Belize, Day (1991) found that growing population and resulting economic policies harmed the environmental stability of the region. Day (1991) concludes, “accelerated rates of forest clearing, agricultural intensification, and the rapid construction of buildings and infrastructure in the karst watershed have negatively impacted the environmental stability of the region”.

According to Day (1991), over 2000 hectares of forest were cleared between 1980 and 1986 on the Hummingbird Karst of Belize, accompanied by increased rates of farming, loss of wildlife habitat, accelerated soil erosion, increased water extraction and contamination, increased hunting, and greater usage of wooded areas. These human activities have resulted in serious environmental problems in the sensitive karst region, such as erosion, sinkhole development, and contamination of water supplies (Day, 1991).

Fisher et al. (2000) examined the Oconee Watershed in the state of Georgia, a highly urbanizing area outside the city of Atlanta, and determined that, “rising population pressures in this region, associated with intensifying agriculture necessary to feed the growing masses of people living in the outlying fringe areas, is accelerating the environmental degradation of the area”. The study determines that land use has largely changed through conversion of land at the rural-urban fringe into agricultural production. This conversion led to environmental degradation and exploitation of watershed
resources, such as soil erosion, sinkhole development and loss of soil fertility (Fisher et al., 2000).

According to Fisher et al. (2000), the location of 550 new poultry operations in the headwaters of the watershed near Athens, Georgia has had a large impact on surface waters, doubling the amount of phosphorous and nitrogen present in the waters. This development has been largely unregulated and crosses several political jurisdictions within the watershed (Fisher et al., 2000).

Lastly, Dojiri et al. (2003) studied the impact of rising population pressures and irregular land use patterns on local watersheds, specifically in the Santa Monica Bay watershed in California. The bay provides economic value via water activities, such as swimming, diving, boating, and fishing, and has been negatively impacted by the increase from 100,000 residents in 1900 to 10 million in 2000. Pollutant discharges into the bay declined following the Clean Water Act of 1972, but the area has seen an exponential increase in non-point source urban runoff since then (Dojiri et al., 2003).

The population explosion in the bay area resulted in fragmented development that led to deforestation, more cultivated areas and environmental degradation of water, soil, and air (Dojiri et al., 2003). This watershed provides a glimpse into the problems being encountered in watersheds throughout America as residents increasingly move into rural areas and put stresses on these sensitive fringe areas.
3.4 ANTHROPOGENIC IMPACTS IN KARST WATERSHEDS

Pollutants enter karst by percolation through soils, infiltration along faults, fractures and lineaments; and direct flow into sinkholes and sinking streams (Doerfliger et al., 1997). Other sources of contamination in urbanizing karst watersheds include mining operations, urban and rural development, industrial activities, sinkholes, and agriculture (Doerfliger et al., 1997). The nature of karst involves short residence time for waters and fast recharge of aquifers due to infiltration through thin soils and integrated conduit systems (Williams, 1993). Thus, mismanaged development, increasing agriculture, leaking sewage systems and bad land uses can seriously impact the hydrology of karst regions. An important development strategy emerging in karst watersheds recognizes that although human impacts on karst are intentional, there may be hope of implementing management plans that could effectively reduce or negate the effect urbanization has upon the physical landscape (Williams, 1993).

The effect cultivation has on watershed quantity and quality, as well as the contribution to sinkhole development, also needs to be understood. These impacts are widely recognized in the literature, though there have been few attempts to document agricultural impacts on the soils, vegetation and landscapes of areas underlain by karst (Hardwick and Gunn, 1993). Williams (1993) explains that, “when forests are cleared for typical agriculture methods, such as slash and burn or clear cutting, erosion rates are accelerated, resulting in numerous problems for karst aquifers, sinkhole development increases, and new vectors are provided for contaminant transport”. Heavy machinery used in typical cultivation results in compaction of soils and increased runoff rates
(Williams, 1993). Since karst is typified by thin-soils that fail to filter contaminants in infiltrating water, the understanding of agricultural impacts in these sensitive areas is extremely important (Williams, 1993).

Smith (1993) explains that agriculture (Figure 28) in karst zones is a major cause of non-point source pollutants, such as nitrates, phosphates and calcium. These organic compounds increase biological activity in karst waters resulting in fish kills, increased rates of algal growth, eutrophication of karstic waters, and bacterial contaminants (Smith, 1993). According to Drew (1996), agriculture is a constant threat to groundwater quality because of the leaching of fertilizers and organic pollutants from the soils.

![Figure 28: Photograph of Cropland in Opequon Creek Watershed](image)

### 3.5 POINT AND NON-POINT SOURCE IMPACTS

According to Cieslewicz (2002), land uses are the key factor behind the water and air quality issues that citizens are facing. These problems can be divided into two
categories, point and non-point inputs. Point sources are easily identified and addressed and include smoke stacks emitting pollutants into the air and pipes that discharge effluents directly into a watershed (Cieslewicz, 2002). Non-point sources, on the other hand, are harder to deal with because of their diffuse nature. These pollutants arrive in the air and water from agricultural and urban runoff, erosion from mismanaged lands, vehicle exhaust and industrial production (Cieslewicz, 2002).

Cieslewicz (2002) goes on to argue that point sources have been largely dealt with through policy and regulation, while non-point sources have continued to increase because of irregular land use patterns. He points out that the leading source of air pollution is vehicle travel, which is strongly correlated to development patterns and land use. As people have to drive farther due to sprawling patterns of development, more pollutants enter the environment via vehicle emissions (Cieslewicz, 2002).

Most researchers agree that with more vehicle miles being driven every year, we need to understand this problem and remedy it using traditional and non-traditional planning tools (Cieslewicz, 2002). The United States has less than 5% of the world’s population, but we consume 33% of all transportation energy (Cieslewicz, 2002).

3.6 URBAN-RELATED KARST ISSUES

Numerous studies have been conducted in various locations globally that can be applied to similar problems in the Opequon Creek Watershed (Barner, 1997; White et al., 1984; Crawford, 1984; Taminskas and Marcinkevicius, 2002). Through these case studies and geomorphic analysis of urbanizing karst watersheds, the literature examines
the prevailing negative impacts and environmental degradation found in karst watersheds from urbanization.

The nature of human-induced impacts in karst watersheds is evident in two emergent themes that pervade the literature. First, *karst waters contamination* examines various causes and effects of pollutant loads in the watershed (Chen, 1991; Santo, 1991; Smith, 1993; Williams, 1993; Doerfliger et al., 1997; Davis et al., 2001; Memon et al., 2002), including sediment as a source of pollution (Hardwick and Dunn, 1993; Smith, 1993; Mahler et al., 1998), agriculturally induced impacts in karst (Hardwick and Gunn, 1993; Smith, 1993; Williams, 1993; Drew, 1996; Xie et al., 2002), and population increases and resultant land use changes (Day, 1991; Sauro et al., 1991; Urich, 1991; Williams, 1993). The second theme addressed in the literature is urbanizing effects on *sinkhole development* in karst (Crawford, 1984; Metcalfe and Hall, 1984; Newton, 1984; White et al., 1984; Crawford and Groves 1996; Atapour and Aftabi, 2002; Yang and Drum, 2002).

### 3.6.1 Karst Waters Contaminations

A large body of literature has documented the impacts of anthropogenic activities on the waters of karst areas (Hardwick and Gunn, 1993). This makes sense because 25% of the world’s population is supplied by these aquifers (Williams, 1993). Smith (1993) divides contaminant sources of carbonate aquifers into hydrological processes to better understand and investigate the causes of contaminants. Smith (1993) says that, “contaminants can be described as originating from point sources, where all recharge in a karst watershed comes from closed depressions, or sinkholes”. Identification of these
sources can be done through field studies to demonstrate the existing link between sinking streams and closed depressions, as suppliers of aquifer input (Smith, 1993). This allows the researcher to pinpoint the source of pollutants through dye tracing, water quality sampling, and analysis of discharge rates.

The second process involves dispersed or non-point sources, which have more diffuse causes. These pollutants are more numerous and harder to track. According to Smith (1993), nitrates from fertilizer are one of the most frequent pollutants found in karst water systems. Runoff from agricultural lands provides the most frequent source of dispersed contaminant flows (Smith, 1993).

Doerfliger et al. (1997) addresses the importance of pollutant mapping and identification through the use of an EPIK model that establishes a method of mapping high risk areas in order to identify and delineate protection zones in urbanizing watersheds. By identifying high-risk areas within a karst watershed, it may be easier to implement planning strategies aimed at mitigating these impacts.

Existing studies have been ineffective because they are not based on a solid hydrogeological framework (Doerfliger et al., 1997). The movement of ground and surface water in karst regions needs to be understood in order to protect the high-risk zones. Doerfliger et al. (1997) examined a region in the Swiss Alps by mapping using the weighting methods of the EPIK model to delineate high risk areas that could later be protected through legislative, mitigation, and conservation efforts.

This provides an excellent example of attempts to address human-related problems in karst. High risk urban mapping in karst watersheds attempts to identify and
alleviate urban-related impacts, and attempts to protect the changing landscape. This method holds enormous potential to address sprawling development patterns and human population increase. By recognizing zones of potential impact, such as sinkholes, watershed groups can plan for future problems associated with development by relocating or readjusting.

Davis et al. (2001) build on the EPIK model in developing a KARSTIC model, which places greater quantitative emphasis on karst features during input of the model’s parameters (Table 6), than previous sensitivity studies. They recognized that the resulting vulnerability maps could be used by planners, politicians, farmers, and residents in an attempt to protect aquifers in the southwestern United States.

**KARSTIC MODEL PARAMETERS**

<table>
<thead>
<tr>
<th>K</th>
<th>Karst sinkholes with surface recharge; includes geologic structure and fractures (numerical weights and ratings for karst development and fractures are multiplied together in the KARSTIC method)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Aquifer medium</td>
</tr>
<tr>
<td>R</td>
<td>Recharge rate</td>
</tr>
<tr>
<td>S</td>
<td>Soil medium</td>
</tr>
<tr>
<td>T</td>
<td>Topography (slope of the land surface)</td>
</tr>
<tr>
<td>I</td>
<td>Impact of the unsaturated zone; includes the effects of depth to water (note: numerical weights and ratings for impact of the unsaturated zone and depth to water are multiplied together in KARSTIC method)</td>
</tr>
<tr>
<td>C</td>
<td>Conductivity (hydraulic) of the aquifer</td>
</tr>
</tbody>
</table>

Table 6: Parameters Considered in KARSTIC MODEL (Source: Davis et al., 2001)

In order to investigate the nature of human-induced impacts in urbanizing karst watersheds, it is first necessary to establish, through field research or literature review,
the existing links between water inputs and karst aquifers in these sensitive areas. Santo (1991) established this critical link between water quality and karst aquifer relationships. This study allowed municipal managers and planners to plan for, and mitigate, anthropogenic impacts in a karst area. By verifying these hydrologic links, the planning and regulatory phase of affected karst areas is made easier.

Later literature became dedicated to understanding the relationships between anthropogenic pollution and water. One area of research that has emerged is wastewater impoundment in karst regions. There is much concern involving this because wastewater impoundments have repeatedly failed and caused irreparable damage to water supplies in karst regions, as well as causing sinkhole development through soil piping. The highly fractured nature of karst, lack of thick soils, and the existence of direct conduits to the subsurface lead to aquifer contamination and impacts in quality and quantity of karst waters (Memon et al., 2002). Faulty sewage systems and slack regulation have led to frequent occurrences of karst water pollution.

Memon et al. (2002) examined the failure of one such wastewater impoundment in Allentown, Pennsylvania. In this instance, improper lining in a wastewater impoundment caused soil piping to form a sinkhole that led to wastewater entering the underlying karst aquifer system. This in turn polluted the city’s water supply, as well as agricultural and rural water wells. It was subsequently determined that municipal drawdown of the aquifer through unregulated water use contributed to sinkhole development (Memon et al., 2002).
Williams (1993) identifies a diversity of common contaminants in these sensitive areas, “such as acid rain, waste water discharge, increased sediment discharge, agricultural pollutants, and chemical wastes”. He provides hope for affected areas by putting forth the idea that if these areas are identified and mapped and sources of karst water pollutants are also identified, an initiative may be developed to counteract negative impacts.

### 3.6.2 Sedimentation of Karst Waters

Another concern of karst watersheds is the sedimentation associated with anthropogenic activities. Sedimentation in karst waters comes largely from agricultural mismanagement and development in the watershed that has led to increased erosion and changes in hydrology (Williams, 1993). These changes deliver higher sediment loads into karst waters. Williams (1993) further suggests that, “human activities such as quarrying, mining, urbanization, industry, and agriculture lead to increased rates of sediment that can bring pollution to water systems”.

Deforestation also leads to loss of vegetative cover and results in increased runoff rates that deliver large amounts of sediment into karst areas (Mahler et al., 1998). This increase in sediment causes water pumps to clog, changes habitats, and decreases soil permeability, which increases runoff rates and provides paths for pollutants (Mahler et al., 1998).

Mahler et al. (1998) studied the Barton Springs aquifer in Texas, which is experiencing about as much urbanization as any aquifer in the nation. The study showed that sediment transport associated with urbanizing karst areas could be a major vector of
contaminant transport, as heavy metals are moved in solution or transported on sediment grains (Mahler et al., 1998). Therefore, sedimentation issues in karst watersheds that are closely linked with urbanization, such as deforestation and hydrology changes due to watershed development, must be addressed before there is any hope of establishing a working management plan to protect vulnerable watersheds.

### 3.6.3 Agriculturally-Induced Impacts

A third topic of concern in the literature is the effect cultivation can have on watershed hydrology quantity and quality, and the contribution of agriculture to sinkhole development. These impacts are widely recognized in the literature, though there have been few attempts to study agricultural impacts on the soils, vegetation and landscapes of karst areas (Hardwick and Gunn, 1993).

Agricultural issues in karst are evident in soil and water quality and hydrologic changes that bring sediment to karst areas. Williams (1993) explains issues of deforestation and the resulting complications that are endured by residents of karst landforms. When forests are cleared for typical agriculture methods, such as slash and burn or clear cutting, erosion rates are accelerated, which results in numerous problems for karst aquifers and provides vectors for contaminant sediment transport (Williams, 1993). Heavy machinery used in typical cultivation results in compaction of soils, which increases runoff rates. Since karst is typified by thin soils, the understanding of agricultural impacts in these sensitive areas is extremely important.

According to Drew (1996), agriculture is a threat to groundwater quality as organic pollutants are delivered via soils. One example of such detrimental impact is
found in the Burren Karst of Western Ireland. Population pressures there have led to scrubland being cultivated, which has greatly increased the rates of environmental degradation and contaminant build-up (Drew, 1996).

Xie et al. (2002) expanded this area of knowledge by researching the effects of various fertilizers on water quality in a karst region of China. The research found that dangerous amounts of heavy metals were present in karst aquifers in the region, as a result of agricultural runoff from fringe areas providing food for a large urban city. It was determined that agriculturally derived erosion and subsequent runoff were responsible for the transport of heavy metals, such as zinc and cadmium, into the drinking waters used by local municipalities, farmers, residents, and industry (Xie et al., 2002).

Chen (1991) builds on the theme of karst water quality degradation in agricultural areas by proposing that sinkholes in karst areas are themselves locations of point-source contaminants. The fact that sinkholes bring contaminated surface water directly into karst aquifers justifies the need to explore further. Particularly, because rural areas tend to use sinkholes as convenient disposal points for household garbage, broken vehicles and machinery, dead animals, and farm wastes. Chen (1991) concludes through field examinations and water quality analysis that sinkholes are in fact important contributors to aquifer contamination and karst water degradation and should be considered in any plan to mitigate or regulate urbanization in karst regions.

Hardwick and Gunn (1993) go on to say that agriculture has led to the destruction of much of the natural landscapes in karst areas, as well as to the loss of habitat, soil degradation, and erosion. Through the development of an agricultural impact matrix their
study was able to better understand the impacts of agriculture in these regions, as well as providing a yard stick against which future planning and conservation measures can be compared.

### 3.6.4 Sinkholes in Karst

The largest impact in urbanizing karst watersheds is the development of sinkholes. That is why this study focuses on sinkholes as the geohazard that manifests as a result of urban pressures. In fact, the largest part of the literature dealing with human-induced impacts in karst areas is the role humans play in accelerating the development of sinkholes. Sinkhole development in karst areas has become more of a threat as watersheds are increasingly urbanized.

Daoxian (1987) identifies sinkholes as the largest environmental problem in karst areas. This study states that they can cause damage to buildings, railways, mines, reservoirs, and farmland. Therefore, sinkholes have become important, not only for geologists and engineers, but for city planners, citizens, and industry in karst territory (Daoxian, 1987). Daoxian (1987) concludes that the most numerous and dangerous sinkholes for engineering purposes are those induced by human activities.

In fact, in many areas throughout the country people are dealing with land subsidence due to the withdrawal of groundwater. Land subsidence is a widespread problem. Land subsidence is defined as “gradual settling or sudden sinking of the Earth’s surface due to subsurface movement of Earth materials” (Galloway et al., 1999). Subsidence is a huge problem with over 17,000 square miles in the United States being directly affected (Galloway et al., 1999). More than 80% of the subsidence is from the
exploitation of underground water (Galloway et al., 1999). Likewise, the increasing development of land and water resources is accelerating the pace and location of subsidence (Galloway et al., 1999).

Human activities can add to the formation of subsurface cavities in carbonate rock types and lead to their collapse. Circular 1182 states that while sinkholes tend to be localized, they can impact large areas by providing point sources for water infiltration and pollution. Five case studies examined for the subsidence circular demonstrate how agricultural, municipal, and industrial ground-water use had combined to deplete ground-water resources and create regional scale subsidence.

Sudden sinkhole development in karst (Figure 29) areas has become more of a threat as watersheds are increasingly urbanized and people move into previously uninhabited areas. Human impacts are felt after development in karst watersheds, which can change the hydrology and infiltration morphology of an area. The result can be localized flows that lead to underground soil piping and eventual soil cover collapse, creating a sinkhole (Newton, 1984).

![Cover Collapse Sinkhole, Winter Park, FL 1981](Source: Galloway et al., 1999)
According to Newton (1984), “Costly damage has resulted from the sudden emergence of sinkholes beneath highways, railroads, buildings, dams, reservoirs, pipelines, vehicles, and people”. However, according to the United States Geological Survey Circular 1182 on Land Subsidence (Galloway et al., 1999), this activity is usually caused by groundwater declines due to pumping or diversion of surface runoff into soluble rocks, such as limestones and dolostones.

Although sinkholes are usually localized, they can funnel contaminants into underlying aquifer systems, which leads to regional impacts (Galloway et al., 1999). The circular goes on to say that about 20% of subsidence in the United States results from the mining of coal, of which there is none in the study area.

Galloway et al. (1999) lists four events that are necessary for the formation of subsurface cavities by dissolution (Table 7).

**SUBSURFACE CAVITY PROCESSES**

| 1) bedrock composed in large part of soluble minerals; |
| 2) waters unsaturated with respect to these minerals; |
| 3) an hydraulic gradient to move water through rock |
| 4) an outlet for the escaping, solute-laden water |

*Table 7: Process for Formation of Subsurface Cavities (Galloway et al., 1999)*

The circular explains that human activities in these regions will accelerate karstification. The changing of surface drainage focuses runoff, which increases mechanical and chemical erosion of limestone, which leads to the formation of sinkholes.
and the failure of preexisting sinkholes (Galloway et al., 1999). Likewise, long-term pumping of ground water can cause lowering of the water table, which can destabilize underlying cavities by reducing the pressure of fluids that support cavity walls and roofs (Galloway et al., 1999).

Therefore, sinkholes are common features in karst terrain and serve as direct links between surface water and underlying groundwater aquifers. Plenty of economic damage has resulted from the emergence of sinkholes beneath highways, railroads, buildings, dams, reservoirs, pipelines, and vehicles (Newton, 1984). The size of a sinkhole, its depth, and diameter depends on many factors, but the general statement is that “the larger the subsurface cavity the larger the sinkhole” (Reuter and Stoyan, 1993).

While there are many different types of sinkholes (Table 8) found in karst, such as collapse and buried sinkholes, most of the literature on sinkhole development concentrates on solution sinkholes (Figure 30) and suffosional, or subsidence sinkholes (Figure 31), which are increased by runoff modifications that come with urbanization (White et al., 1986). Shallow, solution sinkholes that take hundreds or thousands of years to form are the dominant depression type in Opequon Creek Watershed, but this study is more concerned with the human-induced collapse features.
Figure 30: Photography of Sinkhole caused by Dissolution of Soluble Rocks
(Source: Galloway et al., 1999)

Figure 31: Process of Cover Subsidence Sinkhole Development
(Source: Galloway et al., 1999)
## SINKHOLE TYPES IN KARST

<table>
<thead>
<tr>
<th>Type of Sinkhole</th>
<th>Process</th>
<th>Cause</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOLUTION</td>
<td>Movement of material downward along vertical conduits</td>
<td>Result of downward movement of material along previous conduits. Formed by the slow dissolution of rock beneath a soil mantle without rupture of the rock</td>
<td>Gently sloping sides</td>
</tr>
<tr>
<td>COVER SUBSIDENCE</td>
<td>Movement of material downward along vertical conduits</td>
<td>Result of downward movement of material along previous conduits. Ground surface moves slowly downward, as sediment is slowly washed into voids in rock.</td>
<td>Gently sloping sides</td>
</tr>
<tr>
<td>COVER COLLAPSE</td>
<td>Movement of material downward along vertical conduits</td>
<td>Result of downward movement of material along previous conduits. Formed by the relatively rapid movement of soil into voids in the limestone.</td>
<td>Steeply sloping sides</td>
</tr>
<tr>
<td>BURIED</td>
<td>Infilling of existing sinkhole with sediments and organic material</td>
<td>Result of downward movement of material along previous conduits. Vertical conduit at bottom of sinkhole may become plugged and over time depression fills with sediment and organic material</td>
<td>Shallow wet area filled with organic matter</td>
</tr>
<tr>
<td>ROCK COLLAPSE</td>
<td>Failure of rock roof</td>
<td>Collapse of the roof of cavities within the limestone followed by the drop of the unconsolidated soil that was supported by the limestone</td>
<td>Steeply sloping sides</td>
</tr>
<tr>
<td>ALLUVIAL</td>
<td>Slow filling of existing sinkhole with sediments and organic material</td>
<td>Older sinkhole that has been partially or totally filled by sediment</td>
<td>Gently sloping sides</td>
</tr>
<tr>
<td>RAVELING</td>
<td>Movement of material downward along vertical conduits</td>
<td>A rejuvenated alluvial sinkhole</td>
<td>Generally gently sloping sides</td>
</tr>
<tr>
<td>DOLINE</td>
<td>Movement of material downward along vertical conduits</td>
<td>Generally a large solution sinkhole</td>
<td>Generally gently sloping sides</td>
</tr>
<tr>
<td>EROSION</td>
<td>Movement of material downward along vertical conduits</td>
<td>Generally the same as a raveling sinkhole but has been used synonymously with cover collapse</td>
<td>Generally gently sloping sides</td>
</tr>
</tbody>
</table>

Table 8: Various Types of Sinkholes found in Karst (Source: White et al., 1986)
Solution sinks are created by the dissolution of carbonate rock (Figure 32) from reaction with carbonic acid, which comes from the combining of carbon dioxide and calcium carbonate, or limestone, and take many years to form (Galloway et al., 1999).

Figure 32: Process of Dissolution by Carbonic Acid (Source: Galloway et al., 1999)

Suffosional sinkholes, or soil-piping sinkholes, which are more dangerous because they are prone to collapse suddenly, also occur throughout the study area in the Ordovician and Cambrian limestones and dolostones. According to White et al. (1986), suffosional sinkholes occur naturally, but are greatly increased by runoff modifications that come with urbanizing pressures. The movement of soil into underlying voids (Figure 33) can occur through solutionally-enlarged fractures and cross-joints (White et al., 1986). White et al. (1986) goes on to explain factors that increase sinkhole development
including pavement, street, and roof runoff, which accelerate soil transport. Even minor landscape changes in karst have been shown to accelerate sinkhole development.

Daoxian (1987) offers an explanation for the development of sinkholes through the suffosional process: “where the velocity and gradients of downward movement of water and groundwater flow increases resulting from groundwater pumpage”. Cover-collapse sinkholes and subsidence sinkholes develop where soil transport through drains
is enough to remove the soils into underground voids (White et al., 1984). Extensive modifications of natural runoff patterns and use of carbonate aquifers by municipalities and farmers has modified the natural pattern of sinkhole development and greatly increased frequency and intensity of sinkholes in karst areas (Newton, 1984).

Yang and Drumm (2002) examined this effect by studying landfill siting resulting in instability of soils in karst areas. Increasing urbanization of karst watersheds has led to the need for more water by municipalities and other groups, such as farmers and industry (Yang and Drumm, 2002). Examining soil and rock properties of several proposed landfill sites, this study determined that since landfill siting in karst regions require excavation, soil cover is ultimately reduced via a loss of cohesiveness, which leads to increased soil piping and sinkhole development (Yang and Drumm, 2002).

Urbanizing activities in karst watersheds manifest through two major mechanisms: increased hydraulic gradients caused by the lowering of the water table, and modifications of stormwater runoff patterns (White et al., 1986). This means that aggressive water usage and residential and urban construction in karst areas can lead to accelerated sinkhole development. Water table drawdown decreases the hydraulic head underlying karst regions and allows for soil transport and collapse (White et al., 1986).

Metcalfe and Hall (1984) further demonstrate the connections between urbanization and sinkhole development by examining sinkhole collapse caused by groundwater extraction by municipalities in Florida. This study showed that watertable drawdown related to urban activities resulted in development of the dangerous cover-collapse sinkholes.
Atapour and Aftabi (2002) build on this base of knowledge by applying these concepts to mapping in an urbanizing karst watershed in Iran. They show that road building and construction play a larger role in changing karst hydrology than previously thought. The study determines that construction associated with urbanization has lead to massive acceleration of sinkhole development (Atapour and Aftabi, 2002). Establishing the ties between urbanization and geomorphologic, geochemical, and geoenvironmental aspects associated with karst areas, planners and politicians in Iran were able to plan for, and hopefully change or prevent, impacts from hazards resulting from sinkhole development (Atapour and Aftabi, 2002).

Crawford (1984) looked at urbanization effects on sinkhole morphology in Bowling Green, Ohio. The city of Bowling Green uses karst conduits and sinkholes to provide natural storm sewers because of the expense of putting in a traditional storm drainage system. To stop flooding in the late 1970’s the city drilled 400 wells to drain runoff water into the karst conduit systems and alleviate city stormwater runoff channels (Crawford, 1984). This led to development of over 40 sinkholes near the wells in a short time period, due to the changes in hydrology and soil piping (Crawford, 1984). This provides an excellent example of the detrimental aspects of urbanization in karst areas. Any attempt to build in karst watersheds leads to changes in hydrology and geomorphology that can have devastating impacts.

According to Gupta (2003), rock attributes, physical processes, and human intervention in the geologic environment are the elements that govern the nature and appearance of a landform over time. In order to understand the nature of sinkhole
development, it is necessary to quantify their density, development, pattern, and location over time. Sinkholes in karst areas are often elongated in the direction of the dominant joint, which makes them easily identifiable during imagery analysis. This is true of the sinkholes in Berkeley and Jefferson Counties as well. Thus, environmental remote sensing offers enormous potential to quantify and analyze these processes temporally.

Gao et al. (2001) identified 3 major types of human-induced sinkholes in China and the United States: water-pumping sinkholes, mine-drainage sinkholes, and reservoir-induced sinkholes. These are categorized into two sub-types: those related to water table lowering and those related to construction.

Two types of collapse sinkholes (Figure 34) are identified by Cooley (2001): type 1 collapses have an upward-moving, open void where material is moved by water transport as fast as it is created, making a steep-sided collapse; type 2 features are soil-filled voids limited in their rate of upward growth by the rate of soil removal. These have small void spaces and produce a shallow depression (Cooley, 2001). Type 2 features are important because of their effect when loads are placed on them, such as buildings (Cooley, 2001).

These sinkholes also manifest through the two major mechanisms: increased hydraulic gradients, caused by the lowering of the water table, and modifications of stormwater runoff patterns (White et al., 1984). This means that water usage and development of impervious surfaces in karst areas leads to accelerated sinkhole development. Water drawdown decreases the hydraulic pressure underlying karst regions and allows for soil transport and collapse (White et al., 1984).
Likewise, construction in the watershed alters hydrologic patterns and increases erosion. Water table lowering is identified as a common cause for formation of cover-collapse sinkholes in soil (Tharp, 2001). When water pressure drops in a soil void at the rock contact the pore pressure in the surrounding soil drops as well. This leads to stresses that produce soil fractures that eventually make their way to the surface creating a subsurface soil drain that allows the sinkhole to enlarge (Tharp, 2001).
Chapter 4: Nature of Land Use and Land Cover Change in Opequon Creek Watershed

4.1 REMOTE SENSING AND CHANGE DETECTION

One of the major objectives of this research is to quantify and classify land use and land cover change in the Opequon Creek Watershed between 1984-2009, and to examine the nature of development during the last 25 years. One of the best methods within spatial analysis methodologies to achieve this is through temporal change detection. According to Lunetta (1998) as we move into the 21st Century, environmental changes will accelerate with increasing consequences. With the launch of Earth Resources Technology Satellite (ERTS-1, renamed to Landsat I) in 1972 the United States gained the ability to monitor environmental resources from space-based remote sensing platforms (Lunetta, 1998).

Large applications of remotely-sensed data were not possible until recently, because of the lack of processing techniques and computer technology to process large datasets. Early remote sensing studies focused on mapping the environment or ecosystem function and structure. Since then, this technology has changed rapidly with satellite systems being launched regularly gaining global coverage that could be processed by faster computers (Lunetta, 1998). Likewise, with the availability of analytical data processing tools, such as GIS and Definiens Professional, more spatial, temporal, and analytical applications are now possible.
Lunetta (1998) provides an outline of steps for remote sensing change detection projects. These include problem definition, product specification, data requirements, data availability, data acquisition, and data analysis. In the first few steps the objectives of the project are given and tailored to determine exactly what must be gathered to accomplish the project objectives. This research identifies the objective as a need to determine land use and land cover within the watershed during the 25 year period, meanwhile developing a semi-automated methodology for sinkhole counts.

Land use deals with the use of the land surface, such as urban or residential, while land cover describes the physical environment of the land (Gupta, 2003). The repetitive nature of remote sensing systems on satellites and aerial platforms is very useful for land use monitoring (Gupta, 2003). Data requirements need to be examined to determine what information is necessary to carry out the project objectives. The researcher must determine the spectral, temporal and spatial data resolution. This research utilizes LandSat 7 data (30 meter resolution) concurrently with integration of Digital Orthophoto Quadrangles (1 meter resolution) for finer scale resolution to classify land use and map sinkholes between 1984-2009. LandSat ETM+ data from the LandSat 7 satellite and digital aerial photographs for this research were chosen for ready and free availability in existing archives.

Once these decisions are made, the analytical or data processing steps are carried out through a general diagram of data processing for remote sensing change detection applications (Figure 35) that include data acquisition and preprocessing, corrections,
The first step of the change detection process in this research involves acquiring the data and preparing it for data analysis. This included creating data mosaics of the individual scenes, sub-setting to reduce the dataset to watershed boundaries, and masking. For large area studies or temporal examinations through change detection, as is the case with this research, it is necessary to acquire multiple satellite scenes for complete coverage. Therefore, this research used a mosaic of scenes in order to minimize cloud cover and acquire the best quality scenes. After creating the mosaic the study area was then truncated using the subset feature of Definiens Professional to outline only those areas of the scenes within the Opequon Creek Watershed. At this point ancillary data such as hydrologic, county and DLG (Digital Line Graph) maps were brought into the GIS processing system to overlay and clearly define the study area. Masking was then
used to instruct the software to only analyze those features that are pertinent to the research.

Next, both geometric and atmospheric image corrections of the data were performed before change detection analysis. Because analysis is performed on a pixel-by-pixel basis, any misregistration of one pixel or more will give anomalous results for those pixels (Lunetta, 1998). Therefore, the first scene (1984 image) was registered to ground coordinates, with the rest of the images registered to that image.

Image corrections are required to negate atmospheric effects that can distort images. After all corrections of the data were made the data was normalized to account for variations in solar illumination, atmospheric scattering, and absorption that changes land surface reflectance values. According to Lunetta (1998), radiometric data normalization is used to reduce the variability between multitemporal data sets acquired over the same geographic area. This process reduces variability between scenes from atmospheric conditions and radiance angles (Lunetta, 1998). The most commonly used radiometric normalization techniques are: pseudo-variat features (Schott et al., 1998), dark-pixel subtraction (Gonima, 1993) and relative radiometric normalization (Elvidge et al., 1995). This research used Elvidge’s relative radiometric normalization.

Once all data were rectified, geocoded and corrected they were ready for segmentation, classification and ultimately change detection analysis. Two approaches can be used for change detection analysis: post-classification change methods or pre-classification spectral change detection (Lunetta, 1998). Post-classification approaches examine the difference between two different products. This can be done by pattern
recognition or spectral analysis. This research used a post-classification method of pixel comparison due to Definiens Professional’s ability to perform pattern recognition of post-classified images.

After the multiple scenes from different times were classified they were compared to determine changes (see Chapter 4.7). Lunetta (1998) cites this method as advantageous due to a lack of a need for data normalization because the different scenes are classified separately. Pre-classification approaches involve examination of spectral changes and include composite analysis, image differencing, change vector and spectral analysis methods, and principal components analysis (Lunetta, 1998).

Composite analysis was one of the first approaches used in determining land use and land cover change from satellite images. This approach uses an analysis of a multi-date data set using pattern recognition and spectral classification techniques to identify land cover change. This analysis can be done by merging two 4-band data sets into a composite of an 8-band image, which is then analyzed using a maximum-likelihood classification (Lunetta, 1998).

Image differencing is another approach to change detection that involves methods that subtract, ratio, transform and set thresholds to determine pixel change from one scene to another. Image differencing has several advantages which include low costs and ability to process large volumes of data. Disadvantages include optimizing the change/no-change threshold and interpretation of output data (Lunetta, 1998).
4.2 METHODS OF LAND USE AND LAND COVER CLASSIFICATION

This research uses a geographic or spatial approach to land cover and land use analysis in order to more fully understand the nature of urban growth into fringe areas of the watershed, resulting in karst geohazards, such as the development of sinkholes. This is achieved through change detection and image-object analysis of remotely-sensed images, as well as subsequent statistical analysis. Object-oriented image analysis is used to classify land use and land cover and sinkholes. It is hoped that the methodology developed here can be used for inexpensive and accessible sinkhole inventory with a wide range of applications and uses. It is also hoped that through analysis of geographic land use data it will be possible to better understand the relationship between land use change and geomorphic change. This study focuses only on sinkhole development derived from digital imagery as the product of urbanizing change, due to the lengthy and costly nature of detailed geomorphic field analyses and mapping. The methods proposed to achieve this are conducted in three stages:

Stage 1: Study of land use and land cover, temporal and spatial change, and sinkhole development through quantification and classification of imagery (see Chapter 4);

Stage 2: Analysis of classified land use and sinkhole development though object-oriented software packages (see Chapter 5); and

Stage 3: Examination and analysis of selected sites for in-depth study (see Chapter 5.7).
4.3 STAGE 1- The study of land use, land use change, and sinkhole development, through quantification of satellite and aerial images:

Field and laboratory work centers on the monitoring of land use and land cover change over a 25 year period (1984-2009) with satellite data and aerial photography, creating a land use and land cover and sinkhole inventory through image-object analysis. Satellite imagery and aerial photography are used in Definiens Professional to map the size, shape, number, and location of sinkholes that are distinguishable at various scales and resolutions via an object-oriented classification.

Five scenes of 30 meter pixel-resolution between (1984-2003) from LandSat 5 and 7 Thematic Mapper ™ and Enhanced Thematic Mapper Plus (ETM+), as well as various sub-meter Digital Orthophotograph Quadrangle and Color infrared aerial photographs from (1987-2007), were merged to classify land use and land cover and to identify and locate sinkholes (Figure 36). Although LandSat Images only allow the identification of sinkholes larger than 30 meters across, they provide excellent large-area land use and land cover classification and change detection capabilities due to multiple bandwidths, as opposed to three bands for digital aerial photography. The integration of high-resolution aerial photography offers better resolution and higher accuracy in identifying sinkholes.
It is recognized that not all sinkholes will be evaluated and inventoried, but lacking prohibitively expensive high-resolution satellite imagery for analysis or funds for extensive field mapping, the resolution used in this study should be sufficient for the analysis to be representative of the geomorphic and urban processes at work over an extended time period in an urbanizing karst watershed.

A similar study in Jefferson County, West Virginia (Fisher, 2003) identified and interpreted several thousand sinkholes via a morphometric analysis interpreted from LandSat and Digital Orthophoto Quadrangle images. That study’s impressive results show that identification and analysis from digital imagery is possible for large data sets, but approaches need to move beyond simple inventoring via a geographic and temporal
approach, in order to more fully understand the underlying mechanisms and provide for mitigating management practices and watershed plans that can combat these forces.

Temporal analysis and comparison of Landsat and aerial images for change detection at the watershed scale allows the researcher to generate a percentage change of land use and land cover during the study period. Further inventory consists of field examination and mapping of sinkholes selected randomly after analysis of imagery to ascertain classification accuracy. This accuracy is also checked via Definiens Professional accuracy assessment protocols (see Chapter 5.3.8), field examination and groundtruthing (see Chapter 5.4; 5.5) in the watershed and verifying results by cataloguing land use, sinkhole presence, frequency, and location.

4.3.1 Creating a Watershed Basemap

The first step was to create a watershed basemap for use in the study (Figure 37). This was achieved by using satellite images, digital orthophotograph quadrangles, geology maps, topographic maps, and soil surveys of the study area, as well as ancillary data gathered from the West Virginia Geological Survey, such as contours, geonames, and digital elevation models. These were acquired and incorporated into a GIS environment using ArcGIS 9.2. Site-map development in a GIS system is user-friendly and allows for excellent output displays and export of geographically referenced data.
Remote sensing offers a fairly inexpensive means of gaining information on the extent of land cover at local to global scales (Foody and Embashi, 1995). The basic principle in remote sensing methodology comes from the fact that there are different wavelength ranges of the electromagnetic spectrum, and objects on the ground reflect light differently based on physical or compositional attributes (Gupta, 2003). The map-like nature of imagery from remote sensors makes them a popular source of information to study land cover (Lunetta, 1998).

Multispectral remote sensing data has shown huge potential for studies across different fields of geology, including geomorphology, structure, lithological mapping,
mineral and oil exploration, and groundwater and geo-environmental studies (Gupta, 2003). It is therefore reasonable that this technology should be evaluated for its ability to map sinkholes at various scales.

In order to inventory and assess urban-induced change in a watershed, it is necessary to first analyze the temporal changes in land use and land cover. Satellite and aerial datasets are used to quantify these land uses and land covers and their change. According to Carlisle et al. (1989), “The essential goal of modeling and monitoring environmental change from remotely sensed data is to compare images at a spatial and temporal resolution appropriate to the ecological scale (urban growth and sinkholes) of the processes of interest to derive useful spatial and spectral information”.

Land cover classes are usually mapped from digital remotely-sensed data by the process of a supervised digital image classification (Campbell, 1987). To achieve this classification this part of the research involved three stages of image development: training, allocation, and testing. In the training stage the analyst identifies a series of sites of each class to be classified on the image and derives descriptive statistics from each, such as the image tone (digital number) in all selected wavebands (Campbell, 1987).

These quantitative descriptions are then used in the second stage when unknown pixels are assigned to a class. Therefore, every pixel in the image is allocated to a class to which it has the highest probability of belonging (Foody and Embashi, 1995). The third stage is the testing phase in which the accuracy of the classification is gauged through quantification. This is done by comparing the predicted and actual classes of pixels that were not used in the training stage (Foody and Embashi, 1995).
The transition of a pixel from one land use and land cover class to another is a function of the present land use and land cover class of that pixel and the composition and configuration of the area to which the pixel belongs (Dunning et al., 1992). This is a function of the shape of the patch (configuration) and the variety of unique land cover types (composition) found within the patch (Turner, 1989). Therefore, comparing land uses and land covers allows quantification of the interactions at various scales.

It is important to this research that a comprehensive and accurate assessment of current land use, as well as land use change, is inventoried to determine the status and nature of anthropogenic impacts in karst watersheds. Likewise, impervious surfaces are mapped and quantified as a class, since there exists a definite link between runoff and sinkhole development, as established in the literature review (see Chapter 3).

4.3.3 Satellite Imagery

LandSat imagery is used to conduct this research because it is the world’s longest dataset of space-based remote sensing data of the Earth’s surface (Figure 38), and it is free. The LandSat Project was a program of the U.S. Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA), started to gather remotely-sensed data of Earth (USGS, 2003). NASA developed and launched the satellites, while the USGS handled the operations, maintenance, and management of all ground data reception, processing, archiving, product generation, and distribution (USGS, 2003). LandSat satellites have been collecting images for thirty-seven years providing an extensive source for various studies.
The first satellite was launched in 1972, with the most recent, LandSat 7, in 1999. LandSat 5 and 7 continue to collect data, while new missions and satellites are planned for the future to continue this series of data-gathering platforms (USGS, 2003).

The LandSat program’s Global Survey Mission is to “repeatedly capture images of the Earth’s land mass, coastal boundaries, and coral reefs, and to ensure that a sufficient amount of data is acquired to support the observation of changes on the Earth’s land surface and surrounding environment” (USGS, 2003). Multiple bandwidths allow LandSat to gather data across a range of the electromagnetic spectrum (Table 9).
### MULTI-SPECTRAL BAND USES

<table>
<thead>
<tr>
<th>SPECTRAL BANDS</th>
<th>USE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 BLUE-GREEN</td>
<td>Bathymetric mapping; distinguishes soil from vegetation; deciduous from coniferous vegetation</td>
</tr>
<tr>
<td>2 GREEN</td>
<td>Emphasizes peak vegetation</td>
</tr>
<tr>
<td>3 RED</td>
<td>Emphasizes vegetation slopes</td>
</tr>
<tr>
<td>4 REFLECTED IR</td>
<td>Emphasizes biomass content and shorelines</td>
</tr>
<tr>
<td>5 REFLECTED IR</td>
<td>Discriminates moisture content of soil and vegetation; penetrates thin clouds</td>
</tr>
<tr>
<td>6 THERMAL IR</td>
<td>Useful for thermal mapping and estimated soil moisture</td>
</tr>
<tr>
<td>7 REFLECTED IR</td>
<td>Useful for mapping hydrothermally altered rocks associated with mineral deposits</td>
</tr>
<tr>
<td>8 PANCHROMATIC</td>
<td>LandSat 7 carries a panchromatic band (visible through near IR) with 15m resolution for “sharpening” of multispectral images</td>
</tr>
</tbody>
</table>

Table 9: Multi-spectral Band Designations of LandSat (Source: USGS, 2003)

LandSats 4 and 5 had a lower orbital path and included the Multi-Spectral Scanner (MSS) and the higher resolution Thematic Mapper (TM) sensor onboard. The TM sensor on these satellites captures data in different bandwidths than the first MSS scanner, and at a higher resolution of 120 m for the thermal-IR band and 30 m for the other six bands (USGS, 2003). The USGS currently still operates LandSat 5 and 7. The newest LandSat 7 has the Enhanced Thematic Mapper Plus sensor with resolutions of 30
meters for the visible and IR bands, 60 meters for the thermal band, and 15 meters for the panchromatic band (USGS, 2003).

Satellite remote sensing instruments provide measurements at a variety of pixel resolutions, spatial extents, and temporal scales and can be valuable source of information on land use and land cover aspects (Lunetta, 1998). Specific land uses identified in this research are agriculture (cropland, pasture), urban (residential, commercial, and industrial), forest, water, impervious surface and sinkholes. Specifically, LandSat TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper) satellite imagery from 1984 to 2009 are analyzed using a supervised classification method. The scenes were downloaded from the Path 16 Row 33 dataset on the West Virginia View website (www.wvview.org) and imported into ArcGIS 9.2 (Figures 39-43):
SCENE 1: Raw LandSat 5 TM Image of Path 16 Row 33: 9/19/84

Figure 39: LandSat 5 Image from 9/19/84
SCENE 2: Raw LandSat 5 TM Image of Path 16 Row 33: 5/28/89

Figure 40: LandSat 5 Image from 5/28/89
SCENE 3: Raw LandSat 5 TM Image of Path 16 Row 33: 9/28/93

Figure 41: LandSat 5 Image from 9/28/93
SCENE 4: Raw LandSat 7 ETM+ Image of Path 16 Row 33: 11/8/99

Figure 42: LandSat 7 Image from 11/8/99
SCENE 5: Raw LandSat 7 ETM+ Image of Path 16 Row 33: 5/24/02

Figure 43: LandSat 7 Image from 5/24/02

The metadata for these scenes describes cloud cover, band use, projection, bands used, and resolution (Table 10). The scenes were reprojected to the North American Datum Standard 1983 (NAD 83) using the Define Projection tool from the Data Management Category of ArcToolbox.
**IMAGE METADATA**

<table>
<thead>
<tr>
<th>DATE</th>
<th>SYSTEM</th>
<th>REFERENCE SYSTEM</th>
<th>PROJECTION</th>
<th>CLOUD COVER</th>
<th>BAND USED</th>
<th>RESOLUTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>9/19/84</td>
<td>LandSat 5 TM</td>
<td>WGS 84</td>
<td>UTM</td>
<td>0%</td>
<td>1-6</td>
<td>30 meter</td>
</tr>
<tr>
<td>5/28/89</td>
<td>LandSat 5 TM</td>
<td>WGS 84</td>
<td>UTM</td>
<td>0%</td>
<td>1-7</td>
<td>30 meter</td>
</tr>
<tr>
<td>9/28/93</td>
<td>LandSat 5 TM</td>
<td>GRS 80</td>
<td>UTM</td>
<td>0%</td>
<td>1-6</td>
<td>30 meter</td>
</tr>
<tr>
<td>11/8/99</td>
<td>LandSat 7 ETM+</td>
<td>WGS 84</td>
<td>Albers Equal Area</td>
<td>0%</td>
<td>1-8</td>
<td>30 meter</td>
</tr>
<tr>
<td>5/24/02</td>
<td>LandSat 7 ETM+</td>
<td>WGS84</td>
<td>Albers Equal Area</td>
<td>0%</td>
<td>1-8</td>
<td>30 meter</td>
</tr>
</tbody>
</table>

Table 10: MetaData for Images Used in Study

These scenes were then converted to TIFF format for use in Definiens Professional by saving the file as TIFF in the data export option of ArcGIS and ArcCatalog. The TIFF’s were then clipped with the ArcGIS Data Management Category, Raster Clip Tool, using the Opequon Creek watershed shapefile as the clip shapefile, to limit the scenes to the study area.

### 4.3.4 Digital Orthophotograph Imagery

Interpretation of aerial images is usually done visually, since traditional classification programs were not capable of dealing with high resolution datasets
Segmentation-based and object-oriented classifiers, such as Definiens Professional, can overcome this limitation by separating images into homogenous segments and using them as the basis for further classification procedures (Kressler et al., 2005). The classification is then based on the features, or contextual data such as shape or compactness, and calculated for each object during segmentation (Kressler et al., 2005).

High-resolution aerial photographs were used in this study in conjunction with low-resolution LandSat imagery to provide the classification of land use and land cover and sinkholes. Used together within Definiens Professional, these images were joined for sharpened and higher-resolution classification.

The high resolution aerial photographs are 1987 and 1993 color infrared photographs (Figure 44), digital natural color orthophotography from 2003 (Figure 45), and NAIP USDA photography from 2007 (Figure 46). All of the digital aerial photographs are 1:4,800 scale. The 1987, 1993, and 2003 imagery were acquired from the West Virginia Geological Survey (www.wvgs.wvnet.edu), while the 2007 NAIP photography was downloaded from the West Virginia GIS Technical Center (www.wvgis.wvu.edu). The 2003 imagery was created by the West Virginia State Addressing and Mapping Board (SAMB) to improve the quality of 911 emergency dispatch and response in West Virginia, thereby providing statewide, free, high-resolution digital imagery.
Figure 44: 1993 Color Infrared Imagery of Study Area (Source: WVGS)

Figure 45: Index of DOQQ’s used in Study Area
Color infrared and digital orthophotographs combine the imaging nature of a photograph with geometric aspects of a map (Figure 47). The digital orthorectification process converts aerial photography from the original photo negative to a digital product that has been corrected for lens distortion, vertical displacement, and variations in aircraft altitude and orientation (Lunetta, 1998).

The 2003 and 2007 imagery was captured "leaf-off" at a scale of 1" on photo=2400' on the ground, for the purpose of producing natural color digital orthophotos at a 2’ pixel resolution. The extent of the imagery includes all of West Virginia and goes 1500 feet beyond the state border. They were ortho-rectified using ArcGIS 9.2 which gained a <9.8’ horizontal error at a 95% confidence level. The original 10,000' x 10,000' uncompressed 24-bit natural color TIFF files were produced in state plane coordinates (NAD 1983, linear unit of measure: feet) at a pixel resolution of 2.0’.
In 2005, the United States Geological Survey then re-tiled the State Plane images to 3.75 minute "quarter-quadrangles" with UTM Zone 17 North (NAD 1983) coordinates. The TIFF files used in this research are approximately 75 MB in size, while MrSid versions, compressed at an 18:1 ratio, were approximately 4 MB in size. The quarter-quad TIFFS are approximately 360 MB each whereas the MrSid compressed versions are about 20 MB each. Only uncompressed images were used for classification, since data can be lost during compression. The image preprocessing was then performed using the software ArcGIS 9.2 (Figure 48).
4.3.5 Merging LandSat and Digital Photography

After 1984, satellite imagery datasets have similar spectral, spatial and radiometric resolutions which make the datasets comparable with each other (Lunetta, 1998). Therefore, they can be used for temporal examinations of land use and land cover change. Definiens Professional was used to perform this classification. Contemporary land uses were ground-checked during fieldwork. A random sampling of pixels from the satellite/aerial photography data was then located in the field using a GPS unit. These are used to validate the classification results as well as classification accuracy within Definiens Professional.
The uncorrected raw images were georeferenced with respect to the geocoded image from 1984 so that all 5 scenes would overlay (Figures 49-50; 52; 54; 56). Lastly, within Definiens Professional, LandSat and Aerial photography were merged to give higher spatial resolution in preparation for segmentation and classification (Figures 51; 53; 55; 57).

Figure 49: 1984 Cropped LandSat Image of Opequon Creek Watershed
Figure 50: 1989 Cropped LandSat Image of Opequon Creek Watershed

Figure 51: Merged Aerial photography and 1989 LandSat in Definiens Professional
Figure 52: 1993 Cropped LandSat Image of Opequon Creek Watershed

Figure 53: Merged Aerial photography and 1993 LandSat in Definiens Professional
Figure 54: 1999 Cropped LandSat Image of Opequon Creek Watershed

Figure 55: Merged Aerial photography and 1999 LandSat in Definiens Professional
Figure 56: 2002 Cropped LandSat Image of Opequon Creek Watershed

Figure 57: Merged Aerial photography and 2002 LandSat in Definiens Professional
4.4 THE USE OF ARCGIS 9.2

ARCGIS is used in this study to produce base maps, as a spatial analysis tool and to perform data manipulation and export functions for use in Definiens Professional. Spatial statistics, within Definiens Professional, were used to delineate high relationship values between land uses to produce various output maps for examining spatial and geomorphic ties between various land use and land covers and sinkholes. Spatial statistics allow this research to pinpoint conflicting land use clusters and select them for field study through correlation. Output maps then provide both analytical tools and graphic views of research output.

Geostatistical Analyst is an extension to ARCGIS 9.2 and is used to spatially explore the data. The analyst has two main components, the exploratory spatial data analysis toolbox and the interpolation and statistical modeling wizard. The user can select default values to create maps from point data (land uses and sinkholes). A wide range of processing and post-processing (validation diagnostics) options are then included within the extension.

The 2003 and 2007 imagery was captured "leaf-off" at a scale of 1" on photo=2400' on the ground, for the purpose of producing natural color digital orthophotos at a 2' pixel resolution. The extent of the imagery includes all of West Virginia and goes 1500 feet beyond the state border. They were ortho-rectified using ArcGIS 9.2 which gained a <9.8' horizontal error at a 95% confidence level. The original 10,000' x 10,000' uncompressed 24-bit natural color TIFF files were produced in state plane coordinates (NAD 1983, linear unit of measure: feet) at a pixel resolution of 2.0'.
this research to analyze spatial and non-spatial elements of point and area-based data (sinkholes) to identify unusual data values, detect patterns in data values (aggregation of sinks), and formulate hypothesis about the data (Krivoruchko, 2002). The typical goal of GIS data is establishing relationships between layers (spatial regression), reconstructing missing data (spatial interpolation), searching for patterns in complete data (smoothing), classification (grouping), and prediction (Krivoruchko, 2002). GIS is therefore an invaluable tool when comparing data spatially to determine if any relationship exists between land use and land cover, land use change, and sinkhole development.

4.5 IMAGE-OBJECT ANALYSIS FOR LANDSCAPE QUANTIFICATION

Traditional methods for large-scale sinkhole inventory involve interpretative and time-consuming grid-counts from aerial photography or depression contours on topographic maps. These can cause problems with inventories because the capture of a sinkhole on a contour map is scale-dependent and aerial photography is expensive (Angel et al., 2004). The majority of sinkholes in the study area are too small to be represented on 40-foot contour intervals represented on USGS topographic maps as closed-contour depressions. Size of depression, contour interval, and scale of the map are all factors determining if a sinkhole will be mapped on a United States Geological Survey 1:24,000 topographic map (Angel et al., 2004). The 40-foot contour interval of northern West Virginia is too coarse to capture most of the smaller dissolution sinkholes.

Hubbard (2001) verifies this limit, “the use of regional sinkhole maps or closed-contour sinkholes counted from 7.5 minute topographic maps in sinkhole inventories is problematic because the contour interval used in most topographic maps fails to capture
features smaller than the minimum mapping unit or contour interval”. Hubbard (2001) goes on to say that “detailed field mapping often reveals actual sinkholes at an order of magnitude greater than that shown by the topographic map”.

Likewise, use of hard copy aerial photographs for sinkhole identification involves interpretation of visual features and image-objects by the user, which injects user bias, and can be a lengthy and costly process for large or multi-temporal studies. Therefore, these methods are ineffective when assessing regions at the watershed or state scale.

Angel et al. (2004) compared a Geographic Information System technique for sinkhole inventory versus traditional grid counts of topographic maps. Using a tailor-made algorithm and ArcGIS spatial analysis functions, the study was able to compare the effectiveness of automated methods for sinkhole inventory. The GIS method totaled 2,823 sinkholes, while the manual topographic count found 2,830 for a negligible difference, proving the utility of spatial analysis methods for sinkhole inventory.

In addition to an accurate sinkhole count using the GIS technique, spatial analysis with image-object analysis in Definiens Professional offers more possibilities for better statistical and relational data exploration. Definiens Professional’s capability to examine and classify objects based on spectral and geomorphic characteristics goes beyond the traditional GIS, offering a new level of analysis and classification of image-objects (Blaschke et al., 2005).

Therefore, in order to achieve the best analysis of high-resolution images, methodologies need to go beyond traditional statistical analysis and classification of individual pixels (Hay et al., 2003). Classification of images should include object-
oriented analysis through algorithms that recognize image-objects in homogenous regions and can classify them based on contextual information (Hay et al., 2003). Incorporating both spectral (tone and color) and spatial (size, shape, texture, and pattern) information in image analysis, Definiens Professional has these benefits, as well as an automated classification process (Laliberte et al., 2004).

Laliberte et al. (2004) go on to say that “image segmentation into homogenous image-objects is appealing for remote sensing applications because human vision tends to segment images into homogenous regions anyway”. Object-oriented analyses of images are done by using multi-resolution segmentation to divide the image into homogenous regions based on nearby pixels’ spectral and spatial properties. These objects are then classified using a hierarchy of user-defined criteria (Laliberte et al., 2004).

Although fairly new, these object-based classification methods have been used in classification and change detection studies using high spatial resolution images for several years now with impressive results (Blaschke et al., 2005; Walter, 2004). With the use of high-resolution imagery being more common, digital approaches to image analysis are using more contextual information (Walter, 2004). Spatial dimensions can be used in image analysis by using objects to identify homogenous regions. These homogenous regions in an image can then be identified and treated as objects during segmentation. The segmenting of images into image-objects forms various levels. Two or more image-object levels build a hierarchy, in which the objects are linked to those levels above and below (Blaschke et al., 2005).
The resolution at which image segmentation occurs is adjustable based on user needs, allowing for various geographic scales from niche to watershed to be explored (Definiens Professional User Manual, 2005). This software package differs from most by using spatial context in addition to spectral properties to classify digital images, which segments the image into networks of objects based on user-defined needs, such as color, shape and texture, which can then be tailored to sinkhole properties in the study area (Blaschke et al., 2005). Image-object analysis methods involve segmentation to first define the image-object and classification, which assigns the object to a descriptive category (Definiens Professional User Manual, 2005).

The first step in Definiens Professional object-based classification is multi-resolution segmentation of the image into unclassified basic image-objects (Figure 58). Segmentation is the subdivision of an image into separated regions represented by image-objects (Definiens Professional User Manual, 2005). These unclassified image-objects contain data about spectral reflectance, shape, position, texture, and neighboring objects. Various segmentation algorithms provide different results for image-object creation.

The segmentation parameters for this study (see 5.2.1) were determined through a trial and error procedure to find which setting gained the best image-object recognition of sinkholes. Large scale parameters yield large image-objects, while small scale parameters give smaller objects.
Once image segmentation was complete the image-objects were placed into distinctive classes or categories. The first step of land cover classification is deciding which classes will be used, as well as what their features and hierarchical structure. Digital classifications are applied to the study area images to classify the data into modified USGS level 1 land cover classes (Anderson et al., 1976), including sinkholes as a class (Table 11). Therefore, six classes were modified from the USGS level 1 land cover class schema to represent the land cover and land use aspects of the Opequon watershed, as well as providing contextual information for further analysis. The six classes used were forest, agricultural, urban, water, impervious surface, and sinkhole.

Anderson et al. (1976) define Urban or Built-up Land as “areas of intensive use with much of the land covered by structures. Included in this category are cities, towns, villages, strip developments along highways, transportation, power, communications
facilities, and areas such as those occupied by mills, shopping centers, and industrial and commercial complexes”. Identifying this land use class is critical to the research, as much of the sinkhole development in the watershed has resulted from urban pressures.

**LAND USE CLASSES**

<table>
<thead>
<tr>
<th>Level I</th>
<th>Level II</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Urban or Built-up Land</td>
<td>11 Residential</td>
</tr>
<tr>
<td></td>
<td>12 Commercial and Services</td>
</tr>
<tr>
<td></td>
<td>13 Industrial</td>
</tr>
<tr>
<td></td>
<td>14 Transportation, Communications, and Utilities</td>
</tr>
<tr>
<td></td>
<td>15 Industrial and Commercial Complexes</td>
</tr>
<tr>
<td></td>
<td>16 Mixed Urban or Built-up Land</td>
</tr>
<tr>
<td></td>
<td>17 Other Urban or Built-up Land</td>
</tr>
<tr>
<td>2 Agricultural Land</td>
<td>21 Cropland and Pasture</td>
</tr>
<tr>
<td></td>
<td>22 Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas</td>
</tr>
<tr>
<td></td>
<td>23 Confined Feeding Operations</td>
</tr>
<tr>
<td></td>
<td>24 Other Agricultural Land</td>
</tr>
<tr>
<td>3 Rangeland</td>
<td>31 Herbaceous Rangeland</td>
</tr>
<tr>
<td></td>
<td>32 Shrub and Brush Rangeland</td>
</tr>
<tr>
<td></td>
<td>33 Mixed Rangeland</td>
</tr>
<tr>
<td>4 Forest Land</td>
<td>41 Deciduous Forest Land</td>
</tr>
<tr>
<td></td>
<td>42 Evergreen Forest Land</td>
</tr>
<tr>
<td></td>
<td>43 Mixed Forest Land</td>
</tr>
<tr>
<td>5 Water</td>
<td>51 Streams and Canals</td>
</tr>
<tr>
<td></td>
<td>52 Lakes</td>
</tr>
<tr>
<td></td>
<td>53 Reservoirs</td>
</tr>
<tr>
<td></td>
<td>54 Bays and Estuaries</td>
</tr>
<tr>
<td>6 Wetland</td>
<td>61 Forested Wetland</td>
</tr>
<tr>
<td></td>
<td>62 Nonforested Wetland</td>
</tr>
<tr>
<td>7 Barren Land</td>
<td>71 Dry Salt Flats.</td>
</tr>
<tr>
<td></td>
<td>72 Beaches</td>
</tr>
<tr>
<td></td>
<td>73 Sandy Areas other than Beaches</td>
</tr>
<tr>
<td></td>
<td>74 Bare Exposed Rock</td>
</tr>
<tr>
<td></td>
<td>75 Strip Mines, Quarries, and Gravel Pits</td>
</tr>
<tr>
<td></td>
<td>77 Mixed Barren Land</td>
</tr>
<tr>
<td>8 Tundra</td>
<td>81 Shrub and Brush Tundra</td>
</tr>
<tr>
<td></td>
<td>82 Herbaceous Tundra</td>
</tr>
<tr>
<td></td>
<td>83 Bare Ground Tundra</td>
</tr>
<tr>
<td>9 Perennial Snow or Ice</td>
<td>91 Perennial Snowfields</td>
</tr>
<tr>
<td></td>
<td>92 Glaciers</td>
</tr>
</tbody>
</table>

Table 11: Land Use Classes Schema for Classification (Source: Anderson et al. 1976)
Agricultural land is defined by Anderson et al. (1976) as, “arable and regularly tilled for the production of annual field crops, with or without irrigation. It refers to a broad class of resource uses that include all forms of land use for the production of biotic crops, including animal and plants”. In a broader sense, agricultural land includes all land that provides direct benefits for mankind through the production of food, fiber, forage and fodder, biofuel, meat, hides, skins, and timber. Agricultural land is structured to include cropland and pasture, orchards, groves, vineyards, nurseries, ornamental horticultural areas, and confined feeding operation (Anderson et al., 1976). Correctly classifying this land use is also important to the research, as most sinkholes over the last 30 years have developed in an agricultural setting.

Anderson et al. (1976) offer insight into correctly classifying agricultural lands on images by describing agricultural land as “land used primarily for production of food and fiber”. On high-altitude imagery, such as LandSat, agricultural activity is shown by distinctive geometric field and road patterns on the landscape. Distinguishing between land uses is possible using urban-activity indicators, as well as looking at concentrations of population (Anderson, 1971). Anderson (1971) states that, “the number of building complexes is smaller and the density of the road and highway network is much lower in agricultural land than in urban or built-up land”.

The primary definition of Forest Land employed for use with data acquired by remote sensors is similar to that used by the U.S. Forest Service. Forests are usually composed of many individual stands in different stages of development and with different characteristics (Anderson et al., 1976). The International Panel on Climate Change
defines forest as “an ecosystem characterized by more or less dense and extensive tree cover. Typically, the cover is assessed as percent crown cover. Distinctions may be made between open- and closed-canopy forests” (IPCC Technical Paper VI, 2008).

Anderson et al. (1976) clarify by describing Forest land use as “having a tree-crown areal density (crown closure percentage) of 10 percent or more, are stocked with trees capable of producing timber or other wood products, and exert an influence on the climate or water regime”. Forest Land can be identified rather easily on high-altitude imagery.

Water includes any surface water present including streams, creeks, rivers, ponds, lakes, bays, reservoirs, and estuaries. The U.S. Census Bureau defines water as “including all areas within the land mass of the United States that persistently are water covered, provided that, if linear, they are at least 1/8 mile (200 m) wide and, if extended, cover at least 40 acres” (U.S. Bureau of the Census, 1970).

Impervious surface is “concerned with paved areas that create sheet flow of runoff, such as parking lots, roads, and building footprints” (Anderson et al., 1976). This land use is vitally important to the project, as much research has proven the links between impervious surface and the development of sinkholes. Lastly, sinkholes as a land use class are defined in this research as surface depressions of more than one foot.

After segmentation of each image a nearest neighbor classifier algorithm is trained and executed using sample image-objects to place the image-objects into one of the six classes, as well as generating multidimensional membership functions, which can be explored later (Baatz and Schäpe, 2000). In Definiens Professional, a sample is chosen
by highlighting the selected class, starting the sampling mode and selecting image-objects with the cursor (Figures 59 & 60).

![Classification Sampling in Test Area](image1.png)

![Definiens Professional classification in test area](image2.png)

**4.6 DEFINIENS PROFESSIONAL CLASSIFICATION RESULTS**

Object-based classifications were performed on all 5 of the merged LandSat/Aerial scenes with the same parameters (see 5.2.1) to place all image-objects into one of the 6 classes. The results are seen in (Figures 61-65), and are examined during post-classification change detection (see Chapter 4.7) to determine exactly where and how each object changed during the 25 year period. This allows the study to examine the changing landscape and look at those mechanisms that are implementing that change. This was one of the most important parts of the study, so much time was spent
on making sure the classifications were derived with accuracy, in order to provide the best results for the post-classification detection phase.

Classifications were run several times and at several levels with different segmentation parameters (see 5.2.1) for each date with subsequent examination of classification accuracy assessments (see 5.3.8) to ensure the most accurate results that were representative of the class features and image-objects.

Figure 61: Land Use and Land Cover Classification Results for 1984 Imagery
Figure 62: Land Use and Land Cover Classification Results for 1989 Imagery

Figure 63: Land Use and Land Cover Classification Results for 1993 Imagery
Figure 64: Land Use and Land Cover Classification Results for 1999 Imagery

Figure 65: Land Use and Land Cover Classification Results for 2002 Imagery
4.7 CHANGE DETECTION BASED ON OBJECTS

There are many methods available for detecting differences in pixels and to determine if change has taken place, such as image differencing, ratios, and cross-correlation analysis (Blaschke, 2004). Most methods use post-classification comparison, where land cover classes are used as the basis for discriminating change between pixels.

According to Blaschke (2004), “in order to compare objects from two different images in the same area the user must examine the object building process and the comparison of resulting objects”. Isolating and extracting specific features, such as sinkholes, depends on marking those features in Definiens Professional that differentiate sinkholes from other objects. The distinctive shape and texture of sinkholes within an object-based classification allows for this discrimination. As defined earlier, the texture of sinkholes is defined in terms of its smoothness or coarseness.

This research uses an object-based post-classification comparison where each object is compared against multiple scenes to determine if that object changed over time. This post-classification technique is easily achieved and provides accurate results for change detection analysis. Results are shown in percentage change of each land use class and can then be evaluated temporally.

4.7.1 Temporal Change Detection

To examine the extent of land use and land cover conversion and sinkhole development over the 25-year time period object-based post classification comparison change detection was performed. This analysis is probably the easiest of the multitude of change detections available. The object-oriented method of post-classification
comparison detection is an object-based method. The goal is to examine objects extracted during image segmentation and to distinguish the changes between the objects. Each Definiens Professional-classified dataset was exported and brought into ArcGIS as shapefiles with attached attribute tables and put into post-classification analysis. These layers were then stacked so that each object could be compared on multiple datasets. Each layer was rectified and georeferenced to the 1984 image so that each dataset would be registered to each other. Then change detection analysis was performed using the “Feature Compare Tool” of the ArcGIS “Change Detection Analysis Extension”. This tool allows multiple features (extracted objects from Definiens Professional) and multiple data sets to be compared for change. This study defines change areas as those objects which are not classified the same temporally. Using this method, objects with land uses that changed over the 25 year period can be identified and extracted as a an object feature. Objects identified as changed are then output as tabular data that can be further explored for spatial and physical changes. Using the tabular data from this the percentage change can be calculated as:

\[ PR = \frac{V_{\text{present}} - V_{\text{past}}}{V_{\text{past}}} \times 100 \quad (1) \]

where PR is the percentage change and V represents the number of objects in that class (Definiens Professional User Manual, 2005). Post-classification change detection results (Tables 12 & 13) show that during the period 1984-2007 in the Opequon Creek Watershed:
There has been a dramatic increase in the area of urban and built-up lands (177%).

There has been a dramatic decrease in the area of forested (39%) and agricultural lands (35%).

There has been significant change in the number of sinkholes between 1984-2007 (change of 130 for a 16% increase).

There has been a dramatic increase in the area of impervious surface in the watershed (162%).

There has been a slight change in the area of water features (1%).

These results show that image segmentation parameters allowed for the extraction of a similar number of feature objects, while land uses changed temporally over the 25 year period, with the major change being conversion of forested and agricultural lands to urban and impervious surfaces.

In order to determine if the actual area of the various land uses and land covers identified as objects in Definiens had changed during the 25 year time period, I performed a calculation of the area in hectares of the resulting land use and land cover types for each study year and subsequently compared the results. To calculate the total area of each land use class for each dataset the “Calculate Areas” function of the “Utilities” subset of the “Spatial Statistics” tool was used. This tool allows for the calculation of each feature (area) within a polygon feature class (object-classified Definiens output). Each dataset was then added as the input feature class and output data was examined for hectare totals for each dataset. Total area in hectares for Opequon Creek Watershed for each dataset (1984, 1989, 1993, 1999, 2002, 20007) is 50, 529, 619 hectares, rounded to the nearest hectare, with each land use and land cover divided by
the total and multiplied by 100 to determine their percentage of the whole area of the watershed. Results (Table 14) are similar to those achieved by examining object change in Definiens Professional Software and show that between 1984-2007 for the total land area of Opequon Creek Watershed:

- Forested area decreased by 7% from 47% in 1984 to 40% in 2007
- Agricultural area decreased by 5% from 42% in 1984 to 37% in 2007
- Urban area more than doubled from 6% in 1984 to 14% in 2007
- Impervious surface class more than doubled from 3% in 1984 to 7% in 2007
- Water area stayed relatively the same and
- Sinkhole area increased by about a half an hectare
DEFINIENS PRO. LAND USE AND LAND COVER CLASSIFICATION RESULTS FROM LANDSAT IMAGES:
Data is given as the number of image-objects for each land use and land cover class for each data set, which is then overlain and compared to the other images to determine change.

<table>
<thead>
<tr>
<th>DATE</th>
<th>TOTAL IMAGE-OBJECTS LANDSAT</th>
<th>FOREST</th>
<th>URBAN</th>
<th>AGRICULTURE</th>
<th>IMPERVIOUS SURFACE</th>
<th>WATER</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984 LANDSAT</td>
<td>5390</td>
<td>2605</td>
<td>476</td>
<td>1724</td>
<td>342</td>
<td>243</td>
</tr>
<tr>
<td>1989 LANDSAT</td>
<td>5382</td>
<td>2410</td>
<td>668</td>
<td>1642</td>
<td>412</td>
<td>250</td>
</tr>
<tr>
<td>1993 LANDSAT</td>
<td>5399</td>
<td>2297</td>
<td>813</td>
<td>1509</td>
<td>533</td>
<td>247</td>
</tr>
<tr>
<td>1999 LANDSAT</td>
<td>5387</td>
<td>1912</td>
<td>1244</td>
<td>1189</td>
<td>782</td>
<td>260</td>
</tr>
<tr>
<td>2002 LANDSAT</td>
<td>5391</td>
<td>1640</td>
<td>1509</td>
<td>1094</td>
<td>908</td>
<td>240</td>
</tr>
</tbody>
</table>

AMOUNT OF IMAGE-OBJECT CHANGE

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>DATA</td>
<td>NA</td>
<td>-965</td>
<td>+1033</td>
<td>-630</td>
<td>+566</td>
<td>-3</td>
</tr>
</tbody>
</table>

% CHANGE FROM 1984-2002

|                      | NA                            | -37%  | +217% | -36%        | +165%             | -1.2% |

Table 12: Land Use and Land Cover Change of Study Area based on Image-Object Change Detection from LANDSAT Data
CLASSIFICATION RESULTS FROM LANDSAT/AERIAL PHOTOGRAPHY INTEGRATION: Data is given as the number of image-objects for each land use and land cover class for each data set, which is then overlain and compared to the other images to determine change.

<table>
<thead>
<tr>
<th>DATE LANDSAT/AERIAL PHOTOGRAPHY</th>
<th>TOTAL IMAGE-OBJECTS</th>
<th>FOREST</th>
<th>URBAN</th>
<th>AGRICULTURE</th>
<th>IMPERIOUS SURFACE</th>
<th>WATER</th>
<th>SINKHOLES</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984/1987 CIR</td>
<td>903,478</td>
<td>366,278</td>
<td>79,135</td>
<td>302,425</td>
<td>70,142</td>
<td>25,006</td>
<td>802</td>
</tr>
<tr>
<td>1989</td>
<td>903, 512</td>
<td>332,109</td>
<td>115,907</td>
<td>278,190</td>
<td>94,135</td>
<td>24,870</td>
<td>823</td>
</tr>
<tr>
<td>2002/2007 NAIP</td>
<td>903, 496</td>
<td>221,787</td>
<td>217,322</td>
<td>195,322</td>
<td>183,865</td>
<td>24,679</td>
<td>932</td>
</tr>
<tr>
<td>IMAGE-OBJECT CHANGE</td>
<td>NA</td>
<td>-144,491</td>
<td>138,187</td>
<td>-107,103</td>
<td>113,723</td>
<td>-327</td>
<td>130</td>
</tr>
<tr>
<td>% CHANGE 1984-2007</td>
<td>NA</td>
<td>-39.49%</td>
<td>+176.86%</td>
<td>-35.41%</td>
<td>+162.13%</td>
<td>-1.31%</td>
<td>+16.21%</td>
</tr>
</tbody>
</table>

Table 13: Land Use and Land Cover Change of Study Area based on Image-Object Change Detection from LANDSAT/AERIAL Integration
## ARCGIS Calculation of Area for Each Land Use Class, Cover and Dataset: 1984-2007

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Area (Ha)</td>
<td>Area (%)</td>
<td>Area (Ha)</td>
<td>Area (%)</td>
<td>Area (Ha)</td>
</tr>
<tr>
<td>Forest</td>
<td>23,748,921</td>
<td>47</td>
<td>23,243,624</td>
<td>46</td>
<td>22,484,253</td>
</tr>
<tr>
<td>Agriculture</td>
<td>21,222,440</td>
<td>42</td>
<td>20,717,143</td>
<td>41</td>
<td>19,959,199</td>
</tr>
<tr>
<td>Urban</td>
<td>3,031,777</td>
<td>6</td>
<td>3,540,019</td>
<td>7</td>
<td>4,800,314</td>
</tr>
<tr>
<td>Impervious Surface</td>
<td>1,515,889</td>
<td>3</td>
<td>2,017,772</td>
<td>4</td>
<td>2,273,833</td>
</tr>
<tr>
<td>Water</td>
<td>1,010,587</td>
<td>2</td>
<td>1,011,055</td>
<td>2</td>
<td>1,012,014</td>
</tr>
<tr>
<td>Sinkholes</td>
<td>4.64853</td>
<td>.00000919</td>
<td>4.72203</td>
<td>.00000935</td>
<td>4.83403</td>
</tr>
<tr>
<td>Total</td>
<td>50,529,618</td>
<td>100</td>
<td>50,529,618</td>
<td>100</td>
<td>50,529,618</td>
</tr>
</tbody>
</table>

Table 14: ArcGIS Analysis of Total Area (in Hectares and Percentage) of Land Use and Land Cover in Opequon Creek Watershed Between 1984-2007 from Definiens Professional Classification Exports
4.7.2 Analysis of New Sinkhole Development

Sinkholes mapped during Definiens Professional classifications were exported as a shapefile with attribute tables, and brought into ArcGIS for further exploration to examine existing sinkholes in 1984, as well as subsequent sinkholes formed between 1984 and 2007. Since solution sinkhole processes take place on the order of hundreds or thousands of years, it is assumed that new sinkholes in the study area are collapse features (see 3.6.4). Spatial analysis within ArcGIS allows for exploration of sinkhole data to determine if clustering exists, which may indicate underlying causal relationships in the Martinsburg area.

Each scene was georeferenced to the 2003 State Address and Mapping Board Digital Orthophotographs of the watershed. Once the scenes were all rectified and georeferenced to the reference layer, sinkholes locations were extracted as point data using the “add xy coordinate data” tool. This allowed for mapping of sinkholes for each scene, with subsequent production of tabular data for statistical and spatial comparison.

The results show that as of 1984 (Figure 66) there were 803 sinkholes in the study area, interpreted by Definiens Professional Software. Comparison of the location field in the attribute tables for each of the dates shows new sinkholes not found on previous images, suggesting they are collapse features. Using this method, 21 new sinkholes developed between 1984-1989 (Figure 67), 32 between 1989-1997 (Figure 68), 40 between 1997-2003 (Figure 69), and 37 between 2003-2007 (Figure 70). Figure 71 shows all 932 sinkholes, as of 2007, in Opequon Creek Watershed, interpreted by Definiens Professional Software.
Figure 66: Location of 803 Sinkholes as of 1984
Interpreted by Definiens Professional Software

Figure 67: Location of 21 New Sinkholes 1984-1989
Interpreted by Definiens Professional Software
Figure 68: Location of 32 New Sinkholes 1989-1997
Interpreted by Definiens Professional Software

Figure 69: Location of 40 New Sinkholes 1997-2003
Interpreted by Definiens Professional Software
Figure 70: Location of 37 New Sinkholes 2003-2007
Interpreted by Definiens Professional Software
Figure 71: Map showing location of all Sinkholes as of 2007 Interpreted by Definiens Professional Software

Legend
- 1984 Sinkholes
- 1989 New Sinkholes
- 1997 New Sinkholes
- 2003 New Sinkholes
- 2007 New Sinkholes
As shown in Chapter 3 there is a definite connection between changes in runoff morphology brought about by development in the watershed and collapse sinkhole development, as soils and sediment move underground. Therefore, it is important to spatially examine those sinkholes in the watershed that may be collapse features resulting from these urban development pressures.

First, two different size buffers at 5 and 10 kilometers were created in ArcGIS around Martinsburg, the main source of urbanizing changes in the watershed and the largest user of pumped groundwater, which has likewise been shown to produce collapse features. Once these buffers where created an intersect function was performed with each attribute table to find those sinkholes during various dates that were within this buffer, as well as mapping the new sinkholes. The 10 kilometer buffer shows 498 sinkholes present in 1984 (Figure 72), with 86 new collapse sinkholes developing between 1984-2007 (Figure 73). For the 5 kilometer buffer 213 sinkholes are identified by Definiens Professional on the 1984 image (Figure 74), with 56 new collapse sinkholes developing between 1984 and 2007 (Figure 75). These results suggest the new sinkholes since 1984 developed rapidly and must be of the collapse variety.
Figure 72: 498 Sinkholes Interpreted by Definiens Professional in 1984 within a 10 Kilometer Radius of Martinsburg
Figure 73: 86 New Sinkholes Identified by Definiens Professional between 1984-2007 within a 10 Kilometer Radius of Martinsburg
Figure 74: 213 Sinkholes Interpreted by Definiens Professional in 1984 within a 5 Kilometer Radius of Martinsburg
Figure 75: 56 New Sinkholes Identified by Definiens Professional between 1984-2007 within a 5 Kilometer Radius of Martinsburg
To further examine the correlation between newly-developed sinkholes and urban development in the study area several “Spatial Statistics Tools” were utilized to analyze patterns and map clusters. If the increasing population and development in and around Martinsburg is responsible for the development of the 86 new sinkholes between 1984 and 2007, identified using the 10 kilometer buffer and 56 new sinkholes with the 5 kilometer buffer, there should be clustering beyond what random chance would allow for, since collapse sinkholes concentrate as a result of these geomorphic changes. Results are tabulated and shown in Table 15 and Appendix I.

The first tool used for this purpose was “Average Nearest Neighbor” within the “Analyzing Patterns” subset of “Spatial Statistics Tools” found in the ArcToolbox. With this tool an index is calculated that reflects the average distance from a feature to all its neighbors compared to the average distance for a random distribution. This index looks at each feature and the nearest single feature and calculates a mathematical index. The degree of clustering is determined by comparing the indexes of the real versus hypothetical data and examining the degree of change (Allen, 2009).

It begins by measuring the distance between each feature centroid and its nearest neighbor's centroid location. It then averages all these nearest neighbor distances. If the average distance is less than the average for a hypothetical random distribution the features being analyzed are considered clustered. If the average distance is greater than a hypothetical random distribution, the features are considered dispersed. Quantitatively, if the Average Nearest Neighbor ratio is less than 1, the pattern exhibits clustering, while indexes greater than 1 trend toward dispersion.
Each layer representing one of the five scenes was input into the Average Nearest Neighbor tool for statistical exploration and a graphical output display was chosen to show results. For the 498 sinkholes within the 10 kilometer radius of Martinsburg, interpreted by Definiens Professional using the 1984 images, sinkholes are randomly distributed in the watershed (Appendix I) without clustering or dispersion taking place. This is indicated by the low z score (-.65), which is a measure of standard deviation.

The 86 new sinkholes identified by Definiens Professional for images between 1984-2007 (Appendix I) for the 10 kilometer buffer show significant clustering northwest of Martinsburg, as indicated by low observed standard mean distances (.56) and high z scores (-10.56). This indicates that non-natural or human-induced processes must be at work controlling sinkhole development over the last 25 years, as there is no random element that can account for the observed distribution of sinkholes. While geologic controls can lead to sinkhole clustering naturally, the fact that previous imagery shows no significant clustering in this area leads to this conclusion.

For the 213 sinkholes within the 5 kilometer radius of Martinsburg using the 1984 images, sinkholes show only slight clustering within the watershed (Appendix I). This is indicated by the slightly higher z score (-2.34), which are measures of standard deviation, and low observed mean distances (.74). The higher the z score the stronger the intensity of clustering.

The 56 new sinkholes identified by Definiens Professional for images between 1984-2007 (Appendix I) for the 5 kilometer buffer show significant clustering northwest of Martinsburg, as indicated by low observed standard mean distances (.4) and high z scores (-
23.23). This indicates that non-natural or human-induced processes must be at work controlling sinkhole development over the last 25 years, as there is no random element that can account for the observed distribution of sinkholes.

The second tool used to examine the correlation between new sinkhole development and urbanization in Opequon Creek Watershed is the “Getis-Ord High/Low Clustering Tool”, which measures how concentrated the high or low values are for a given study area and examines clustering by value. The General G statistic looks at the similarity of values of features within a defined proximity of each other. Areas with similar values have high clustering. High z scores indicate higher standard deviations, which point to clustering of high or low values within the data set. For this study, a high z score for this statistic means significant clustering of sinkholes that can be indicative of urban impacts in the watershed. For the 5 kilometer buffer around Martinsburg, which includes the 213 sinkholes found on the 1984 image, the “High/Low Clustering Tool” shows a low z score (.66) signifying that there is no significant clustering of existing sinkholes as of 1984 (Appendix I) and that the random nature of sinkhole occurrence here is more random than human-induced.

The Getis-Ord High/Low Clustering Analysis of the 56 sinkholes that developed between 1984-2007 shows (Appendix I) that there is significant clustering of the high values, as is represented by the high z score (11.6). This suggests that urbanization impacts in the watershed may be controlling new sinkhole development, as there is less than a 1% chance that the clustering of high values is random chance.

The third tool used to analyze the sinkhole data is the “Multi-Distance Spatial Cluster Analysis” tool, also known as based on Ripley’s K Function (Figure 76). This tool determines
whether data is clustered by location using multiple features and multiple distances. It is another way to analyze the spatial pattern of point data. A distinguishing feature of this method from others is that it summarizes spatial dependence (sinkhole clustering or dispersion) over a range of distances. When exploring spatial patterns at multiple distances and spatial scales, patterns change, often reflecting the dominance of particular spatial processes at work. Ripley's K function illustrates how the spatial clustering or dispersion of feature centroids changes when the neighborhood size changes. It is also different from the Nearest Neighbor tool in that it can detect a more subtle clustering effect than can be found with the nearest neighbor (Allen, 2009). In other words it can be used to see if sinkholes are clustering due to factors beyond the next nearest feature (ie. urban impacts).

Figure 76: Multi-Distance Spatial Cluster Analysis Results Interpretation
For the 86 new sinkholes identified between 1984-2007 using the 10 kilometer buffer the “Multi-Distance Spatial Cluster Analysis Tool” shows clustering closest to the center of Martinsburg (Appendix I), while increasing distance from town leads to a more dispersed pattern of sinkhole development. Likewise, the results for the analysis of the 56 new sinkholes identified using the 5 kilometer buffer (Appendix I) shows clustering at shorter distances and dispersion of sinkholes at farther distances from the center of town. This suggests that sinkhole development is strongly correlated to proximity to the urban development of Martinsburg.
### SPATIAL ANALYSIS RESULTS USING VARIOUS STATISTICAL TOOLS

<table>
<thead>
<tr>
<th>SPATIAL STATISTICS TOOL</th>
<th>DATASET</th>
<th># OF SINKS</th>
<th>Z SCORE</th>
<th>GENERAL G INDEX</th>
<th>OBSERVED MEAN DISTANCE</th>
<th>RESULTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Nearest Neighbor Distance</td>
<td>1984 10km radius</td>
<td>498</td>
<td>-.65</td>
<td>NA</td>
<td>93</td>
<td>-Random distribution of Sinkholes -No clustering or dispersion</td>
</tr>
<tr>
<td>Average Nearest Neighbor Distance</td>
<td>New Sinkholes 10km radius 1984-2007</td>
<td>86</td>
<td>-10.56</td>
<td>NA</td>
<td>.56</td>
<td>-Significant clustering northwest of Martinsburg beyond random chance</td>
</tr>
<tr>
<td>Average Nearest Neighbor Distance</td>
<td>1984 5km radius</td>
<td>213</td>
<td>-2.34</td>
<td>NA</td>
<td>.74</td>
<td>-Slight clustering</td>
</tr>
<tr>
<td>Average Nearest Neighbor Distance</td>
<td>New Sinkholes 5km radius 1984-2007</td>
<td>56</td>
<td>-23.23</td>
<td>NA</td>
<td>.4</td>
<td>-Significant clustering northwest of Martinsburg</td>
</tr>
<tr>
<td>Getis-Ord Hi/Low Clustering General G Statistic</td>
<td>1984 5km radius</td>
<td>213</td>
<td>.66</td>
<td>.14</td>
<td>NA</td>
<td>-No significant clustering of existing sinkholes</td>
</tr>
<tr>
<td>Getis-Ord Hi/Low Clustering General G Statistic</td>
<td>New Sinkholes 5km radius 1984-2007</td>
<td>56</td>
<td>11.6</td>
<td>.18</td>
<td>NA</td>
<td>-Significant clustering of high values shown by high z score -Suggests urban impacts may be influencing new sinkholes</td>
</tr>
<tr>
<td>Multi-distance Spatial Cluster Ripley’s K Function</td>
<td>New Sinkholes 10km radius 1984-2007</td>
<td>86</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>-Shows clustering near Martinsburg -Increasing distance from center of town leads to dispersion (4100m)</td>
</tr>
<tr>
<td>Multi-distance Spatial Cluster Ripley’s K Function</td>
<td>New Sinkholes 5km radius 1984-2007</td>
<td>56</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>-Clustering at shorter distances -Dispersion at greater distances</td>
</tr>
</tbody>
</table>

Table 15: Spatial Statistics Analysis Results showing number of sinkholes for various statistical tools
Lastly, sinkhole area was compared in ArcGIS to examine if new sinkholes developed in the watershed between 1984-2007 are significantly different in size from pre-existing 1984 sinkholes. For this analysis the “Calculate Areas” function found in the “Utilities” subset of the “Spatial Statistics Tool” was used to measure the area of the pre-existing 1984 sinkholes and the new sinkholes layer, which includes those developing between 1984-2007 (Figure 77). This tool calculates area values for each feature in a polygon feature class with polygon areas added as a new field (Figure 78).

![Figure 77: Map used in Calculating Sinkhole Areas with Calculate Areas Tool](image1)

![Figure 78: Calculate Areas subset of the Spatial Statistics Tool allows for Quantification of Sinkhole Areas in Watershed](image2)
Results of this analysis show that of the 213 sinkholes identified by Definiens Professional on the 1984 image the average sinkhole size was 34.9 m² (Table 16). This was found by taking the total sinkhole area (7433.7 m²) and dividing by 213 (the number of sinkholes interpreted by Definiens Professional). The 56 new sinkholes within the 5 kilometer buffer of Martinsburg showed an average sinkhole size of 49.2 m². This was determined by taking the total sinkhole area for the 56 new sinkholes (2755.2 m²) and dividing by 56. This increase in the area of new sinkholes versus that of existing solution sinkholes in the watershed suggests that the new collapse features may indeed be connected to urbanizing processes in the watershed, since the collapse features are larger than the preexisting solution sinkholes.
SINKHOLES WITHIN 5 KILOMETER RADIUS OF MARTINSBURG

Table 16: Tabular Data of Sinkholes within 5 Kilometer Buffer of Martinsburg used for Comparison of Sinkhole Areas of 1984 Sinkholes vs. New Sinkholes Developed between 1984-2007

4.7.3 Cross-Plot Analysis

Scatter plots are another statistical analysis that can be useful for examining the correlations between land use and land cover classes and sinkholes. Definiens Professional allows for the analysis of the correlation of two features using cross plots where two variables are examined simultaneously. Not only is image-object analysis proving accurate at classifying large study areas, but it provides powerful statistical
exploration capabilities of data sets. By cross-plotting image-objects from different land use and land cover classes against statistical variables such as shape, color, texture, and pattern, the user is able to explore the correlation between sinkholes and other land use and land cover types. This may provide invaluable insight for planners, municipalities, farmers, engineers, residents and many others. Early examination of cross plots of various classes shows strong correlation between various classes.

The “Image-Object Information” and “Feature View windows” provide tools to select various variables in order to statistically plot these classes against each other using parameters such as shape, texture, and brightness within the “2D Feature Space Plot” tool. The user can then acquire information about where an object or a group of objects is situated in a two-dimensional feature space. The 2D Feature Space Plot dialog box facilitates the examination of the distribution of feature values plotted on x-y-axes of two different assigned features.

The classification results for the 2007 image were used as inputs. Results show a strong correlation between density and distance from Martinsburg, shown by a linear relationship between these two variables (Figure 79). The upward direction of points shows that there is a positive relationship, while the densely packed nature of the data highlights the strength of this relationship. The plot also shows that sinkhole density is at its maximum between one and four kilometers from Martinsburg, which fits with the conclusion that new sinkholes are influenced by the proximity to the development taking place near Martinsburg.
Figure 79: Scatter Plot showing Strong Positive Correlation between Sinkhole Density and Proximity to Martinsburg

Scatter plots also showed strong correlation between sinkhole area (given in square meters) and distance from Martinsburg in the 2007 image (Figure 80). The linear relationship between these two variables reinforces the suggestion that the new sinkholes observed in the watershed between 1984-2007 are collapse features. The upward direction of the points shows the positive relationship, while the densely clustered data shows the strength of the relationship. The maximum clustering between three and seven kilometers from Martinsburg also supports the theory that development is contributing to geomorphic changes, for those sinkholes within 10 kilometers, since sinkholes beyond this distance become increasingly less in number.
In order to examine sinkhole relationships to different land uses and land covers in the 2007 image the sinkholes and forest class were plotted against each other as xy coordinate data, using the distance and density variables (Figure 81). Results showed a negative correlation between these land use classes, represented by the downward trend line. At the same time the tight nature of the points around that trend show the strength of this correlation. Sinkholes are not significantly found in or near the forest class, and as proximity to forest increases, the number of sinkholes in the area decreases. Although, this is not definitive, since sinkholes may be obscured by tree cover or the program is failing to identify them. For urban versus newly-formed sinkholes a strong correlation is also shown when using “distance to features” and “density” variables (Figure 82). The
upward trend line shows that as urban area increases the number of new sinkholes also increases. The tight clustering around the trend line shows the strength of this correlation.

**Figure 81: Scatter Plot showing Strong Negative Correlation between Sinkholes and Forest Class; Forest data is shown in brown and Sinkholes in Black**

Next, urban and impervious surface classes are plotted. These classes show a strong correlation when using “distance to features”, “area”, and “density” variables (Figure 83). The upward trend line shows that as urban area increases so does the area of impervious surface, which makes perfect sense, since these variables would be directly related. The tight clustering around the trend line shows the strength of this correlation.
Figure 82: Scatter Plot showing Strong Positive Correlation between New Sinkholes and Urban Class; Sinkholes shown in black and Urban in Red

Figure 83: Scatter Plot showing Strong Positive Correlation between Impervious Surface and Urban Class; Impervious Surface shown in gray and Urban in Red
4.7.4 Regression Analysis

Lastly, to further examine any meaningful correlations between these variables, the datasets were exported from Definiens Professional as .csv files and imported into ArcGIS 9.2 for further statistical analysis. Regression analysis usually includes any technique that can model or analyze variables by focusing on the relationship between dependent and independent variables (i.e., sinkholes, land uses, land covers).

To perform this function, I used the regression function of the “multivariate statistical analysis” subset of the “Spatial Analyst” tools suite within ArcGIS 9.2’s ArcGrid Workstation, as well as the “Geographically Weighted Regression” function of the “Modeling Spatial Relationships” subset of the “Spatial Statistics Tools”. These tools perform a multiple, or linear, regression by calculating coefficients for the independent variable (land uses), which then allows for the exploration of the dependent variable (sinkholes). The .csv files were imported into ArcGrid where the text editor was used to create a file that is used during the regression. The regression function interprets the first column as the dependent variable and subsequent columns as the independent variables. The regression returns a constant value and a coefficient for each of the independent variables. Using these coefficients, I created a raster of predicted values for the dependent variable using the “Map Algebra” tool and this equation:

\[
\text{prediction or } (y) = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots \quad (2)
\]

where \(a_0, a_1, a_2, \text{ and so on}\) are the coefficients from the regression and \(x_1, x_2, \text{ etc.}\) are the corresponding independent rasters where the coefficients were derived. Datasets imported included: sinkholes; forest class, agriculture class and impervious surface class.
Fifteen total regressions were performed (Table 17 and Appendix II) using each land use class of interest (independent variable) that could impact the development of sinkholes (dependent variable).

**MULTIPLE REGRESSION ANALYSIS RESULTS**

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Independent variable</th>
<th>Coefficient</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sinkholes in 1984</td>
<td>Forest Class</td>
<td>-0.0001722</td>
<td>0.0056</td>
</tr>
<tr>
<td>Sinkholes in 1984</td>
<td>Agricultural Class</td>
<td>0.5674841</td>
<td>0.7814</td>
</tr>
<tr>
<td>Sinkholes in 1984</td>
<td>Urban Class</td>
<td>0.6934625</td>
<td>0.8115</td>
</tr>
<tr>
<td>Sinkholes 1984-1989</td>
<td>Forest Class</td>
<td>0.0000722</td>
<td>0.0022</td>
</tr>
<tr>
<td>Sinkholes 1984-1989</td>
<td>Agricultural Class</td>
<td>0.4617572</td>
<td>0.6943</td>
</tr>
<tr>
<td>Sinkholes 1984-1989</td>
<td>Urban Class</td>
<td>0.6351343</td>
<td>0.7485</td>
</tr>
<tr>
<td>Sinkholes 1989-1993</td>
<td>Forest Class</td>
<td>-0.0005093</td>
<td>0.0285</td>
</tr>
<tr>
<td>Sinkholes 1989-1993</td>
<td>Agricultural Class</td>
<td>0.4251689</td>
<td>0.8993</td>
</tr>
<tr>
<td>Sinkholes 1989-1993</td>
<td>Urban Class</td>
<td>0.7280642</td>
<td>0.9293</td>
</tr>
<tr>
<td>Sinkholes 1993-1999</td>
<td>Forest Class</td>
<td>0.0013278</td>
<td>0.0032</td>
</tr>
<tr>
<td>Sinkholes 1993-1999</td>
<td>Agricultural Class</td>
<td>0.4376996</td>
<td>0.6589</td>
</tr>
<tr>
<td>Sinkholes 1993-1999</td>
<td>Urban Class</td>
<td>0.5546865</td>
<td>0.7056</td>
</tr>
<tr>
<td>Sinkholes 1999-2007</td>
<td>Forest Class</td>
<td>-0.0014290</td>
<td>0.0424</td>
</tr>
<tr>
<td>Sinkholes 1999-2007</td>
<td>Agricultural Class</td>
<td>0.4367434</td>
<td>0.9113</td>
</tr>
<tr>
<td>Sinkholes 1999-2007</td>
<td>Urban Class</td>
<td>0.6130976</td>
<td>0.8586</td>
</tr>
</tbody>
</table>

*Table 17: Multiple Regression Analysis Results*
R² values range from 0-1 with small values indicating that the model does not fit the data well, while larger values show a strong relationship. Regression coefficients, one for each independent variable, are values that represent the strength and type of relationship the independent variable has to the dependent variable. When the relationship is positive, the sign for the associated coefficient is also positive. Likewise, coefficients for negative relationships will have negative signs. Also, when the relationship is a strong one, the coefficient is large, while weak relationships are associated with coefficients near zero.

Results (Table 17) show that when the distribution of sinkholes versus various land uses is plotted using the linear regression model, a linear proportion of explained variation (R²) is small for the forested class and large for agriculture and urban classes. Likewise, coefficients for forested class are small and in some cases negative, while for agriculture and urban classes the coefficient is quite large. The poor correlation between sinkholes and forested classes suggest that there is no statistically significant relationship, since similar results are seen with all datasets for this class. At the same time, the small R² values for the forested class suggest that it is only a minor driver of sinkhole development during the study. At the same time the high coefficients and R² values for agriculture and urban classes suggest that there exists a strong linear relationship and that these classes are indeed influencing sinkhole development.

Therefore, this chapter has shown through various change detection and statistical methods that there have been significant changes taking place in the watershed during the last 25 years. While forested and agricultural land areas have decreased, there has been a
dramatic increase in urban and impervious surfaces, as well as the number of sinkholes that have developed during this time frame. Statistical analysis has shown that not only has the area and number of sinkholes increased during the study period, but the likely agent of change is the increasingly developed nature of the watershed, indicated by the strong correlations between agricultural and urban lands when plotted against sinkholes.
Chapter 5: Image-Object Suitability for Landscape Inventory in Karst Watersheds

5.1 Stage 2: Analysis of land use and sinkhole development via object-oriented software classification of digital imagery to determine suitability for inventory

5.1.1 Object-Oriented Analysis

Classification of imagery using pixel-based methods (Table 18) has been used less in recent years, due to an inability of these methods to deal with high-resolution imagery. According to Mansor et al. (2002), “pixel-based methods produce inconsistent classifications, while lacking an ability to extract objects of interest”. Pixel-based classifications are based on the mean digital number, or spectral reflectance, in that pixel.

**PIXEL VS.OBJECT-ORIENTED CLASSIFICATION**

<table>
<thead>
<tr>
<th>Pixel-Based Classification</th>
<th>Object-Oriented Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Corrects atmos. distortion</td>
<td>• Segments imagery into image-objects</td>
</tr>
<tr>
<td>• Requires gain and offset values, sun elevation angle, ground visibility, etc</td>
<td>• User-defined segmentation parameters allow for goal-oriented image-object production</td>
</tr>
<tr>
<td>• Based on the spectral mean of each band in the image</td>
<td>• In addition to available bands, DEM band, brightness &amp; vectors can be used for classification parameters</td>
</tr>
<tr>
<td>• Classification is made at one time only</td>
<td>• Step by step classification can be applied to image. Classification can be conducted throughout process in order to expand the classes from minimum of two classes to more (Parent/Daughter classes)</td>
</tr>
<tr>
<td>• Can apply a mode filter to reduce distortion</td>
<td>• No filter is needed because image is already divided into desired polygons during segmentation</td>
</tr>
</tbody>
</table>

Table 18: Pixel-based vs. Object-oriented Classification (Source: Mansor et al., 2002)
Oruc et al. (2004) go on to add that “the overall objective of traditional image classification is to automatically place all pixels of an image into land use and land covers using multispectral data. The spectral pattern for each pixel is used as the numerical basis for categorization”. This means that different features show different combinations of digital numbers based on their spectral reflectance properties. Therefore, a spectral pattern is derived from radiance measures of different wavelengths in each pixel (Oruc et al., 2004). Spectral pattern recognition can then be used on a pixel-by-pixel basis to classify the image.

Object-based classification offers the potential for more accurate classifications based on nearest-neighbor technologies and classifications based on shape and spectral reflectance, as well as providing methods for extracting object layers, such as sinkholes (Yoon et al., 2003). According to Yoon et al. (2003), “object-based classifications are premised on the idea that information needed to interpret an image is not present in pixels, but in image-objects and their relationships”. These image-objects then become the building blocks for subsequent image analysis (Figure 84).
The Definiens Professional process of object-based image analysis involves:

1. Creating a hierarchical network of image-objects with multi-resolution segmentation
2. Classifying the objects by their physical properties
3. Describing the relationship of the network’s objects in terms of super or sub-objects
4. Aggregating the classified image-objects into groups that can be segmented again based on classification

One advantage of object-based image analysis is the extra data that is gained from image-objects versus that available from individual pixels (Yoon et al., 2003). A pixel has only information representing each band or layer in a data set. With digital imagery, the spectral response information is stored as digital numbers, while image-objects are made of multi-pixel groups, allowing exploration of statistics, such as mean and standard deviation, from an object’s underlying digital number (Yoon et al., 2003).
In addition to spectral data, information based on object size, shape, and context can be calculated, as can information pertaining to an object’s sub- or super-objects, if a multi-level image-object hierarchy has been created (Chubey et al., 2006). Therefore, the analysis of an image within Definiens Professional flows more smoothly and allows for multiple levels of segmentation and classification until the user-defined parameters are achieved (Figure 85). This allows for image processing using both coarse and high-resolution imagery to be refined until land use and sinkholes are clearly identified at various levels.

![Diagram of object-oriented image analysis work flowchart](image)

**Figure 85: Object-Oriented Image Analysis Work Flowchart used to Classify Images in Study Area (Mansor et al., 2002)**

The algorithms used within Definiens Professional describe what the various processes will do. This can be to generate image-objects, merge split or classify objects.
The two main functions of algorithms within Definiens Professional are to generate or modify image-objects and classify image-objects (Definiens Professional User Manual, 2005). These categories of algorithms are available for image-object processing and are used at various phases during this research:

- Segmentation
- Classification
- Pre-processing
- Level operation
- Reshaping
- Sample operation
- Thematic layer operation
- Process related operation

According to Schiewe (2002), “segmentation is the process of completely partitioning a scene into non-overlapping regions (segments) in scene space. Segmentation results in a network of image-object primitives. These image-object primitives represent the image information in an abstracted form serving as building blocks and information carriers for subsequent classification”.

The Definiens Professional analysis process (Figure 86) involves a continuous cycle of image segmentation, modification and classification, in which the image-object hierarchy is constantly being reshaped and modified according to user-defined parameters (Definiens Professional User Manual, 2005).
Likewise, user-defined view settings allow the various bands of data to be examined and stretched so that layers of the dataset can be mixed, thus changing the visual display of the image, but not the underlying data. This allows for a more precise classification during supervised classification (Figure 87). Multiple views of the post-classification results can also allow more detailed and accurate examination of classes (Figure 88).
Figure 87: Views of Same Project via Layer Mixing
(Definiens Professional Use Manual, 2005)

Figure 88: Post-classification Views (Top left: Pixel view w/outlines; Top Right: Classification View; Bottom Left: Feature View; Bottom Right: Object Mean View w/outlines and skeleton (Definiens Professional User Manual, 2005)
5.1.2 Image-Objects

Each image-object represents a spatially-connected region of the image. The pixels of the associated regions are linked to the image-object with an *is-part-of* link (Definiens Professional User Manual, 2005). Two image-objects are considered neighboring if their associated regions are adjacent to each other. An image is then segmented into these image-objects. All together, the image-objects of a segmentation (Figure 89) form an image-object level.

*Figure 89: Image-Object Levels (Definiens Professional User Manual, 2005)*

Within Definiens Professional the user is able to move through the different levels of the image-object hierarchy in order to gain information on different levels and to perform classifications (Definiens Professional User Manual, 2005). This allows objects to be split, merged or modified until the desired spatial extent of the feature objects is achieved (Figure 90). This process is used in the study to refine segmentation and classification until sinkholes and land use objects can be readily distinguished.
Figure 90: Image-Object Levels 1 and 2 (Definiens Professional User Manual, 2005)

Two or more image-object levels build the image-object hierarchy (Figure 91). In the image-object hierarchy, every image-object of a lower level is linked to image-objects of its super-level (Definiens Professional User Manual, 2005). Since regions in the image provide more information than single pixels, there are a large number of different image-object features for measuring color, shape, and texture of the regions (Definiens Professional User Manual, 2005).

Figure 91: Image-Object hierarchy with 3 levels (Definiens Professional User Manual, 2005)
5.1.3 Image-Object Domain

According to the Definiens Professional User Manual (2005), “the image-object domain describes the region of interest where the process algorithm will be executed in the image-object hierarchy. Examples of image-object domains include the entire image, image-object level, or all image-objects within a class”.

By applying different statistics in the software to the basic image-object domains, many different image-object domains can be generated. The process (Figure 92) then loops over the set of image-objects in the domain and applies the algorithm to every single image-object.

![Image-Object Process Sequence](image-object-process-sequence.png)

**Figure 92: Image-Object Process Sequence (Definiens Professional User Manual, 2005)**

5.1.4 Object Features

Object features are the data that is found within image-objects, such as spectral, shape, and hierarchical characteristics. Features are used as a source of information to define whether to include or exclude image-objects during classification (Definiens Professional User Manual, 2005). This information is needed to gain a representative classification of
image-objects in the scene. They are achieved by evaluating image-objects themselves. There are two major types of features: image-object features, which are attributes of image-objects, and global features, which are not connected to an individual image-object. These image-object features were used in this research for analysis within Definiens Professional (Table 19):

**OBJECT FEATURES TABLE**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td><em>Thematic attributes:</em> object’s thematic properties may be evaluated. Depending on the attributes of the thematic layer, a large range of different features become available.</td>
</tr>
<tr>
<td>2.</td>
<td><em>Layer values:</em> evaluate mean and standard deviation of an image-object’s pixel value and object’s relations to other image-object’s pixel values. Can then describe image-objects with information derived from spectral properties.</td>
</tr>
<tr>
<td>3.</td>
<td><em>Shape:</em> evaluate image-object’s shape. Shape features are calculated based on the object’s pixels. If image-objects of a certain class stand out because of their shape, you are likely to find a form feature that describes them.</td>
</tr>
<tr>
<td>4.</td>
<td><em>Texture:</em> can be evaluated using different texture features. New types of texture features based on an analysis of sub-objects. These are especially helpful for evaluating highly textured data.</td>
</tr>
<tr>
<td>5.</td>
<td><em>Hierarchy:</em> provides information about the embedding of the image-object in the image-object hierarchy.</td>
</tr>
</tbody>
</table>

Table 19: Object Features used in Study (Definiens Professional User Manual, 2005)

5.1.5 Class-Related Features

Class-related features refer to the classification of other image-objects found in the image-object hierarchy. This location can be defined by a vertical distance in the image-object hierarchy (superobjects and subobjects) or by a horizontal distance (neighbor
objects) (Definiens Professional User Manual, 2005). The distance is determined by the feature distance. These distance features are available in Definiens Professional and were used in the project (Table 20):

**DISTANCE FEATURES TABLE**

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Relations to neighbor objects</strong></td>
<td>describe an image-object by its mutual relationships to other image-objects assigned to a certain class on the same level.</td>
</tr>
<tr>
<td><strong>Relations to subobjects</strong></td>
<td>describe an image-object by its relationships to other image-objects, assigned to a certain class on a lower level. Since the resolution increases the lower you move in the image-object hierarchy, subscale information can be evaluated using these features.</td>
</tr>
<tr>
<td><strong>Relations to superobjects</strong></td>
<td>describe an image-object by its relations to other image-objects assigned to a certain class on a higher level in the image-object hierarchy. Analogous to the relations to subobjects, it is possible to evaluate super-scale information here.</td>
</tr>
<tr>
<td><strong>Relations to classification</strong></td>
<td>Use these features to find out about the current or potential classification of an image-object.</td>
</tr>
</tbody>
</table>

Table 20: Distance Features used in Study (Definiens Professional User Manual, 2005)

5.2 MULTI-RESOLUTION IMAGE SEGMENTATION

The most widely used method to derive areas of interest, when conducting environmental monitoring of a region, is image segmentation (Blaschke et al., 2005). Traditional image segmentation methods are divided into three approaches: pixel, edge, and region-based segmentation methods (Blaschke et al., 2005). These methods lack the use of contextual information for segmentation (Blaschke et al., 2005). Definiens Professional uses this contextual information to refine and produce a more accurate
segmentation (Figure 93) for subsequent classification, resulting in image-objects that more fully represent the user-defined criteria.

Therefore, the first step in the Definiens Professional object-based classification is multi-resolution segmentation of the image into unclassified basic image-objects, which extracts image-objects at various scales with user-defined criteria for shape and color (Figure 94). This technique starts by recognizing each pixel as a separate object, then merging them to create larger, more homogenous segments (Definiens Professional User Manual, 2005).
The Definiens Professional User Manual (2005) defines segmentation as “a basic procedure for knowledge-free and unsupervised segmentation of homogeneous, basic, unclassified image-objects in any chosen resolution. This method was developed to work even on highly textured image data, such as aerial photography and high-resolution satellite imagery”.

According to Darwish et al. (2003), the merging of objects is based on homogeneity criterion, which describes the similarity between adjacent image-objects. Pairs of image-objects with the smallest increase in the defined criterion are merged. The process ends when the homogeneity exceeds a user-defined threshold (i.e. Scale Parameter; see Chapter 5.2.1). This means that a higher scale parameter will allow more merging and bigger objects.

This process breaks down the image at the pixel or image-object level using user-defined resolution, such as color, shape, smoothness, and compactness. These unclassified image-objects contain data about spectral reflectance, shape, position, texture, and neighboring objects. This data contained in the image-objects are called “features” in Definiens Professional. Different segmentation algorithms provide different results for image-object generation based on input parameters (Figure 95).
Segmentation algorithms are used to subdivide the image from other domains into smaller images. Segmentation algorithms are needed to create new image-objects levels based on the image layer information. But they are also a great tool for refining existing image-objects by subdividing them into smaller pieces for more detailed analysis, or into larger objects for generalized studies (Definiens Professional User Manual, 2005).

The outcome of segmentation is directly related to different user-defined criteria (scale parameter, color, and shape). Segmentation can be performed at various scales depending on the scale of object needed for study. High resolution imagery can be used for fine classification of small objects, such as sinkholes (Figure 96), while lower-resolution satellite imagery (LandSat) can be used for coarse segmentation for land use and land cover and larger sinkholes classification.
The object mean view of the segmented objects (Figure 97) can also be used during segmentation to examine more subtle differences between objects, as well as looking at membership statistics and functions (Definiens Professional User Manual, 2005).

Likewise, the scale parameter is a measure of the maximum change in heterogeneity that may occur when merging two image-objects (Definiens Professional User Manual, 2005). A larger scale parameter value leads to bigger objects, while a smaller scale parameter leads to smaller objects. The scale parameter should meet the criteria for the
scale at which the study is being conducted. Producing objects that are too small or too large is useless for study. Therefore, it is critical to the research that various scale parameters be explored to find the one that is most useful for identifying sinkholes.

The homogeneity criterion is a combination of color (spectral value) and shape (smoothness and compactness). According to the Definiens Professional User Manual (2005), “homogeneity in the spectral domain is determined via a weighted standard deviation of the spectral channels”. Homogeneity of the shape factor depends on the ratio of an object’s border length to the object’s total number of pixels (compactness), and the ratio between the length of an object’s border to the length of the object’s bounding box (smoothness) (Yoon et al., 2003).

Adjusting the shape factor, affects the overall value that is computed by Definiens Professional, based on both spectral and shape heterogeneity and allows for the creation of a hierarchical network of image-objects. Choosing the optimal scale parameter and shape factor is critical to the quality of classification (Definiens Professional User Manual, 2005). By modifying the shape criterion (Figure 98), the user indirectly defines the color criteria, since by decreasing the value assigned to the shape field, the user defines the percentage that spectral values of the image layers will contribute to the entire homogeneity criterion (Definiens Professional User Manual, 2005).
This is then weighted against the percentage of the shape homogeneity, which is defined in the shape field. Changing the weight for the shape criterion to 1 results in objects that are more spatially homogenous. The shape criterion cannot have a value more than 0.9, since without the spectral information of the image, resulting objects would not be related to the spectral information (Definiens Professional User Manual, 2005).

The segmentation algorithm is described by (Baatz and Schäpe, 2000) as a “region-merging technique in which individual pixels are merged into small objects, followed by successive iterations in which small objects are incrementally merged into larger ones in such a way that heterogeneity of the resulting image-objects is minimized”. The merging process then will continue until a user-defined threshold is reached (Baatz and Schäpe, 2000).

The scale parameter determines the maximum allowed heterogeneity for resulting image-objects. For heterogeneous data the resulting objects for a given scale parameter will be smaller than in more homogeneous data (Definiens Professional User Manual, 2005).
By modifying the value in the Scale parameter window the user can vary the size of image-objects.

The objectives of the segmentation phase of this study were:

(a) to delineate homogeneous classes of land uses;
(b) to isolate sinkholes within these areas; and
(c) to characterize resulting image-objects

These tasks were accomplished using a multi-step segmentation method. Each individual image was segmented at a resolution that was coarse enough to aggregate groups of pixels representing homogeneous areas into recognizable land use class objects while preserving data.

A second image-object level was created by sub-segmenting the original image-objects using the same input parameters, but with a scale parameter setting 50% finer than the original segmentation. This second segmentation level was intended to show homogeneous land use classes (urban, agricultural, etc.) in order to increase the likelihood that these segmentations would be representative of the image. A third image-object level was created so that land use and land cover classes can be described according to the size, shape, and spatial arrangement. The texture objects were created by sub-segmenting the original image-object level using a very fine scale parameter setting.

5.2.1 Scale Parameter Settings

Large (200), medium (70) and small (5) scale parameters were examined for suitability. A medium scale parameter of 40 was used to segment the images because it
was found that the small scale created millions of image-objects (Figure 99), which were too small for sinkhole recognition and continually crashed the software during analysis. The second image segmentation used a scale of 120 and the third used a scale of 10. The medium scale segmentation of the merged LandSat and digital photography resulted in about 900,000 image-objects allowing sinkhole-sized objects to be discernable and used as training data for the land cover classification.

Likewise, other parameters (color, shape, compactness) were explored for best results during segmentation. It was found that a color parameter of 0.1 and a shape parameter of 0.9 gave the best results for image-object segmentation, while compactness and smoothness were set at 0.5. More emphasis was placed on shape (0.9) than color (0.1) during segmentation because of the distinct morphology that sinkholes have (Figure 100).
The following figures are the segmentations of image-objects in Definiens Professional using the multi-resolution segmentation algorithm and settings of .9 for shape, .1 for color, scale parameter of 40, compactness of .5, and smoothness of .5 (Figures 101-105):

Figure 100: Distinctive shape of a sinkhole in the study area

Figure 101: Segmented 1984 Imagery
Figure 102: Segmented 1989 Merged Imagery

Figure 103: Segmented 1993 Merged Imagery
Figure 104: Segmented 1999 Merged Imagery

Figure 105: Segmented 2002 Merged Imagery
5.3 SAMPLING AND CLASSIFICATION

According to Antunes et al. (2003), “classification, in Definiens Professional, is a procedure that associates image-objects with an appropriate user-defined class. The class describes the meaning of image-objects within the image. The classes then form a network called the class hierarchy” (Figure 106). Object-based classification starts with the grouping of pixels into objects based on the user-defined parameters. Classification is done based on a fuzzy logic where class descriptions consist of expressions that allow the evaluation of specific features (Antunes et al., 2003). The classes in this study were described using spectral and shape properties.

![Class Hierarchy](image)

**Figure 106: Class Hierarchy used in Study**

The class hierarchy is the framework Definiens Professional uses to create the knowledge base for a given classification. It has all of the classes used and is organized in a hierarchy. This grouping allows for the passing down of class descriptions to child classes and groupings of classes that allow for user-defined analysis (Yoon et al., 2003).
During classification of an image, each object is compared to each of the class descriptions. Membership values for each object are produced and each object is then labeled or classified according to the highest membership value. This process of labeling objects and placing them in a specific class, depending on membership values, is called defuzzification (Definiens Professional User Manual, 2005).

Likewise, during the classification process, each class description in the class hierarchy is applied to each image-object in the hierarchy. If the membership value of an image-object is lower than the predefined minimum membership value, the image-object will remain unclassified (Definiens Professional User Manual, 2005).

5.3.1 Nearest Neighbor Classifier

According to the Definiens Professional User Manual (2005), “the Nearest Neighbor (NN) classifier places image-objects in a given feature space based on given samples for the classes concerned. The distance in the feature space to the nearest sample object of each class is calculated for each image-object. The image-object is then assigned to the class represented by the closest sample object. The descriptions of feature space are then used during calculations while the classifier is placing image-objects into relevant classes”. Therefore, the classifier can be trained to give statistics that can represent the study objectives (i.e. discerning sinkholes from surrounding classes, etc.).

The Nearest Neighbor classifier is used within Definiens Professional as a classification of image-objects based on user-defined sample image-objects within a defined feature space. After a representative set of sample objects has been assigned for
each class, each image-object is assigned to the class that comes nearest to the sample object in the feature space.

The Nearest Neighbor (NN) classifier requires samples for each class as well as a defined feature space that can be any combination of features (Definiens Professional User Manual, 2005). As discussed above the following feature space definitions were used: Hierarchy, Texture, Layer Values, and Shape. With only a few samples this classifier produces fast results that can quickly be improved upon by adding or removing samples to achieve the user-defined criteria for classification. The use of the Nearest Neighbor (NN) as a classifier works best when used in conjunction with several object features for class descriptions. There are several reasons for the use of the Nearest Neighbor (NN) classifier in this study:

1) **Nearest Neighbor (NN) classifier more accurately evaluates the correlation between object features**

2) **Overlaps in the feature space increase with larger datasets and are more accurately corrected with the Nearest Neighbor (NN).**

3) **Nearest Neighbor (NN) classifier allows for faster computation of the class hierarchy.**

The Nearest Neighbor (NN) allows for fast and easy handling of the class hierarchy.

After the classifier is selected the feature space to be classified by the NN algorithm is defined by selecting those attributes (Figure 107) to be used by the classifier. Then the classes for which these should be applied is selected (Figure 108). I applied the NN classifier to all of the classes using metrics such as shape, and texture as defining space.
5.3.2 Editing Standard Nearest Neighbor Feature Space

The edit standard nearest neighbor feature space option was used to examine the various object features when applying the nearest neighbor classifier, as well as being
able to train the classifier in order to gain the most statistics for use during analysis. During this phase texture, hierarchy, layer values, and shape data were used to describe image-objects in order to train the classifier algorithm. Within the shape object feature, x max/min, and y max/min, shape index, compactness, and roundness were used to describe the image-objects (Figure 109).

![Edit Standard Nearest Neighbor Feature Space](image)

**Figure 109: Editing Feature Space for Nearest Neighbor Algorithm with Shape**

From the texture function of object features: GLCM mean and GLCM standard deviation were selected (Figure 110). The layer values used include mean and standard deviation of the image bands (Figure 111). These feature settings were chosen as they would give the most useful information and object statistics for post-classification analysis of classes and objects.
From the hierarchy function of object features (Figure 112), level, # of neighbors, # of sub-objects, # of sub-levels, and # of higher levels were chosen in order to achieve
post-classification statistics that would be useful when analyzing the classes and their objects.

**Figure 112: Editing Feature Space for Nearest Neighbor Algorithm with Hierarchy**

### 5.3.3 Sampling

The sample editor (Figure 113) is used to assign samples using a nearest neighbor classification or to compare an object to already existing samples in order to determine to which class an object belongs. It is also useful for getting a quick overview of the different feature values of an object. The sample editor is a graphical display for histograms of feature values. It shows the histograms of the feature values for a selected class of samples. The same can be done for all image-objects of a level or of all levels in the image-object hierarchy.
The sample editor was mainly used in this study for comparing the attributes or histograms of image-objects and samples for different classes. It is a useful tool for getting an overview of the feature distribution of image-objects or of the samples of specific classes. The features of an image-object can be compared to the total distribution of this feature over one or all image-object levels (Definiens Professional User Manual, 2005). By assigning samples, features can also be compared to the samples of other classes.

According to the Definiens Professional User Manual (2005), “to compare samples or layer histograms the classes or the levels that you want to compare in the active class and compare class boxes are selected. Values of the active class are displayed in black in the diagram, the values of the compared class in blue. The value range and standard deviation of the samples are displayed to the right of the diagram”.

At this point the Nearest Neighbor classifier needs training areas in order to classify image-objects. Therefore, a representative selection of image-objects, or sample objects, is collected by selecting samples in the image. The class to collect samples for is
selected, which makes that class active, so any samples collected are assigned to that class. The image-object is then double-clicked. The feature values of the sample object can be examined in the sample editor box to compare different objects with regard to their feature values to see if the sample is the most accurate for that class (Definiens Professional User Manual, 2005). In this way the most accurate samples can be chosen for classification.

Lastly, the samples membership value and its distance to the selected class and to all other classes within the feature space was examined to determine if the sample includes new information to describe the selected class (low membership value to selected class, low membership value to other classes), if it is really a sample of another class (low membership value to selected class, high membership value to other classes) or if it is a sample needed to distinguish the selected class from other classes (high membership value to selected class, high membership value to other classes).

For each of the images in this study the nearest neighbor classifier algorithm was trained and executed using samples to place the image-objects into one of the six classes, as well as generating multi-dimensional membership functions which can be explored later (Baatz and Schäpe, 2000). In Definiens Professional a sample is chosen by highlighting the selected class, starting the sampling mode and selecting image-objects with the cursor (Figures 114-118).
Figure 114: Sampling of 1984 LandSat Image

Figure 115: Sampling of 1989 LandSat/Aerial Photography Image
Figure 116: Sampling of 1993 LandSat/Aerial Photography Image

Figure 117: Sampling of 1999 LandSat/Aerial Photography Image
5.3.4 Assessing Sample Quality

After at least one sample has been assigned to a class, the quality of a new sample can be assessed (Figure 119) in the Sample Selection Information window (Definiens Professional User Manual, 2005). This function allows the researcher to decide if an object contains new information for a class, or if it should be placed in another class.

![Sample Selection Information](image)

Figure 119: Sample Selection Information used during Sampling
During the sampling of each scene for classification, sample quality was assessed to assure that the samples being chosen for classification fit into the membership for each class, with minimal minimum and mean distances. This allowed for the use of the best samples during classification to achieve better results with the final classifications.

For the separation of these classes all data layers were compared and class descriptions were built based on the spectral features, as well as on topological and textural features, in combination with the Nearest Neighbor classifier (Definiens Professional User Manual, 2005). After the class descriptions were determined and organized in a hierarchical order, the classification was performed and enhanced by adjusting the features.

The object-oriented approach resulted in classifications of higher quality than would have been achieved by pixel-based methods. Likewise, another advantage of the land cover classification within Definiens Professional is the wider range of class descriptions compared to using a traditional pixel-based approach (Definiens Professional User Manual, 2005). The ability to use various topological, textural, form and other features, in addition to spectral information, enabled the minimization of shadows and other image problems to a significant extent. The classification results can then be used to visualize changes in the study area over the 25 year period. The object-based approach using the nearest neighbor classifier requires fewer training samples than pixel-based training, since one sample object includes several pixel samples, otherwise the heterogeneous character of the samples would not be fully considered (Baatz et al., 2004).
5.3.5 Classification of LandSat/Aerial Images

The first step of land cover classification is deciding which classes, features and hierarchical structures will be used. As described in Chapter 4.5, the digital classifications applied to the LandSat images in this study used a modified USGS level 1 land cover classes (Anderson et al., 1976), including sinkholes as a class. The six classes used include forest, agricultural, urban, water, impervious surface, and sinkhole.

5.3.6 Classification based on Membership Functions

According to the Definiens Professional User Manual (2005), “the classification process in Definiens Professional can be compared to a simple database query. Each object is compared to the previously defined class descriptions. The contained and inherited expressions contained in the contextual information then produces membership values for each object. Then based on the highest membership value each object is labeled or classified”.

The fuzzy logic used in Definiens Professional allows for manual or automatic creation of membership functions (Figure 120). This allows for the incorporation of user-knowledge about the class descriptions of the classes being defined. In this study, for each class, membership functions were manually determined that would best classify each class based on class descriptions. For all 6 classes brightness, compactness, mean values, number of objects, pixels, sublevels and unclassified objects were used (Figure 121).
Figure 120: Membership Functions for each class determined by Class Descriptions

Figure 121: Class descriptions for Membership Function
A classification must have at least one image-object level and a class hierarchy, which were previously defined (see Chapter 5.3.3) during sampling. So when an image is classified each object is compared to each class description.

5.3.7 Edit Minimum Membership Value

An image-object is assigned to the class that returns the highest membership value. If the membership value is lower than the threshold, the object will remain unclassified. This ensures reliability and accuracy of classification. On the first classification run of each scene this study used a minimum threshold of .1 on a 0-1 scale. Upon examining the results it was found that almost 40 objects remained unclassified, so the minimum threshold was raised to .25 on the second run, which produced better classification results with less than 10 unclassified objects per scene.

5.3.8 ACCURACY ASSESSMENT & POST-CLASSIFICATION ANALYSIS

Another area that is increasingly examined by remote sensors is classification accuracy. Accuracy assessment tries to quantify how well the classifier did in cataloguing objects into correct classes (Blaschke et al., 2005). Definiens Professional supplies a method to assess the accuracy by error matrix based on test areas (ground truth). By defining the ground truth mask, Definiens Professional generates an error matrix automatically (Definiens Professional User Manual, 2005).

The Definiens Professional accuracy assessment method is used to produce statistical outputs which can be examined to check the quality of the classification results. Using the accuracy assessment dialog box the image-object level is chosen, as well as the
selection of classes for the statistics to be produced. Lastly, the type of statistics to be performed on the data is chosen. This study created a new level for each accuracy assessment of the individual classes as a whole and was performed on each of the datasets (Figure 122).

![Accuracy Assessment Dialog Box](image)

**Figure 122: Definiens Professional Accuracy Assessment Dialog Box**

According to Anderson (1971), classification systems for land use and land cover employing orbital and high-altitude remote sensors should meet the criteria listed in Table 21.
CLASSIFICATION CRITERION TABLE

1. The minimum level of interpretation accuracy in the identification of land use and land cover categories from remote sensor data should be at least 85 percent.

2. The accuracy of interpretation for the several categories should be about equal.

3. Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.

4. The classification system should be applicable over extensive areas.

5. The categorization should permit vegetation and other types of land cover to be used as surrogates for activity.

6. The classification system should be suitable for use with remote sensor data obtained at different times of the year.

7. Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensor data should be possible.

8. Aggregation of categories must be possible.

9. Comparison with future land use data should be possible.

10. Multiple uses of land should be recognized when possible.

Table 21: Classification Criterion (Source: Anderson, 1971)

Classification accuracy in remote sensing is used to determine the agreement between the selected reference images and the classified data (Lunetta, 1998). It is important to be able to derive and assess accuracy for individual classifications if the resulting data are to be useful in change detection analysis. There are a number of ways to do this in Definiens Professional. Accuracy assessment methods in Definiens Professional are used to produce statistical outputs that can be used to check the quality of the classification results, which can validate or invalidate the results (Definiens Professional User Manual, 2005). Tables can be saved as .txt files or exported as rasterized graphical representations.
Definiens Professional can conduct accuracy assessment for each class individually or all together, allowing for more detailed examination and cross-plotting of results (Definiens Professional User Manual, 2005). This study employed the use of these statistical examinations conducted on each class separately and for each scene as a whole in order to gauge classification accuracy of the Definiens Professional results:

- Classification Stability
- Best Classification Results
- Error Matrix based on TTA (Training and Test Area) Mask

The USGS standard of image data classification was originally set to 85% for overall accuracy (Anderson et al., 1976), but the actual accuracy of image classification has not often reached that standard. Therefore, the accuracy of land use and land cover maps that are derived with digital remote sensing data is usually represented in terms of producer’s accuracy, user’s accuracy, and overall accuracy, which are commonly calculated from an error matrix (or confusion matrix) (Congalton and Green, 1999).

User and producer accuracy are two widely used measures of class accuracy. The producer’s accuracy refers to the probability that a certain land-cover of an area on the ground is classified correctly (Congalton and Green, 1999). Producer’s accuracy is represented as the percentage of a particular land use and land cover type on the ground that is correctly classified in the image, thereby measuring the error of omission. It is calculated as the ratio of the number of correctly classified pixels for a class to the total number of ground truth pixels for that class (Congalton and Green, 1999).
User’s accuracy refers to the probability that a pixel labeled as a certain land-cover class in the map is really this class (Congalton and Green, 1999). It is shown as the percentage of a class in the image that matches the corresponding class on the ground, and measures the error of commission. The user and producer accuracy for any given class do not have to be the same. For example, if a classification returns a user’s accuracy of 90% and a producer’s accuracy of 70%, as a user of the classification it is expected that roughly 90% of all the pixels classified as forest are indeed forest (Congalton and Green, 1999). However, at the same time the fact that only 70% of all the pixels that are really forest classified as forest is not very good.

To assess the quality of the final land cover classifications, each image in this study was subjected to several verification processes. First an accuracy assessment was conducted on the final classifications in Definiens Professional, using the above statistical examinations. This verification is based on samples that were taken during fieldwork and those generated by Definiens Professional during post-classification analysis. As the field samples had been taken before the classification process was started they were independent from the land cover classifications, which is important for validation. Roughly 3000 samples for each scene were generated and used for Definiens Professional accuracy assessments. Next the classification results were compared against manual methods of inventory, such as grid counts and review of aerial photography and topographic maps, (see Chapter 5.5) in order to include further accuracy gauging.

Kappa Statistics derived from the Definiens Professional accuracy assessment are another excellent method for examining the classification results (Congalton and Green,
Kappa coefficient is an index which compares the agreement against what might be expected by chance. So Kappa is the chance-corrected agreement, with values that range from +1 (perfect agreement) to 0 (no agreement above that expected by chance) to -1 (complete disagreement) (Congalton and Green, 1999). Kappa looks at reliability by examining the agreement between two individuals or answers (pixels, classes).

In remote sensing it is a statistical measure of the agreement, beyond chance, between two maps (output classification and original digital imagery) and is represented by the symbol kappa hat or k hat (\( \hat{K} \)) (Congalton and Green, 1999). The idea is that correctly assigned pixels could have been assigned by chance and not based on the classification decision rule that I assigned during the classification process (Congalton and Green, 1999). The kappa value (\( \hat{K} \)) indicates how accurate the classification output is after this chance, or random portion has been accounted for.

There are a number of ways to show how the kappa value is calculated (Congalton and Green, 1999). Definiens Professional expresses kappa in terms of observed accuracy and expected accuracy. A kappa value closer to 1 indicates a strong correlation and reliability of classification. By comparing kappa statistics of all 5 dates, accuracy of Definiens Professional classification of land use and sinkholes can be gauged. Single class accuracy is a measure of the accuracy of one class (eg. Sinkholes) and is expressed as a percentage. Single class accuracy, \( S \), is calculated as shown below, where \( A \) is the number of pixels assigned to the correct class and \( B \) is the number of pixels that actually belong to that class (Definiens Professional User Manual, 2005).

\[
S = \frac{A}{B} \times 100
\] (3)
Congalton (1996) explains: “Kappa values are characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement”. According to this standard, the accuracy achieved by the classifications in this study can be compared to examine the relevance and accuracy of each individual class or the classification as a whole (Table 22).

### KAPPA STATISTICS RANGES

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0</td>
<td>No Agreement</td>
</tr>
<tr>
<td>0.0-0.20</td>
<td>Slight Agreement</td>
</tr>
<tr>
<td>0.21-0.40</td>
<td>Fair Agreement</td>
</tr>
<tr>
<td>0.41-0.60</td>
<td>Moderate Agreement</td>
</tr>
<tr>
<td>0.61-0.80</td>
<td>Substantial Agreement</td>
</tr>
<tr>
<td>0.81-1.00</td>
<td>Almost Perfect Agreement</td>
</tr>
</tbody>
</table>

Table 22: Kappa Statistics Interpretation (Source: Congalton, 1996)

#### 5.3.8a Classification Stability

This accuracy assessment examines the difference between the best and the second best class assignment and is calculated as a percentage (Definiens Professional User Manual, 2005). The statistical output displays basic statistics (number of image-objects,
mean, standard deviation, minimum value and maximum value) performed on the values per class, which allows the user to examine the stability and accuracy of each class, as well as the classification as a whole.

Similar stability results are seen for all 5 classified scenes. The results all suggest that there are some stability issues with classification of water and impervious surface. This could be due to the similar spectral responses between water and forest, or an inability to distinguish between urban and impervious surface. Overall, the classifications exhibit excellent stability (see Appendix II for expanded tables) with the exception of water and impervious surface classes, but even these are within acceptable limits, making the 5 classifications reliable:

- 1984 LandSat image: urban (0.9484), sinkhole (0.9879), forest (0.9734) and agriculture (0.9632) classified with the highest stability, as noted by their high mean, minimum and maximum membership values and low standard deviations; impervious surface (0.8931) and water class (0.9012) had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes could be refined further to attain more stable image-object memberships

- 1989 merged LandSat/Aerial image: urban (0.9583), sinkhole (0.9651), impervious surface (0.9984) and agriculture (0.9922) classified with the highest stability, according to their high mean, minimum and maximum membership values and low standard deviations. Forest (0.9073) and water class (0.9090) had the lowest mean membership values, highest standard deviations and lowest minimum and maximum membership values, suggesting that while moderately stable, forest and water classes could be refined further to attain more stable image-object memberships

- 1993 merged LandSat/Aerial image: urban (0.9868), sinkhole (0.9499), forest (0.9714), impervious surface (0.9747) and agriculture (0.9675) classes were all classified with the highest stability, as seen by their high mean, minimum and maximum membership values and low standard deviations. Water class (0.9143) had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, making the
argument that while fairly stable it could be refined further to attain more stable image-object memberships.

- 1999 merged LandSat/Aerial image: urban (0.9614), sinkhole (0.9753), forest (0.9553) and agriculture (0.9767) were again classified with the highest stability, as seen by their high means, minimum and maximum membership values and low standard deviations. Impervious surface (0.9143) and water class (0.9135) again had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes could be refined further to attain more stable image-object memberships.

- 2002 merged LandSat/Aerial image: urban (0.9833), sinkhole (0.9893), forest (0.9695) and agriculture (0.9939) are classified with the highest stability, according to their high means, minimum and maximum membership values and low standard deviations. Impervious surface (0.9201) and water class (0.9249) again had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes could be refined further to attain more stable image-object memberships.

5.3.8b Best Classification Results

Definiens Professional’s best classification result is designed to compare samples to determine the first versus second and third classifications, in order to determine which class yields the best classification results (Definiens Professional User Manual, 2005). The statistical output for the best classification result was evaluated per class. Basic statistics (number of image-objects, mean, standard deviation, minimum value and maximum value) are performed on the best classification result of the image-objects assigned to a class (Definiens Professional User Manual, 2005). As with the stability assessment, the results show that the best classification values for all land cover classes and sinkholes are high (see Appendix II for expanded tables), except for “water” and “impervious surface”. Class mean values and standard deviations show that most of the
objects were classified with high membership values, which resulted in the best expected classification possible for these classes. At the same time, impervious surface and water exhibited lower mean values and had higher standard deviations:

- **1984 image:** urban (0.9844), sinkhole (0.9973), forest (0.9712) and agriculture (0.9893) were classified with the highest best classification results, as shown by their high means, minimum and maximum membership values and low standard deviations. The impervious surface (0.9104) and water class (0.9109) had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes are not giving the best classification.

- **1989 merged LandSat/Aerial image:** urban (0.9732), sinkhole (0.9839), forest (0.9771) and agriculture (0.9832) were classified with the highest best classification results, denoted by their high means, minimum and maximum membership values and low standard deviations. The impervious surface (0.9090) and water class (0.9302) again had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes are not giving the best classification.

- **1993 merged LandSat/Aerial image:** urban (0.9839), sinkhole (0.9813), forest (0.9617) and agriculture (0.9919) were classified with the highest accuracy, shown by their high means, minimum and maximum membership values and low standard deviations. The impervious surface (0.9103) and water class (0.9226) had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes are not giving the best classification.

- **1999 merged LandSat/Aerial image:** urban (0.9801), sinkhole (0.9893), forest (0.9773) and agriculture (0.9817) are classified with the highest accuracy, shown by their high means, minimum and maximum membership values and low standard deviations. The impervious surface (0.9220) and water class (0.9039) again had the lowest mean membership values, highest standard deviations and the lowest minimum and maximum membership values, suggesting that impervious and water classes are not giving the best classification.

- **2002 merged LandSat/Aerial image:** urban (0.9903), sinkhole (0.9788), forest (0.9828) and agriculture (0.9883) were classified with the highest accuracy, as shown by their high means, minimum and maximum membership values and low standard deviations. The impervious surface (0.9297) and water class (0.9189) again had the lowest mean membership values, highest standard deviations and
the lowest minimum and maximum membership values, suggesting that impervious and water classes are not giving the best classification.

5.3.8c Error Matrix Based on TTA Mask

In Definiens Professional, a TTA (Training and Test Area) mask can be used to create sample objects for supervised classification using the nearest neighbor algorithm (Definiens Professional User Manual, 2005). It can also be used to define test areas for an accuracy assessment of the classification results. In this study, the test areas were used as a reference to check classification quality by comparing the classification with “groundtruth” based on pixels.

To generate the error matrix, thematic information was recorded from sample pixels that display the same ground area on both the groundtruth map and the classified image. Calibration data is then recorded from the reference map and validation data from the classified map (Definiens Professional User Manual, 2005). The TTA mask for this study was created within the classification samples box by selecting “create TTA mask from samples”. This allowed for the selection of objects that can be placed within a known class after field examination. After field verified samples (see Chapter 5.4) were placed within known classes the TTA mask was created from these samples. This file was then saved and loaded during accuracy assessment for each date.

Error matrices are tables that display statistics for assessing image classification accuracy by showing the degree of misclassification among the classes (Definiens Professional User Manual, 2005). The error matrix is a means of comparing two maps for accuracy. This is usually done in tabular form. In remote sensing image analysis, the
two maps are often a “ground truth” map (the reference map) and a map derived from automated image classification (the classified map) (Lunetta, 1998). The error matrix permits the calculation of a range of measures that describes the accuracy of the classified map with respect to the reference map (Definiens Professional User Manual, 2005).

As stated above, the producer’s and user’s accuracies can be excellent methods for gauging classification accuracy. The producer’s accuracy for each class will be different. This is because some classes are spectrally different than others and will be classified more accurately. By summing the producer’s accuracy for each row in the matrix and dividing by the number of classes, the “mean accuracy” for the classified map can be determined (Definiens Professional User Manual, 2005).

Overall accuracy is also determined within Definiens Professional. This is the percentage of correctly classified pixels within the classification. Overall accuracy, O, is calculated as:

\[ O = \frac{\sum A}{\sum B} \times 100 \]  

(4)

where A is the number of pixels assigned to the correct class and B is the number of pixels that actually belong to that class. It is a good measure of the accuracy of a classification scheme as it is not biased towards the smaller classes (Definiens Professional User Manual, 2005).

The error matrix highlights the classification errors. The matrix can also be used to assess accuracy more meaningfully, via producer’s accuracy, user’s accuracy and overall accuracy (Story & Congalton 1986; Congalton 1991). As stated, the producer’s accuracy
estimates the probability that a point was correctly classified. Meanwhile, the user’s accuracy provides an estimated probability to how well the classification of the segmented objects correctly predicts the proper class.

Overall accuracy for the test area is calculated by summing the correct classifications and dividing by the total, which gives how many objects were correctly identified in the various classifications (Definiens Professional User Manual, 2005). The overall Kappa statistic for each classification is calculated and considered more useful than the overall accuracy because it takes into account the probability that classification and reference agreement may be coincidental, which makes it a more preferred estimate of general accuracy (Congalton & Green 1999).

- 1984 LandSat image: overall accuracies are urban (95%), agriculture (98%), water (90%), forest (98%), sinkhole (98%) and impervious surface (86%), while the kappa coefficients are urban (96%), agriculture (97%), water (93%), forest (97%), sinkhole (99%) and impervious surface (87%). This means that a user of the 1984 classified image can be “extremely certain” that an object classified as “urban”, “agricultural”, “forest” and “sinkhole” are correctly classified relative to the objects on the ground, while there is less certainty that “impervious surface” and “water” were correctly classified. Errors of inclusion and commission are relatively small for objects classified as urban, sinkhole, agricultural and forest, but are larger for the water and impervious surface classes. There also exists some confusion between impervious surface/urban and agriculture/forest, with cross-classification taking place. This is probably due to spectral similarities that cause problems during classification. Overall, however, the classification is highly accurate with very few errors of omission and commission. The overall accuracy for all classes for the 1984 scene is 94%, while the overall kappa is 95%. According to Congalton’s (1996) kappa interpretation, this represents “almost perfect agreement”. This means that Definiens Professional is adept at classifying these images based on the land use and land cover classification scheme.

- 1989 merged LandSat/Aerial image: overall accuracies are urban (94%), agriculture (92%), water (90%), forest (96%), sinkhole (97%) and impervious surface (78%), while the kappa coefficients are urban (91%), agriculture (93%), water (91%), forest (94%), sinkhole (95%) and impervious surface (82%). This means that a user of the 1989 classified image can be extremely certain that an
object classified as “urban”, “agricultural”, “forest” and “sinkhole” are correctly classified relative to the objects on the ground, while there is less certainty that “impervious surface” and “water” were correctly classified. Errors of inclusion and commission, are again relatively small for objects classified as urban, sinkhole, agricultural and forest, but are larger for the water and impervious surface classes. There also exists some confusion between impervious surface/urban and agriculture/forest, with cross-classification taking place. This is probably due to spectral similarities that cause problems during classification. But overall for the 1989 image, the classification is highly accurate with very few errors of omission and commission. The overall accuracy for all classes for the 1984 scene is 92%, while the overall kappa is 92%. According to Congalton’s (1996) kappa interpretation, this represents “almost perfect agreement”.

• 1993 merged LandSat/Aerial image: overall accuracies are urban (94%), agriculture (93%), water (92%), forest (95%), sinkhole (97%) and impervious surface (75%), while the kappa coefficients are urban (95%), agriculture (94%), water (90%), forest (96%), sinkhole (96%) and impervious surface (73%). This means that a user of the 1993 classified image can be extremely certain that an object classified as “urban”, “agricultural”, “forest” and “sinkhole” are correctly classified relative to the objects on the ground, while there is less certainty that “impervious surface” and “water” were correctly classified. Errors of inclusion and commission, are also relatively small for objects classified as urban, sinkhole, agricultural and forest, but are larger for the water and impervious surface classes. There is some confusion between impervious surface/urban and agriculture/forest, with cross-classification taking place. This is probably due to spectral similarities that cause problems during classification. But as a whole the 1993 image classification is highly accurate with very few errors of omission/commission. The overall accuracy for all classes for the 1993 scene is 91%, while the overall kappa is also 91 %. According to Congalton’s (1996) kappa interpretation, this represents “almost perfect agreement”.

• 1999 merged LandSat/Aerial image: overall accuracies are urban (93%), agriculture (91%), water (93%), forest (93%), sinkhole (96%) and impervious surface (82%), while the kappa coefficients are urban (94%), agriculture (92%), water (94%), forest (92%), sinkhole (97%) and impervious surface (80%). This means that a user of the 1999 classified image can be extremely certain that an object classified as “urban”, “agricultural”, “forest”, “water” and “sinkhole” are correctly classified relative to the objects on the ground, while there is less certainty that “impervious surface” was correctly classified. Errors of inclusion and commission are relatively small for objects classified as urban, sinkhole, agricultural and forest, but are larger for the water and impervious surface classes. There is some confusion between impervious surface/urban and agriculture/forest, with cross-classification taking place. This is probably due to spectral similarities that cause problems during classification. But overall, for the 1999 image the
classification is highly accurate. The overall accuracy for all classes for the 1999 scene is 92%, while the overall kappa is 89%. According to Congalton (1996) kappa interpretation, this represents “almost perfect agreement”.

- 2002 merged LandSat/Aerial image: overall accuracies are urban (94%), agriculture (91%), water (90%), forest (93%), sinkhole (92%) and impervious surface (79%), while the kappa coefficients are urban (91%), agriculture (93%), water (88%), forest (91%), sinkhole (93%) and impervious surface (77%). This means that a user of the 2002 classified image can be extremely certain that an object classified as “urban”, “agricultural”, “forest”, “water” and “sinkhole” are correctly classified relative to the objects on the ground, while there is less certainty that “impervious surface” was correctly classified. Errors of inclusion and commission, are relatively small for objects classified as urban, sinkhole, agricultural, water and forest, but are larger for the impervious surface class. There also exists some confusion between impervious surface/urban and agriculture/forest, with cross-classification taking place. This is probably due to spectral similarities that cause problems during classification. Overall for the 2002 image, the classification is highly accurate. The overall accuracy for all classes for the 2002 scene is 90%, while the overall kappa is 89%. According to Congalton (1996) kappa interpretation, this represents “almost perfect agreement”.

The high averaged producer’s accuracy achieved by the 5 scenes (91%) validates the classification scheme I developed, while the excellent average user’s accuracies encountered (94%) verifies the reliability of the classification output. The high overall averaged accuracy of 92% corresponds to the errors of omission and commission, which were low for all 5 datasets and which also validates the classification results. As stated, Anderson (1976) sets the classification accuracy limit at 85%, so the overall accuracy of the 5 scenes at 92% is excellent. Lastly, the high overall averaged kappa statistics of 91% shows that there is excellent agreement during the classification after the random element is accounted for.
5.4 Stage 3: Field Analysis- Examination and analysis of randomly-selected sites for groundtruthing accuracy of classification.

Groundtruthing, information acquired by field study for the purpose of calibration and/or verification of remotely sensed data, was done at several stages to gauge the accuracy of the five Definiens Professional classifications. The fieldwork was conducted in early March and late fall 2008 and May 2009 during leaf-off conditions and involved field checking of random samples from the Definiens Professional Classification output to verify accuracy results of the Definiens Professional image-object analysis, as well as to gather morphometric data on sinkholes for future analysis.

The final classified images from Definiens Professional were imported into ArcGIS 9.2 for random sampling of each data set. The sampling was done by the ArcGIS spatial analyst “Extraction by Random Locations Sampling Tool”, which allows for random extraction of point data from a dataset. The tool was used on each of the five merged LandSat/Aerial photography dates (1984, 1989, 1993, 1999 and 2002) to derive a list of 90 random samples (Figure 123). For verification in the field, four sinkhole points were extracted from each of the datasets.

These sites were each located using GPS and photographed, noting land use and land cover. For sinkholes, morphometric measurements were taken for future examination. Results showed that of the ninety random samples only five were incorrectly classified, for an accuracy of 94%. The five objects incorrectly classified were two impervious surfaces that were actually urban, two waters that were actually forest, and one sinkhole, which was actually forest class.
Feature classes were then created within ArcGIS and populated with the exported .csv files for each land use and land cover class, so that field data could be stored in tabular form for future spatial analysis, as well as for recording pertinent information on each point location. Field examination results are shown in Appendix III.

Another twenty sinkholes were randomly extracted using ArcGIS from the sinkhole feature class for field examination during May 2009, in order to further gauge classification accuracy and to gather morphometric data about the sinkholes and land use and land cover that can be examined in the future for further correlations Appendix IV. These twenty locations were visited and photographs and information was gathered
including: sinkhole type, morphometric measurements of sinkholes, land use classes, and GPS coordinates.

5.5 MANUAL METHODS FOR ACCURACY GAUGING IN CONTROL AREA

As previously stated, the traditional method of counting depressions on contour maps is limited by the sinkhole size, map scale, contour interval, and slope, but can provide a backdrop for gauging digital inventory methods, in addition to the Definiens Professional Accuracy Assessment. Due to the small size of most of the sinkholes in the Opequon Creek watershed (most <10 meters), most sinks are not mapped at the 40 foot contour interval used by the USGS to map the quadrangle. Therefore, a comparison of the results between a Definiens Professional classification of image-objects and a manual sinkhole count based on topographic depressions on USGS quadrangles and aerial photography was undertaken in a control area (Lewisburg Northwest Quarter Quadrangle) where sinkholes are mapped at a 20 foot minimum mapping unit. This can aid in accuracy assessment of the software’s ability to correctly classify sinkholes.

Several traditional methods, such as grid-counting sinkholes from topographic maps and aerial photography were conducted in the test area. A hand count of topographic depressions on United States Geological Survey topographic map was done for the control (Lewisburg, WV Northwest Quarter Quadrangle in southern West Virginia), where sinkholes are large enough to have been mapped at the twenty foot contour interval and are represented on topographic maps as contour depressions (Figure 124).
Likewise, digital aerial orthophotograph coverage of the Lewisburg Northwest Quarter Quadrangle at a 1:4,800 scale was acquired from the West Virginia Geological Survey (Figure 125). This coverage was photographed leaf-off in the spring of 2003 as part of the SAMB (State Addressing and Mapping Board) Project to gain statewide low-altitude high-resolution aerial imagery at the 2’ pixel size.
The Greenbrier Group, the most abundant rock in the control area, is composed mainly of marine limestones (Cardwell, 1968). The central coordinates of the test area are (80° 28’ 8” W, 37° 50’ 37” N). The site was chosen because the Greenbrier River watershed, like Opequon Creek Watershed, has experienced increased growth in recent years and there are numerous and easily-recognizable closed-depression contours on the Lewisburg U.S. Geological Survey 7.5 minute topographic map. Furthermore, most sinkholes in the area are large enough to have been mapped and are easily recognizable on digital imagery as negative depressions. The predominant exposed rock in the area is
carbonate and the area is typified by karst topography with hundreds of sinkholes (Figure 126). The Lewisburg Northwest Quarter Quadrangle covers a forty-two square kilometer area where Mississippian Age rocks come to the surface.

![Figure 126: Photograph of Karst Topography of Greenbrier County (Source: Jones, 1997)](image)

The quadrangle is mapped at the twenty foot contour and the sinks in this area are much larger than those in the study area. By examining Definiens Professional accuracy of classifying land use and land cover and sinkholes in the test area accuracy for the study area can be gauged. Another resource used was from the West Virginia Geological Survey’s mapped historical karst subsidence and linear features for this area. This map was completed for planning purposes and shows areas of subsidence and sinkhole collapse in Greenbrier and Monroe Counties (Lessing, 1979). This data allowed for integration with the aerial photography for subsequent comparison to the Definiens
Professional classification to determine accuracy.

Lessing (1979) states that, “the linear alignments of sinkholes observed in this area can be attributed to predictable orientations along fractures and cracks in the limestone” (Figure 127). The same structural linear alignment of sinkholes is observed in the Opequon Creek watershed, leading one to surmise that lithologic controls are regulating sinkhole orientation.

Figure 127: Map of Karst Subsidence and Linear Features in Lewisburg NW QQ (Source: Lessing, 1979)

Sinkholes were hand counted using a grid overlay method on both a paper copy of the 1998 U.S. Geological Survey topographic map of the Lewisburg Quadrangle, Greenbrier County, West Virginia, and the 2003 State Address and Mapping Board (SAMB) aerial
photograph of the same quarter quadrangle (Figure 128). The Lessing (1979) map and the 2003 SAMB aerial photography were brought into ArcGIS 9.3 and registered and georeferenced to the 1998 topographic map.

Figure 128: Map of Karst Subsidence Draped on Aerial Photography

Each grid cell overlain on top of the aerial and topographic map was 1 km square with a total of 42 grid cells. Summing each grid cell, totals were made to determine each cells number of sinkholes. The sum of all of the grid cells gives a total for all sinkholes in the quarter quadrangle (see Chapter 5.5.1).

The morphology of sinkholes in the Lewisburg Quadrangle and the test area as a
whole consists of four major types (Figure 129) of sinkholes simple, complex, ponded, and compound (Angel et al., 2004). Simple sinks have one depression contour, while complex sinkholes have several. Compound sinkholes are large, irregularly-shaped depression contours with two or more nested depression contours (Angel et al., 2004). Ponded sinks can be any of the other three types but are water-filled.

Figure 129: Sinkhole Morphology in Test Area (Adapted from Angel et al., 2004)

Following Angel et al. (2004), sinkhole counts were tallied by adding the total of simple and ponded sinkholes with the number of innermost depression contours for complex and compound sinks. Each sinkhole was then marked after being counted to make sure that it was not counted twice.
5.5.1 Test Area Results for Definiens Professional/Topographic Sinkhole Grid Count

The result of the topographic sinkhole count in the test area showed that sinkholes per grid cell varied throughout the quarter quadrangle (Figure 130). The sum of all grid cells for the quarter quadrangle shows that there were three-hundred and fourteen sinkholes in the Lewisburg Northwest Quarter Quadrangle according to the 1998 topographic map.

![Grid Count of Topographic Sinkholes on Lewisburg NW QQ](image)

The Lewisburg NW Quarter Quadrangle was imported into Definiens Professional as a TIFF image (Figure 131). The image was segmented (Figure 132) using the same criteria for shape, color, and scale parameters that were used to classify the study area scenes. Land cover was then classified using the same parameters as the study area.
scenes. A nearest neighbor algorithm was trained and used to assign each image-object to a particular class.

Figure 131: Lewisburg NW QQ Imagery Imported into Definiens Professional

Figure 132: Lewisburg NW QQ Segmentation
Membership statistics were then examined to determine the total number of image-objects classified as sinkholes, as well as the other land use and land cover classes. The result of the image-object analysis using Definiens Professional showed three-hundred and eighty-two total sinkholes (Table 23) in the Lewisburg NW Quarter Quadrangle based on the classification of the digital aerial photography.

The topographic count of depressions using a one square kilometer grid system yielded a total of three-hundred and fourteen sinkholes, while the Definiens Professional object-oriented method found three-hundred and eighty-two sinkholes. The most accurate traditional method of grid counting sinkholes using stereopair analysis of high-resolution aerial photography yielded three-hundred and seventy-four sinkholes. These results meet expectations as the topographic count should be the lowest due to the minimum mapping unit imposed by the USGS (twenty foot contour) excluding those that are smaller. The high resolution aerial photography allowed Definiens Professional to be more accurate while assigning image-objects to individual classes, thereby more correctly classifying more sinkholes than were mapped by the USGS.
## COMPARISON OF ANALYSIS METHODS

<table>
<thead>
<tr>
<th>Method</th>
<th># of Sinkholes</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOPOGRAPHIC GRID COUNT</td>
<td></td>
</tr>
<tr>
<td>LEWISBURG NW QQ</td>
<td>314</td>
</tr>
<tr>
<td>DEFINIENS PROFESSIONAL OBJECT-ORIENTED ANALYSIS</td>
<td>382</td>
</tr>
<tr>
<td>AERIAL IMAGERY GRID COUNT</td>
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</tr>
<tr>
<td>DEFINIENS PROFESSIONAL vs. GRID COUNT</td>
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</tr>
<tr>
<td>DEFINIENS PROFESSIONAL vs. TOPOGRAPHIC COUNT</td>
<td>68</td>
</tr>
<tr>
<td>AERIAL COUNT vs. TOPOGRAPHIC COUNT</td>
<td>60</td>
</tr>
<tr>
<td>ACCURACY OF DEFINIENS PROFESSIONAL METHOD vs. MANUAL AERIAL COUNT</td>
<td>97%</td>
</tr>
<tr>
<td>ACCURACY OF TOPOGRAPHIC vs. DEFINIENS PROFESSION</td>
<td>82%</td>
</tr>
<tr>
<td>ACCURACY OF TOPOGRAPHIC vs. AERIAL</td>
<td>83%</td>
</tr>
</tbody>
</table>

Table 23: Aerial & Topographic Count vs Object-Oriented Analysis in Test Area

Assuming that grid-counting sinkholes from high-resolution aerial imagery stereopairs is the most accurate traditional manual method, the image-object based Definiens Professional method exceeded expectations by identifying three-hundred and eighty-two sinkholes in the Quarter Quadrangle. Random sampling of forty of the Definiens Professional-identified sinkholes to the aerial photography was undertaken to make sure
that the image-objects classified as sinkholes were actually sinkholes. For the forty random sinkholes sampled from the aerial photography, all but one had been correctly identified as sinkholes by Definiens Professional. When compared against the aerial count (three-hundred and seventy-four), this yields an accuracy of 97% percent, for a negligible difference.

The over-classification in sinkhole counts within Definiens Professional may be attributable to new sinkholes occurring between the production of the 1998 USGS Quadrangle and the flight of the 2003 aerial photography coverage, as well as a small margin of error during Definiens Professional classification. Some objects will be incorrectly classified because of lack of pixel data, parameter settings, scale, etc. This classification error can be minimized by using a larger number of samples during supervised classification training, as well as adjusting scale, color, shape, and texture parameters during segmentation and classification.

By comparing the topographic grid count total (three-hundred and fourteen sinkholes) to the aerial photography sinkhole count (three-hundred and seventy-four) an accuracy of 84% is achieved. This makes it obvious that the topographic method is lacking an ability to correctly identify all of the sinkholes in a watershed. As discussed previously this is due to the nature of sinks not being mapped at the minimum mapping unit in the field, but identified by object-oriented methods using high-resolution photography.

Therefore, the results validate the automated image-object analysis and offer potential for being very useful in spatial and contextual examinations of landscapes, especially sinkhole inventory. The distinct shape and morphology of sinkholes allow utilization of
image-object recognition software, such as Definiens Professional, when classifying land use and land cover of large areas and is much faster and automated than traditional methods. Further ground-truthing and field examination of land cover classes in the study area may revise these accuracy assessments.

5.5.2 Manual Aerial Photography Sinkhole Grid-Count in Study Area

As a further control to gauge the accuracy of the Definiens Professional image-object based classification of land use and land cover and sinkholes, another traditional method of landscape inventory based on evaluating and interpreting stereopair aerial photography from the study area was conducted. One square kilometer grids were overlain on hard-copy aerial photographs of various dates from the Middleway Quadrangle of Berkeley County, acquired from the West Virginia Geological Survey. Definiens Professional classification accuracy can be gauged by comparing the results to a traditional inventory derived by a manual hand-count method of examining aerial photography.

Several dates were used in order to examine temporal changes in sinkholes in the study area. The first photographs examined were 1:20,000 black and white oblique aerial photographs of the Middleway quadrangle flown on 9-8-55, during the AGW and AGS projects (Figure 133). Stereopairs of the quadrangle were examined with stereoscopes. Standard stereoscopic examination allowed classification of land use and sinkholes. I also examined photos from 3-31-47 but found those to be too coarse for use in identifying positive or negative relief.
Another source of aerial photography was the Middleway quadrangle aerial photographs from 4-1-97 with a scale of 1:40,000 (Figure 134). These were color infrared photography flown during the USGS NAPP (National Aerial Photography Program), which began in 1987 and replaced the National High Altitude Photography Program (NHAPP). The NAPP photography has a spatial resolution of one meter.
Lastly, I used the USDA NAIP Photography that was shot in May of 2007 in the Middleway Quadrangle (Figure 135). This photography was shot at the 1:4,800 scale and was downloaded from the West Virginia GIS Technical Center data depot. This image
was ortho-rectified to <9.8’ horizontal error at a 95 percent confidence level within ArcGIS 9.2 and was brought into Definiens Professional as an uncompressed TIFF file.

![Image of NAIP USDA Photography of the Middleway Quadrangle, 5-2-07](image)

**Figure 135: NAIP USDA Photography of the Middleway Quadrangle, 5-2-07**
(Source: West Virginia GIS Technical Center)

Selected samples of agriculture, water, urban, and forest classes were extracted from Definiens Professional for analysis against the aerial photography in ArcGIS 9.2. The entire class of image-objects classified as sinkholes was exported as a table and likewise brought in to ArcGIS 9.2 for analysis against the aerial interpretations. The aerial photographs were brought into ArcGIS 9.2, georectified and georeferenced against the USGS Topographic Quadrangle to ensure that interpreted features from the aerial
photography could be matched against existing topographic features. The aerial photographs were seamed together to represent the entire quadrangle so that the Middleway quadrangle could be evaluated using the four datasets available (B&W, CIR, NAIP, Definiens Professional Classification). In this manner was possible to compare historical sinkholes and land use on the aerial photography against the Definiens Professional output classifications.

5.5.3 Manual Aerial Photography Sinkhole Grid-Count Results

The manual methods used to evaluate the Definiens Professional methodology involved overlaying a grid on aerial photographs to determine the accuracy of the image-object analysis. Likewise, land use and land cover was sampled randomly at 69 different locations on the aerial photography and compared via interpretation for accuracy. The results of this comparison were based on the Middleway Quadrangle, and show that the image-object analysis within the Definiens Professional software has an impressive accuracy at correctly classifying land use and land cover and number of sinkholes into appropriate classes (see Table 24).
## MANUAL VS. AUTOMATED METHODS

<table>
<thead>
<tr>
<th>Method</th>
<th>Sinkhole</th>
<th>Agriculture</th>
<th>Urban</th>
<th>Forest</th>
<th>Water</th>
<th>Imperv. Surface</th>
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<tr>
<td>B&amp;W Aerial photography 9-8-55</td>
<td>122</td>
<td></td>
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<td>CIR Aerial photography 4-1-97</td>
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<td>SAMB Aerial photography 2003</td>
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<td>NAIP USDA 2007</td>
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<tr>
<td>Definiens Professional Analysis</td>
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<td>Field Examination: Actual Land Use</td>
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<td>11</td>
<td>24</td>
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<td>5</td>
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<td>.970</td>
<td>.931</td>
<td>.833</td>
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Table 24: Image-Object Classification vs. Manual Interpretation
Chapter 6: Land Use Planning Tools that Reduce Urban Impacts in Watersheds

This chapter explores traditional planning tools that may be used in conjunction with watershed management to combat the effects that increased urbanization has in karst watersheds. As Chapters 4 & 5 show, over the last 25 years the amount of urban land in the Opequon Creek Watershed has increased by 8%, or almost 3.5 million hectares, while there has been a significant loss of agricultural (5%) and forested lands (7%). At the same time there have been 130 new collapse sinkholes (see 4.7.2), with the most likely underlying cause being urban influences as the watershed developed.

Each tool is examined below for its ability to curb these landscape and morphological changes. The nature of watersheds changing geographically demands tailor-made plans to address the sprawling patterns that lead to environmental hazards. A tool that works in one location may be ineffective in another, as hydrology, geology and geomorphology change laterally and vertically. Most watersheds require in-depth studies to determine these factors and spend years developing plans. This research hopes to shorten that time frame.

Conventional tools used elsewhere by local, county and regional governments and private organizations to combat sprawl in areas impacted by urban growth include diverse measures, such as conservation easements, purchase of development rights (PDR), transfer of development rights (TDR), urban growth boundaries (UGB), growth management programs, agricultural zoning, and land conservation initiatives (Weitz and Moore, 1998). However these tools by themselves have been largely ineffective in areas
lacking strong land use legislation or having fragmented land use patterns, as is the case with many watersheds at the rural-urban fringe (Arrandale, 1997). The lack of enabling legislation or regulatory authority to implement and police management measures in multi-jurisdictional watersheds weakens the effectiveness of these sprawl-related tools in combating the destruction of greenspace, loss of agricultural land, and water quality and quantity degradation (Arrandale, 1997). Much effort through research and literature has gone into solving these problems associated with urbanizing areas at the rural-urban interface (Kline and Alig, 1999; Bullard et al., 1999). For this study, traditional land use planning tools are analyzed for their potential to mitigate these impacts at both a site-specific and regional scale.

Kline and Alig (1999) define land conservation programs as “consisting of legislative efforts that authorize state and local programs to implement growth management and land use protection measures in an attempt to stop the disappearance of greenspace and correct environmental impacts associated with urbanization at the rural-urban fringe”. These laws are enacted to provide funding, incentive, cooperation and education to groups that want to combat sprawl (Kline and Alig, 1999). It is widely recognized that sprawl causes environmental impacts and inhibits effective growth management (Bullard et al., 1999). This unplanned growth hurts community budgets by needing more infrastructure and maintenance, and can make access to housing, mass transit, hospitals and schools difficult, and expensive (Bullard et al., 1999).

The problem with using these conventional tools to remedy urban growth-related problems is that they have proven to be insufficient in areas lacking strong land use-
enabling legislation and/or in regions with fragmented political jurisdictions (Arrandale, 1997). States that have strong land use enabling legislation and regulations directing urban growth, such as Wisconsin, Maryland, Virginia and Pennsylvania, have been successful at implementing land conservation programs and other planning tools to combat sprawl and the destruction of lands (Arrandale, 1997).

Therefore, in order for these tools to be most effective in the Opequon Creek Watershed, there needs to be effective legislation at the state level that can enable and implement these types of local and regional measures. Fortunately, there are several bills as of the 2009 session in the senate and house that are up for adoption attempting exactly that. Recently, House Bill 2831 was passed, which allows for counties that are designated as high-growth counties to establish programs that can purchase valuable land and set it aside from development. This provides both the framework and impetus for land conservation programs at the county and regional level that may be employed in protecting high-risk karst watersheds. The task remains one of both informing watershed constituents and gaining a better understanding of the underlying mechanisms of landscape change over time.

6.1 PLANNING TOOLS TO ADDRESS KARST WATERSHED IMPACTS

Hubbard (2001) recognized that the greater the degree of relative sinkhole development, the greater the potential for karst associated hazards including subsidence, sinkhole flooding, and groundwater contamination associated with land use modifications. Therefore, communities in karst areas have begun to develop regulations that attempt to address the urbanization/karst interface. For instance, the New Jersey
Limestone Ordinance attempts to regulate and protect municipalities in karst regions of New Jersey by recognizing that dissolution of bedrock in these areas creates subsurface subsidence and surface collapse. Alteration of drainage patterns by increasing impervious surface in urban areas leads to land subsidence and groundwater contamination (New Jersey Limestone Ordinance, 1993). Therefore, this ordinance was enacted to “protect, preserve, and enhance a sensitive groundwater resource area and to reduce the frequency of structural damage to public areas of limestone geology within the state, thereby protecting the public health, safety and welfare, and insuring orderly development within New Jersey Municipalities” (New Jersey Limestone Ordinance, 1993).

Tools used to combat irregular growth can only be efficient if we understand the nature and character of the urban growth over an extended time period. Using such legislation, communities and governments can regulate human activities in karst areas by requiring studies, permits, impact assessments, watershed plans, etc. before construction and development can take place, thereby regulating and mitigating negative impacts associated with urban development in sensitive karst regions and redirecting development to less risky areas.

### 6.2 LAND USE MANAGEMENT SUGGESTIONS FOR OPEQUON CREEK WATERSHED

The rest of this chapter explores those land use management practices and traditional planning tools that may address sprawling development patterns in Opequon Creek Watershed to mitigate their influence on collapse sinkhole development. These
suggestions are based on the analysis of the changing landscape in Opequon Creek Watershed (see Chapter 4 and 5).

Several nonprofit groups are currently organizing and developing charters to protect farmland, orchards and open space in the study area. The Land Trust of the Eastern Panhandle, Berkeley and Jefferson County Farmland Protection Boards, The Nature Conservancy, Potomac Conservancy, National Park Service, and the Shepherdstown Battlefield Protection Association are acting separately and cooperatively to identify appropriate land and develop conservation strategies (WV Farmland Preservation Board, Berkeley County, 2007). These groups should be greatly interested in the dissemination of the results from this work, as they can provide a roadmap to mitigation strategies.

6.3 CONSERVATION EASEMENTS

One tool that has proven largely effective in some areas at protecting sensitive watersheds is the use of conservation easements. These are land use planning tools that allow land of value to be set aside from permanent development. By restricting development on the property, the landowner benefits via a reduction in taxes, and citizens benefit by less harmful development in these sensitive areas (Rudolph, 2000).

There are currently two types of conservation easements being used in land conservation programs throughout the country: public and private easements. Private conservation easements allow nonprofit land trusts to work directly with landowners to protect dwindling open spaces, while leaving land in private ownership (Ryan, 1999). These easements are the most common in the effort to combat urbanization at the rural-
urban interface and could easily be applied to karst watersheds to mitigate sinkhole
development (Table 25). By putting sensitive land aside, a buffer is created that could
protect sinkhole-prone karst.

### AREA PRESERVED BY LAND TRUSTS

<table>
<thead>
<tr>
<th>Region</th>
<th>Hectares Owned In Fee</th>
<th>Hectares Under Easement</th>
<th>Hectares Transferred or Protected under other means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid-Atlantic</td>
<td>57,260</td>
<td>164,127</td>
<td>192,349</td>
</tr>
<tr>
<td>Midwest</td>
<td>44,169</td>
<td>34,172</td>
<td>46,788</td>
</tr>
<tr>
<td>Northeast</td>
<td>182,064</td>
<td>338,791</td>
<td>181,666</td>
</tr>
<tr>
<td>Northwest</td>
<td>9,602</td>
<td>207,408</td>
<td>57,441</td>
</tr>
<tr>
<td>Pacific</td>
<td>83,657</td>
<td>65,023</td>
<td>362,847</td>
</tr>
<tr>
<td>South Central</td>
<td>7,356</td>
<td>21,925</td>
<td>13,602</td>
</tr>
<tr>
<td>Southeast</td>
<td>20,853</td>
<td>68,857</td>
<td>70,828</td>
</tr>
<tr>
<td>Southwest</td>
<td>96,987</td>
<td>147,675</td>
<td>40,804</td>
</tr>
</tbody>
</table>

Table 25: Hectares Preserved by Land Trusts in US (Modified from Merenlender, 2004)

Public conservation easements involve government acquisition of land through
sale using land buying grants (Williams, 1997). Land acquisition programs use public
funding to buy land that is historically or aesthetically important, to remove it from
development pressure (Williams, 1997). Although land acquisition programs have strong
public support, they are less likely to significantly contribute to land conservation
initiatives because of the expense of such programs, but they do offer aid against urbanization impacts at the fringe (Williams, 1997). If even very small areas are purchased to buffer known karst areas, there could be a significant decrease in geohazards.

Private conservation easement acquisition is a voluntary, incentive-based approach that relies on private ownership and management of land to meet conservation goals (Merenlender et al., 2004). The aim is to avoid the high costs and political issues related to public acquisition of land. The enticement of these easements is that there is no pre-existing content (Merenlender et al., 2004). This means that the easement can say whatever the parties agree to.

A conservation easement may be established in one of two ways: as a legal agreement between landowners and a conservation agency that permanently restricts the property’s land use, or through the outright acquisition of land by government or private agency (Ryan, 1999). According to Ryan (1999), “Conservation easements are popular because of their flexibility and ease of implementation. They are amenable to landowners because they can be specifically tailored to landowner wishes. The landowner may grant as much, or as little, use of the land to the underwriting land trust as they wish”.

Ryan (1999) asserts that this planning tool may offer potential to mitigate environmental impacts in impacted areas, particularly at the watershed level, by setting aside land that is deemed to be of environmental and conservation significance. The only way this will work is through conscious effort from both landowners and planning
officials. If organizations become sidetracked with political issues like boundaries and jurisdictional lines, these watersheds will continue to be infringed upon.

Therefore, once an area is identified as a potentially high-risk karst zone, conservation easements may offer the potential to stop harmful land use practices and mitigate negative impacts, such as landslides, sinkholes, and aquifer contamination, by setting aside the development rights on sensitive lands and creating a buffer zone that will ensure that no development within the high-risk zone takes place.

6.3.1 Conservation Easements in Opequon Creek Watershed

Productive farmland is being permanently converted to non-agriculture uses in many watersheds. West Virginia, in particular, is losing over 100,000 acres of productive farmland every year to development (WV Farmland Preservation Board, Berkeley County, 2007). Berkeley and Jefferson County are the fastest growing counties in the state, and as shown in Chapters 4 & 5, are being transformed by the expanding urban sprawl of the Washington-Baltimore Metropolitan Area. Agricultural and forested lands are converted to urban and residential development. As a result, the water table is being lowered and new sinkholes are developing at increasing rates (see 4.7.2).

Conservation easements have met with early success in this region and may provide a valuable tool that can mitigate urban impacts when paired with other growth management policies and strategies (West Virginia Farmland Protection Board, 2007). However, protecting this disappearing greenspace means finding the funding to purchase conservation easements, while the landowner retains their land. Although West Virginia has traditionally had less funds than neighboring states, monies are available at the
county, state, and federal levels via various programs, and donations from private individuals (West Virginia Farmland Protection Board, 2007). Likewise, these easements can be acquired when landowners donate their development rights outright.

While groups attempting to raise funds for this purpose are largely in their infancy, there has been some progress. According to Peter Fricke, chairman of the Jefferson County Farmland Protection Board, “since 2002 the Jefferson County Farmland Protection Board has purchased conservation easements on 1,754 acres on 17 farms. Likewise, with recent easements established on 114 acres in Shanghai, the Berkeley County Farmland Protection Program has approved 23 conservation easements over the past four years, conserving 2,068 acres. Another easement on 195 acres in Berkeley has been approved and is expected to close before the end of the year”.

Furthermore Fricke says, “the smallest farm offered for easement has been 20 acres. The average value of a conservation easement, that is the difference between the value of land sold for development and land sold as farmland, in Jefferson County has been $5,340/acre and has changed little over the past five years” (Barrat and Lillard, 2007).

The problem lies in the fact that not everyone has the same environmental ethic that is geared toward protecting farmland and open space that can protect these karst lands. Rather, some view growth as good for the economy, while ignoring its environmental impacts. Peter Fricke, chair of Jefferson County Farmland Protection Board, characterized landowners in the study area this way:
Jefferson County landowners and farmers are dedicated individuals who work very hard to make their living, but this does not mean that they all share the same values toward protecting farmland for future use. Some view land as a commodity to buy, sell, or rent as market forces dictate. Others view their farms as a heritage asset that they wish to pass on to their family or to another farmer; we have a number of Bicentennial Farms in the county, and these farms demonstrate the attachment to the land of individual families. Still other landowners wish to protect their land as farmland, recognizing its importance for food production, water quality, and the quality of life of everyone in the county.” (Shepherdstown Observer, November 2007, p. 13)

Traditionally, landowners interested in conservation easements tend to be motivated by their desire to keep their land as open space or farmland, or to maintain areas for wildlife habitats (Arrandale, 1997). The vast majority of conservation easements in America, about 37 million acres, are donated by the landowner (Barrat and Lillard, 2007). Their financial incentives can include tax deductions for the value of the easement, lower property tax rates, and estate planning benefits (Barrat and Lillard, 2007). Therefore, for the Opequon Creek Watershed, it seems likely that the best approach would be in educating the landowners about impacts of various development patterns and population increases in karst watersheds, in order that they may provide easements to the land for buffering.

Legislative efforts in the last few years have attempted to address the problem by creating boards at the county and regional level to implement and regulate some of these ideas. The Berkley and Jefferson County Farmland Protection boards are government entities, which were created as a result of the Voluntary Farmland Protection Act, passed by the West Virginia Legislature in 2000. The Berkeley and Jefferson County Farmland Protection Boards were then empowered by the County Commissioners. These two were
among the first three in the state. Now there are 18 Farmland Protection Boards in West Virginia at the county level (West Virginia Farmland Protection Board, 2007).

The Voluntary Farmland Protection Act outlined specific guidelines for each Farmland Protection Board to follow, including the methods of farmland protection, the value of a conservation easement, the criteria for easements acquisition, and the use of land after acquiring a conservation easement (West Virginia Farmland Protection Board, 2007). So the framework is already provided to enact these initiatives in the Opequon Creek Watershed.

Incentive in the form of lower property taxes, tax deductions and estate planning benefits must be provided to Berkeley and Jefferson County land owners in order to further encourage the ethic already fostered by these environmentally-conscious people, so that land may be set aside to buffer the urbanizing karst watershed of Opequon Creek. In addition to providing incentives at the county and state level, governments and private conservation groups need to foster good relationships at the grass-roots level in order to encourage land owners to provide conservation easements that will have the same results.

Conservation easements by themselves will not be sufficient to counteract the impacts of changing land use and land cover in the urbanizing watershed of Opequon Creek, but it is definitely a step in the right direction. With programs in the panhandle area being young, conservation easements are finally being established and may be able to help steer development away from potentially hazardous areas.
6.4 PURCHASE OF DEVELOPMENT RIGHTS

The purchase of development rights (PDR) in urbanizing areas to protect farmland and open space has gained momentum and popularity as a growth management tool in recent years (Daniels, 2001). But PDR’s have yet to be used in any comprehensive manner to protect sensitive watershed regions from this irregular development (Daniels, 2001). It is my contention that PDR’s, although expensive compared to other planning methods, may offer another tool to planners and citizens alike to protect and set aside land in sensitive watersheds from development, thereby helping to mitigate karst geohazards.

A purchase of development rights program pays the landowner to place restrictions and limitations on the use of the property, in order that future development can be regulated and controlled (Daniels, 2001). This involves a voluntary exchange of money in return for deed restrictions on the property. Land rights usually include mineral rights, the right to sell property, and the right to develop the property. These rights may be sold separately or all together. In other words, the landowner can sell the development rights to the land to a government entity or private interest group, while retaining title to the property (Daniels, 2001).

These development rights are often called negative easements for this reason (Daniels, 2001). An appraisal of the land is made before and after the development rights are sold. The difference between the two is the development rights value, which is what the property would be worth on the market at its’ highest value, and the property value in its’ current use (Daniels, 2001). Some states have instituted public PDR programs (Table
where the state buys development rights to areas deemed “significantly at-risk” (Daniels, 2001). This could easily be applied in the Opequon Creek Watershed, as the county and state governments can raise monies for stopping development and relocating it to areas of less significance.

**AREA PRESERVED BY STATE PDR PROGRAMS**

<table>
<thead>
<tr>
<th>State</th>
<th>Acres/Farms Preserved</th>
<th>Monies Allocated (In Millions of $)</th>
</tr>
</thead>
<tbody>
<tr>
<td>California</td>
<td>460/3</td>
<td>$0.84</td>
</tr>
<tr>
<td>Colorado</td>
<td>1,878/3</td>
<td>$0.8</td>
</tr>
<tr>
<td>Connecticut</td>
<td>25,566/169</td>
<td>$74.83</td>
</tr>
<tr>
<td>Delaware</td>
<td>16,107/85</td>
<td>$20</td>
</tr>
<tr>
<td>Maine</td>
<td>540/3</td>
<td>$0.5</td>
</tr>
<tr>
<td>Maryland</td>
<td>139,828/968</td>
<td>$140.6</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>40,040/441</td>
<td>$96.1</td>
</tr>
<tr>
<td>Michigan</td>
<td>579/4</td>
<td>$1.97</td>
</tr>
<tr>
<td>New Hampshire</td>
<td>11,732/57</td>
<td>$10.49</td>
</tr>
<tr>
<td>New Jersey</td>
<td>43,972/278</td>
<td>$167.8</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>111,752/861</td>
<td>$172.2</td>
</tr>
<tr>
<td>Rhode Island</td>
<td>2,429/31</td>
<td>$14</td>
</tr>
<tr>
<td>Vermont</td>
<td>69,693/202</td>
<td>$34.8</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>464,576/3,105</strong></td>
<td><strong>$734.93</strong></td>
</tr>
</tbody>
</table>

*Table 26: PDR Programs at State level (Modified from Daniels, 2001)*
Purchase of development rights programs began in the 1970’s as a way to control growth and permanently preserve farmland and open space on a local or regional scale (Brabec and Smith, 2002). Other farmland protection techniques exist, but these provide farmers with no compensation for the development restrictions placed on the land (Brabec and Smith, 2002). Therefore, farmers and landowners are hesitant to place valuable land that could be developed under a restriction without any kind of monetary compensation. Tax breaks cannot compare to the money being offered by developers, so much of this fringe land is carved up in the spread of suburbs (Brabec and Smith, 2002).

The town of Riverhead on Long Island is touted as the yardstick for using PDR’s. Their program was implemented in 1977 as one of the nation’s first PDR programs at the local level (Brabec and Smith, 2002). Over $40 million dollars was used to purchase 7000 acres of land in order to protect them from fringe development, which has been largely successful in restricting development to areas deemed low-risk for potential hazard developments.

6.4.1 Purchase of Development Rights in Opequon Creek Watershed

Not everyone is able to make an outright donation of their land through a conservation easement. These donations can be worth several hundred thousand to millions of dollars. Therefore, entities like the Jefferson and Berkeley County Farmland Protection Boards can purchase development rights for some easements. This initiative, while being expensive, can be used in Opequon Creek Watershed to protect at risk lands that have yet to be developed. Landowners end up happy because they can feel good about their environmental ethic, while being compensated monetarily for the loss of
development rights. This can also be a long-term method of controlling development and mitigating sinkholes by relocating development to less-sensitive areas of the watershed.

In recent years, activists in West Virginia opposing the disappearance of farmland have worked to create policy that allows for protection of these open spaces. Over the course of 33 years (1964-1997), West Virginia lost more than 1.8 million acres of farmland and more than 20,000 acres of orchard land (West Virginia Farmland Protection Board, 2007). An increasingly popular way to achieve protection of these lands is to rely on Purchase of Development Rights (PDR). Following the acquisition, the purchaser (either a government agency or a land trust) retires the property for purposes of preventing its development. While the existing use of development rights primarily is used for protecting farmland in regions that are experiencing rapid urban sprawl, similar programs can be adopted in rural areas (Brabec and Smith, 2002).

PDR programs are used by entities in two ways: to conserve land (either to protect farmland, or to protect habitat for endangered species), or to steer development toward other geographic areas (Brabec and Smith, 2002). PDR’s offer potential to steer development away from karst areas of the Opequon Creek Watershed into the predominately shale areas, where sinkholes will not be a problem.

Likewise, conservationists have argued that PDR programs are good ways to encourage the preservation of land, because instead of using regulatory policy to mandate what can and cannot be done with land, the agency pays the landowner for his or her inaction (Stalebrink and Wilkinson, 2007). Main et al. (1999) argue that, “conservation via regulation does not sufficiently reward landowners, who will in turn foster anti-
conservation sentiments”. They advocate PDR programs, while noting that there are huge resource limitations to their implementation.

PDR programs are designed to protect farmers by allowing these landowners to continue their own economic activity on the land after the rights have been sold (Stalebrink and Wilkinson, 2007). Therefore, PDR programs serve as a type of subsidy. While subsidies typically are used to protect or promote economic growth, PDR programs do not affect the market of the good produced on the property (Stalebrink and Wilkinson, 2007). They serve as a second means of income for the property owner.

One way of implementing this type of program that has gained interest in recent years in West Virginia is the use of a real-estate transfer tax (West Virginia Farmland Preservation Board, 2007). The idea is that by applying this kind of tax during the transfer of real estate, the sale of the land can be discouraged, or at least revenue generated for the PDR program if it must be sold. For example, revenue could be raised during the sale of a farm to housing developers, and again during the sale of the new houses to those doing the buying.

The money raised from this increased taxation would then be used to fund Purchase of Development Rights programs at the county or watershed level. According to the Natural Resource Conservation Service in West Virginia (2008), an increase of as small as $1.00 per $500 of value could provide the necessary funds to protect identified high-risk areas, while at the same time encouraging high-density development which would limit impacts, as well as curbing the rampant transfers of real estate.
The Natural Resource Conservation Service (2008) continues, “development rights for 6121 acres of farmland in West Virginia have been purchased from 44 different sellers in the last 5 years. The development rights cost a total of $17,359,712. The federal government funded $6,978,277 of that; West Virginia counties funded the remaining $10,381,435. The average cost per acre was $2836”. The counties that have protected the most farmland include Berkeley, Jefferson and Morgan, which possess 3581 acres of the total (NRCS, 2008). But this number is small in regards to the sheer amount of land that is being threatened by development in the Opequon Creek Watershed. Therefore, a drastic plan is necessary that can have far-reaching effect on the aggressive change of land use and land cover that is taking place in the watershed.

Two concerns have arisen wherever purchase-of-development-rights programs, or PDRs, are enacted. First, money used to buy easements might be better spent buying parks (Stalebrink and Wilkinson, 2007). Easements can be a valuable way to curb sprawling development, but they rarely allow for public access to these lands. This concern should be weighed against the importance of protecting the karst watershed from development and geohazards.

The second concern is that some states are criticized for buying development rights from landowners who would preserve this land even without the money (Stalebrink and Wilkinson, 2007). This concern may be true but the fact remains that PDR programs are huge motivators for people to protect lands, whether done with ulterior motives by the landowner or not. As the Opequon Creek Watershed is aggressively carved up by
development, new methods such as the PDR must be explored for the potential to reverse the impacts being felt (see Chapter 4 & 5).

6.5 TRANSFER OF DEVELOPMENT RIGHTS

Another technique being employed in the fight against sprawling urban development patterns involves the transfer of development rights (TDR). This is similar to the PDR programs being used around the country except that development is relocated, not stopped. A TDR program is usually a regional program which defines an area to be protected from development (sending area) and an area where development will be allowed (receiving area) (Brabec and Smith, 2002).

When development rights are transferred from one piece of land to another, the first land can no longer be developed, and is protected. This tool may offer potential, in conjunction with other tools, for protecting sensitive karst watersheds and mitigating karst impacts by relocating impervious surface and leap-frogging development to lower-risk areas that are less prone to geohazardous developments. By designating a watershed as a sending area planners and officials can permanently protect the area from development and redirect unwanted development to receiving areas, which are better able to handle the sprawling patterns. In the Opequon Creek Watershed this tool could be used by redirecting development from high-risk fringe areas that have yet to be developed to areas within the city limits of Martinsburg, that already concentrate development. This tool may offer more potential than PDR’s or UGB’s because it is fairly inexpensive in comparison.
Montgomery County in Maryland in 1980 became one of the first places in the nation to adopt a TDR program for agricultural preservation (Brabec and Smith, 2002). The county identified an agricultural reserve (sending area) of over 90,000 acres, protecting a significant area from future development (Figure 136).

![Figure 136: Montgomery County, MD Agricultural Reserve (Source: Brabec & Smith, 2002)](image)

6.5.1 Transfer of Development Rights in Opequon Creek Watershed

In Opequon Creek Watershed, further studies need to be conducted to determine where “sending” and “receiving” areas can be placed to protect high-risk karst areas that are prone to sinkhole development. Implementing TDR’s at the local and regional level in Opequon Creek Watershed the various governments can strive to keep farmland intact and undivided, while simultaneously encouraging the retention of open lands. With this program local governments can allow the landowner to sell the right to subdivide to someone else who can then use the rights at another property.
In other words, the farms and sensitive spaces stay in one piece and another property in the receiving area becomes the site of more intense development. Thus, there is a transfer of development rights from a high-risk area that may produce sinkholes to one where development has already occurred, thereby decreasing the chance of geohazards. When the development rights are sold for a property, they are transferred to the buyer who can then use them to increase the building density on another property (Brabec and Smith, 2002). This is a good way of limiting sprawl throughout the county without restricting the rights of any landowner.

West Virginia House Bill 2831 authorizes counties designated as growth counties to establish a transfer of development rights program, in order to “preserve natural resources, protect scenic, recreational, and agricultural qualities of open lands, and facilitate measured growth”. Although the legislation has been enacted that allows for the implementation of a program of transferring development rights, the actual establishment of a transfer of development rights program must be approved by the majority of voters in the growth county before the program can be developed and implemented.

Therefore, in order to become an effective program that may aid in the fight against sprawling patterns in the Opequon Creek Watershed the county constituents must first be convinced that the program is effective and would be in their best interest. The results of this dissertation could aid in this decision by making the watershed’s inhabitants more aware of problems resulting from sprawling development and population pressures in the watershed. This study also maintains that when used in
conjunction with conservation easements and a Purchase of Development Rights Program, a TDR program can be a valuable tool against unregulated urban growth impacts in the Opequon Creek Watershed.

### 6.6 URBAN GROWTH BOUNDARIES

Another planning tool that may offer help in abating urbanization impacts in karst watersheds involves urban growth boundaries (UGB) that are established around the urban area under development (Figure 137). Coupled with other land use planning tools, urban growth boundaries have been successfully integrated into land conservation programs throughout the country, the first one being around Lexington, Kentucky in 1958 (Ding et al., 1999).

![Urban Growth Boundary around Portland, Oregon](Source: Ding et al., 1999)

Since then, the popularity of UGB’s has grown rapidly (Ding et al., 1999). In 1973 Oregon passed legislation requiring all cities to include UGB’s in their comprehensive land use plans, which met with tremendous success at saving valuable land at the fringe of urbanizing areas (Ding et al., 1999). Since then other states have followed suit, recognizing the important potential of this planning tool. High-density
areas of Europe have also had much success at implementing UGB’s to curb and direct
development to areas deemed less impacted. For example, the Swiss have been very
successful at directing development to desired areas using UGB’s developed in their 1970
Land Use Plan (Maria-Pia et al., 2009).

In 1997 the American Planning Association gave credence to this tool by
recommending that UGB’s be established in affected areas to “promote compact and
contiguous development patterns that can be efficiently served by public services to
preserve and protect open space, agricultural land, and environmentally sensitive areas”
(Ding et al., 1999). Therefore, the planning community has realized through trial and
error that this tool can be an effective part of the planning toolbox to mitigate and
remediate the woes currently being encountered in these sensitive watersheds. Ding et al.
(1999) go on to show that UGB’s not only conserve land but increase social welfare by
creating more densely settled areas instead of spread-out, low-density settlements that
result from sprawl.

Carlson and Dierwechter (2007) evaluated the effectiveness of the UGB in Pierce
County, Washington, that has been in use since 1995. Using a kernel density calculation
based on geocoded residential building permit data from 1991-2002, the study found that
building density had increased substantially within the boundary, while construction
outside the boundary had decreased dramatically. They concluded that the UGB was
highly effective at redirecting development to areas that were already developed, thereby
limiting the amount of sprawling patterns outside the growth boundary in sensitive areas
(Figure 138).
The evidence suggests that UGB’s can be applied around sprawling regions in order to protect sensitive watersheds from unwanted and negative development. By curtailing and regulating the pace and style of development outside urban areas, planners and environmentalists may be able to cohesively apply planning tools to mitigate negative impacts in watersheds by buffering these areas. If this growth can be directed to areas already developed it is hoped that karst geohazards can be limited to areas already under development in these sensitive regions, thereby curtailing the number of new sinkholes as a result of surface runoff morphology changes and watertable drawdown.

Figure 138: Permits Issued In/Out of UGB, Pierce Co, WA (Source: Carlson & Dierwechter, 2007)
6.6.1 Urban Growth Boundaries in Opequon Creek Watershed

As stated earlier, an urban growth boundary (UGB) is a regional boundary developed in an attempt to control urban sprawl by allowing the area inside the boundary to be used for higher-density urban development and the area outside the boundary reserved and protected. An urban growth boundary encircles the urbanized area and is used by local governments as a guide to zoning designations and for making decisions on different land uses.

This management strategy may offer the most potential in Opequon Creek Watershed for protecting high-risk fringe areas outside the city of Martinsburg and Inwood. As Chapters 4 & 5 show, although there have been urban-related geohazards inside of Martinsburg, most new sinkholes have developed in the surrounding areas of the watershed in agricultural lands, as the water table is drawn down and runoff morphologies have been changed over the last 25 years. West Virginia needs to recognize the threat to karst watersheds from sinkholes related to urban development and enact legislation that requires each city and county to make UGB’s part of their local, regional and watershed plans, as they are increasingly developed.

By establishing a growth boundary around the city of Martinsburg and restricting all of the high-density development to this area, it is highly probable that the impacts in the high-risk karst areas, with conduits to the underlying aquifers, can be protected from water quality and quantity issues, as well as from geohazards, such as sinkholes and landslides.
At this point there are no urban growth boundaries in the state of West Virginia. In order to be most effective a UGB must be designed to have enough land for all of the housing needs for the next 20 years, as population continues to grow. This means that extensive studies on the trends of population, housing densities, incomes, etc. would be necessary for Martinsburg and Opequon Creek Watershed. This plan should then be reviewed every 5 years or so and adjusted as needed as the local and regional needs change.

In addition to redirecting development to lower-risk areas within the watershed, an Urban Growth Boundary in Opequon Creek Watershed would provide motivation to develop and redevelop land and buildings in the urban cores, helping keep "downtowns" in business and avoiding the phenomenon of urban decay, as business and factories move to the suburbs. Likewise, businesses and local governments would know exactly where to place infrastructure (such as roads and sewers) needed for future development, which would save significant amounts of public and private funds. Also, instead of building roads further out as urban sprawl moves into the countryside, money could be spent to make existing roads and transit services more efficient. This redirecting of growth to areas that are less sensitive would encourage efficient land use.

This method should also be very appealing to the Opequon Creek Watershed region as it is very cost-efficient compared to the other methods discussed. There is no need to build funds for the purchase of development rights or conservation easements of the landowners' rights to the property, because the Urban Growth Boundary can be designed and incorporated into the next comprehensive plan for Berkeley County, as the
2020 regional plan nears its end. This is very appealing to constituents as there is no need to raise taxes or provide levies for funding the purchases of rights.

A boundary around Martinsburg would promote compact and contiguous development patterns that could be served by existing public services, without the need for the tremendous cost of extending existing infrastructures (sewer, water, road, electricity) into newly developed areas outside the boundary. This would also preserve open space, agricultural land, and environmentally-sensitive land (karst exposures of Opequon Creek Watershed) that are not suitable for urban development.

A growth boundary around Martinsburg would thereby manage leapfrogging or sprawling development, support densities need to expand the existing urban transportation system within the city (having other positive environmental impacts, such as reducing air and water pollution), protect the watershed’s natural resources and farmland, as well as the numerous orchards in the area.

Critical in the establishment of an urban growth boundary in the Opequon Creek Watershed is setting the correct size for the boundary, in order to maintain the positive economic industries of the city and surrounding area, while simultaneously protecting the sensitive karst environment. Many UGB programs have met with failure at this point by failing to make the boundary large enough to provide for future growth, while protecting those sensitive areas (Carlson and Dierwechter, 2007). But if the boundary contains too much land, it becomes an ineffective tool for achieving the goal of protecting the nearby karst lands. Therefore, extensive studies need to be undertaken to determine these
mitigating factors in order to integrate them into the development of a UGB in Opequon Creek Watershed during the planning of the next comprehensive plan for the region.

### 6.7 SMART GROWTH INITIATIVES

Lastly, “smart growth” plans are being used by municipalities and regional organizations throughout the United States to control and regulate the type and placement of development, “in order to ensure sustainable, healthy growth, as well as protecting valuable farmland and open space in urbanizing areas” (Miller and Hoel, 2002).

According to Miller and Hoel (2002), “smart growth plans attempt to reevaluate previous notions that all development and growth are good for the economy”. This type of method involves revising the existing environmental and development ethics found in city and regional plans, to integrate planning and conservation ideas in the planned growth around a city as it expands (Miller and Hoel, 2002).

This is more of a holistic approach than the individual tools that have been previously examined. Although offering enormous potential in mitigation of urban-related geohazards, it may be the toughest to implement because it involves changing the prevailing traditional idea that all growth is good growth, especially for an economically depressed state, such as West Virginia, where any growth is usually viewed as good for everyone. Therefore, it is only logical that a smart growth plan can be developed to protect sensitive watersheds in karst regions, such as the Opequon Creek Watershed, if officials and landowners deem it important.

At the heart of this smart growth initiative is the debate between the rights of individuals versus the overall goal of the community (Miller and Hoel, 2002). There is a
lot of concern over the role that state and local officials should play in regulating land development through “smart growth”. This movement involves a range of regulatory, financial, and educational practices that may help coordinate land use through integrated planning (Miller and Hoel, 2002).

In this manner, municipalities and regions can decide how much, where, and what type of growth fits with their individual comprehensive plans, then go about implementing these through various planning tools (Miller and Hoel, 2002). Proponents believe that smart growth can reduce urban sprawl through better land use and transportation planning. Smart growth has different meanings for different groups, but the common theme involves a response to the effects of urban sprawl.

Miller and Hoel (2002) go on to identify three categories that smart growth initiatives can represent: regulatory, financial, and educational. Regulatory initiatives are often implemented at the local level and generally address zoning, in terms of density, type, mixture, or impact fees (Miller and Hoel, 2002). The urban growth boundaries of Oregon are prime examples. Financial initiatives involve the provision of funds for citizens, employers and associations to influence development in ways that will benefit the entire area. Maryland offers a “Live Near Your Work Program” where employers, local governments and state governments each contribute $1000 to employees that purchase homes near their work site in designated areas (Miller and Hoel, 2002). Educational initiatives target associations, communities and individuals. It is hoped that through broader educational tactics and dissemination of relevant planning literature and
urbanization impacts, those involved will be better able to make more informed decisions surrounding growth and development.

6.7.1 Smart Growth Initiatives in Opequon Creek Watershed

The Opequon Creek Watershed has become a receiving area for growth from Washington, D.C. and Hagerstown, Maryland. The lack of extensive taxes and a plentiful supply of cheap land and housing have led to unprecedented growth over the last 25 years. This is at complete odds with tradition in the region. Therefore, existing urban plans in the region have been insufficient in accounting for this growth and providing the tools necessary for implementation of far-reaching measures that can address this problem.

In order for these tools to be effective more smart growth initiatives need to be incorporated into local and regional plans. For this to occur, extensive polling of public opinion should be conducted to assess the direction that Opequon Creek Watershed residents wish for the region to take. The idea that all growth is good needs to be reevaluated in light of the impacts that unchecked growth manifest. As shown in Chapters 4 and 5, urban growth in Opequon Creek Watershed has lead to increasing geohazards, such as sinkhole development and landslides and should be further examined to determine if growth in all areas is beneficial to watershed constituents, or if attention to location and pace of more orderly development should be addressed to minimize these impacts.

This is by no means an exhaustive list of potential remedies for urbanization in karst watersheds, but is intended to be a starting point for discourse on attempts to
address these issues. As this dissertation has shown, there are consequences for unchecked urban development into new watersheds, particularly those of karst geology. Therefore, a new ethos must be developed in Opequon Creek Watershed to address those problems.
Chapter 7: Discussion, Conclusions and Future Work

7.1 FUTURE WORK

7.1.1 LiDAR DATA SETS

LiDar (Light Detection and Ranging) is a remote sensing technology that measures properties of scattered light to find range and/or other information on a distant target. The best method to determine distance to an object or surface is to use laser pulses (Carter et al., 2001). Like radar technology, which uses radio waves, the range to an object is determined by measuring the time delay between transmission of a pulse (Figure 142) and detection of the reflected signal (Canaan Valley Institute Website: www.canaanvi.org).

According to the CVI Website LiDar uses “Pulses of light that are sent from the sensor to the ground, which is then reflected back to the sensor, allowing for a calculation of distance based on the time interval. With lidar, much shorter wavelengths of the electromagnetic spectrum are used, typically in the ultraviolet, visible or near-infrared”.

In geology, a combination of aircraft-based LIDAR and GPS is being used as an important tool for detecting faults and measuring tectonic movements. The output of the two technologies can produce extremely accurate elevation models for terrain that can measure ground elevation through trees. Therefore, it is only reasonable that this technology can be adapted to inventory and analyze sinkholes in karst terrains. The bare-
Earth scenes give a cutaway view of depressions without tree or groundcover, thereby allowing for more precise morphometric analysis of these features (Figure 139).

![Figure 139: Sinkholes derived from Lidar DEM (Carter et al., 2001)](image)

The Canaan Valley Institute in West Virginia acquires terrain data and digital color or color-infrared imagery using an aircraft-mounted Optech ALTM 3100 sensor, which can fire up to 100,000 laser pulses per second (CVI Website: [www.canaanvi.org](http://www.canaanvi.org)). The CVI Website goes on to say that “Along with the ALTM 3100, CVI uses an integrated 3-band digital camera. The ALTM 3100 system actually records four hits from each of the laser pulses, meaning that elevation information will be gathered not only for the ground but for surface features as well”.

Once the data is collected, various geographic information systems (GIS) and remote sensing software packages can be used to process the data. GIS software helps connect LiDAR data with information, such as linking data with parcels, land use, road names, stream names, or building names ([www.canaanvi.org](http://www.canaanvi.org)).
CVI has offered to provide at-cost LiDar imagery of any area that I am willing to investigate. Therefore, low-cost LiDar imagery can be obtained to examine and compare to Definiens object-based method. Upon receiving grant monies, I plan to acquire imagery for one square kilometer in the Martinsburg Quadrangle in order to compare methods and examine LiDar’s capabilities for examining sinkholes in karst watersheds.

7.1.2 CLIMATE DATA EXPLORATION

Another area of future examination relating to this study is related to the effect that climate can have on sinkhole development. I would like to examine the history of weather in Opequon Creek Watershed during the study time frame to determine if heavy rains and/or flooding have impacted or contributed to sinkhole development. This can be achieved by performing regression analyses on climate data in relation to the statistical output on sinkholes and land use and land cover classes from Definiens Professional. This exploration may shed some light on whether intense rain periods led to any of the new sinkholes that developed during the study.

7.1.3 MORPHOMETRIC ANALYSIS

Morphometric analysis is one means of quantifying the size, shape, distribution, and hydrogeologic controls on development of sinkholes in karst topography. This technique has been used since the 1940’s (eg., Cramer, 1941, who measured sinkhole densities). In 1968 Lavalle created the elongation ratio (length/width) to quantify various shapes. Basically, it involves measurements of the shape of a sinkhole to examine growth and distribution patterns and density relationships. The use of satellite imagery, as opposed
to traditional morphometric analysis using topographic maps or aerial photography, is a relatively new method.

Problems using topographic methods to inventory sinkholes include shading, scale, displacement, vertical exaggeration and variations in contrast ratios (Fisher, 2003). Therefore, this method can explore a new approach to examining sinkhole relationships, with variables examined in this study (length, width, depth and density), such as urban density, distribution of sinkholes, geology, soils, climate, and land uses. By examining these dimensions, previously gathered during fieldwork, morphometric analysis can determine how sinkhole density correlates to different stratigraphic units (e.g. Beekmantown Limestones), as well as to groundwater relationships, rock types, soils, urban development, formation size, etc. Definiens Professional offers enormous potential for morphometric evaluations of these variables and should be explored in the future to examine its’ ability to perform these functions.

Using the variables gathered during fieldwork/labwork for the study area (Table 27) other parameters can be calculated, including index of pitting and length to width ration (Figure 140), which can then be used to determine the product of symmetry (Fisher, 2003). As discussed by Williams (1971), the product of symmetry can be used to correlate sinkholes against multiple variables to examine their relationships (Figure 141). This could enlighten the discourse about human impacts in karst watersheds by providing quantitative examinations of these interactions.
<table>
<thead>
<tr>
<th>Sinkhole #</th>
<th>Length</th>
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<tr>
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<td>15'11”</td>
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</tr>
<tr>
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<tr>
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<td>10'4”</td>
<td>7'3”</td>
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<td>15'3”</td>
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<tr>
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<td>52'9”</td>
<td>21'8”</td>
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</tr>
<tr>
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Table 27: Field Examination of Randomly Extracted Sinkholes
Figure 140: Sinkhole geometry (length/width) used to measure Product of Symmetry: Modified from (Williams, 1971)

Figure 141: Morphometric Variables for Sinkholes: Modified from (Troester et al., 1984)
7.2 CONCLUSIONS

This study attempts to catalogue and inventory land use and land cover in an urbanizing karst watershed over a twenty-five year period, as well as to evaluate and analyze a new method for examining these sensitive areas that are prone to sinkhole development. Further, this research attempts to determine if Definiens Professional is better able to conduct this research than more traditional pixel-based approaches. Traditional methods of sinkhole inventory are time-consuming, costly and highly user-interpretative, leading to results that are often unreliable.

Earlier methods used to inventory sinkholes have failed to accurately identify sinkholes because of limited functionality when dealing with inherent spatial issues, such as scale of the watershed and the pace and location of urbanizing developmental influences. The method presented in this dissertation goes beyond the limited pixel-based approach to classification or the time-consuming and subjective nature of manual examinations of aerial photography by integrating multiple resolutions of images for higher accuracy and using object-based shape analysis of features in datasets in addition to traditional spectral-based analysis. This allows for more accurate and representative inventories at various scales, including the watershed.

Therefore, while representative of these processes, earlier methods fail to achieve the accuracy of sinkhole counts necessary to examine underlying mechanisms leading to the development of collapse sinkholes at the watershed level. For example, Angel et al. (2004) achieved impressive results with their GIS-based analysis of sinkholes, but were limited in results available by the inherent inability of GIS-based spectral analysis
functionalities. Definiens overcomes this limitation by offering a sliding-scale approach between shape and spectral reflectance, when attempting to distinguish sinkholes at the watershed scale. Object-oriented approaches to landscape inventory have been on the market now for ten years or so and have met with increasingly good results (Baatz and Schape, 2000). In this study, the results show that Definiens Professional was not only highly accurate at distinguishing between image-objects, but was also able to correctly place objects into their classes with an accuracy that exceed 90% in most cases. Likewise, comparison of manual methods versus object-based showed that Definiens Professional was more accurate than traditional topographic and aerial grid counts.

Results of this study show the development of 130 new collapse sinkholes between 1984-2007 in addition to the 803 identified solution sinkholes that were previously found on the 1984 images. Spatial statistical analysis showed significant clustering of sinkholes northwest of Martinsburg, which is interpreted to mean there is a strong correlation between the development of new sinkholes and the urbanizing influences of development taking place in the watershed. Further analysis strengthened this conclusion with the results of the multiple distance autocorrelation analysis, which showed that increasing distance from Martinsburg led to a more dispersed pattern of sinkholes, whereas proximity to the town contributed to clustering of sinkholes. Likewise, spatial analysis of land use, land cover and sinkholes using scatter plot diagrams show significant correlation between sinkhole development, sinkhole area and proximity to Martinsburg, as well as between sinkholes and urban and impervious surface land uses. These results lead the researcher to believe that there can be no doubt that the
development taking place within Opequon Creek Watershed, particularly in the northwest section of the watershed, is negatively impacting the sensitive karst environment through the development of dangerous collapse sinkholes.

The high averaged producer’s accuracy achieved in the five scenes (91%) validates the classification scheme used in this study, while the excellent average user’s accuracy encountered (94%) verifies the reliability of the classification output (see 5.3). The high overall averaged accuracy (92%) is an excellent return and further validates the classification results (see 5.3). Likewise, the high overall averaged kappa statistics (91%) shows that there is excellent agreement during the classification after the random element is accounted for (see 5.3).

Fieldwork also validated the results of the Definiens classifications using ninety randomly extracted samples that were groundtruthed. Results from this showed that 94% of the extracted samples were correctly classified, with the five errors illustrating the same problems that were encountered during post-classification accuracy assessment, namely confusion and an inability to sometimes distinguish between impervious surface and urban classes, as well as confusion between water and forested objects. Lastly, the control area results also show that Definiens encountered a much higher accuracy rate (97%) than either topographic grid counts (82 %) or interpretation from aerial photography (83%).

It is unlikely that further field or lab work would return different results, so this study concludes that Definiens can provide excellent interpretation of large-area landscape features and land use and land cover classes, as well as being able to correctly
identify sinkholes of various types in karst landscapes. It has also shown to be effective at classification of land use and land cover both temporally and spatially for large and multiple data sets.

The implications of this research are useful as Definiens Professional can provide an invaluable tool to cash-strapped municipalities and watershed organizations that are attempting to address the issue of urban impacts and geohazardous issues in karst watersheds. It is hoped that by being able to use existing, free imagery for watershed land use and land cover and sinkhole inventory, local and regional governments and organizations can utilize this method that can inventory and identify potential problem areas. This leads to analysis that can tailor best management practices aimed at mitigating and reversing human impacts in these sensitive watersheds. High risk areas can be delineated by mapping existing sinkholes and karst areas in the watershed. Using ArcGIS or some other spatial analysis program buffers can be drawn around potential problem areas as boundaries future development can avoid, thereby mitigating potential problems from collapse sinkholes.

Each watershed is different, with different hydrological, geological and land use issues that impact runoff morphology and ground and surface water flows. Therefore, each watershed must evaluate and institute different watershed plans aimed at curbing these problems. It is hoped that this work can not only shed light on the impacts that increasing urbanization has had on the Opequon Creek Watershed, as development spills over from urbanizing centers up to sixty miles away, but can also be a roadmap for municipalities and environmental groups all over the country, as they encounter
spreading patterns of development. Therefore, a geographic perspective on impact assessments and subsequent development of local and regional plans should be integrated into the planning phases whenever these groups attempt to assess and address these issues.
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APPENDIX I: SPATIAL STATISTICS ANALYSIS RESULTS

Average Nearest Neighbor Statistic for 498 Sinkholes within 10 Kilometer Radius of Martinsburg in 1984 showing Random Distribution
Average Nearest Neighbor Statistic for 86 New Sinkholes within 10 Kilometer Radius of Martinsburg between 1984-2007 showing Clustering of Sinkholes
Average Nearest Neighbor Statistic for 213 Sinkholes within 5 Kilometer Radius of Martinsburg in 1984 showing some Clustering of Sinkholes
Average Nearest Neighbor Statistic for 56 New Sinkholes within 5 Kilometer Radius of Martinsburg between 1984-2007 showing Significant Clustering of Sinkholes
Results for Getis-Ord High/Low Clustering Tool Analysis of 213 Sinkholes Identified on 1984 Images by Definiens Professional Software; Low z score indicates Random Distribution of Sinkholes within the 5 Kilometer Buffer
Results for Getis-Ord High/Low Clustering Tool Analysis of 56 New Sinkholes Identified on 1984-2007 Images by Definiens Professional Software; High z score indicates Non-Random Clustering of Sinkholes within the 5 Kilometer Buffer.
Results of Multi-Distance Spatial Cluster Analysis of 86 New Sinkholes 1984-2007 extracted from 10 Kilometer Buffer; Distance in Meters from center of Martinsburg
Results of Multi-Distance Spatial Cluster Analysis of 56 New Sinkholes 1984-2007 extracted from 5 Kilometer Buffer; Distance in Meters from center of Martinsburg
APPENDIX II: MULTIPLE PREDICTION RESULTS

### Multiple Regression Analysis Results for Sinkholes in 1984 and Forest Class

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Multiple Regression Analysis Results for Sinkholes in 1984 and Forest Class

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Multiple Regression Analysis Results for Sinkholes in 1984 and Agriculture Class

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Multiple Regression Analysis Results for Sinkholes in 1984 and Urban Class

| OBJECT | Shape | Shape琮 | Observed | Source | Wood | LocalB2 | Predicted | Intercept | RsltLKR | Residual | DError | Sil2Dep | Sil2DepC | Sil2DepC, L | Sil2DepC, Lf | Source_ID |
|--------|-------|---------|----------|--------|-------|---------|-----------|-----------|---------|----------|--------|--------|--------|--------|--------|--------|----------|
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| 2 | Polygon | 431.67016 | 3.83323 | 0.97524 | 431.32321 | -2.963.229 | 6.17884 | -25.85426 | 41.03894 |
| 3 | Polygon | 700.74520 | 3.85501 | 0.58683 | 683.56897 | -1.637.993 | 8.10847 | 47.99642 | 73.42363 |
| 4 | Polygon | 604.53042 | 3.62072 | 0.8065 | 703.79110 | -2.032.243 | 8.45114 | 5.53232 | 32.57127 |
| 5 | Polygon | 108.75804 | 3.21765 | 0.94191 | 299.24937 | -3.260.701 | 6.72453 | -6.70372 | 37.50799 |
| 6 | Polygon | 85.25641 | 3.65015 | 0.97754 | 110.25394 | -11.21894 | 8.11587 | -24.93804 | 40.77643 |
| 8 | Polygon | 9.81561 | 3.61595 | 8.97062 | -2.46500 | 9.04631 | 5.58696 | 34.30547 | 34.23561 |
| 9 | Polygon | 70.25028 | 3.69565 | 9.82990 | -1.181.303 | -5.152.127 | 9.71273 | -17.30503 | 42.84946 |
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| 11 | Polygon | 63.78076 | 3.37145 | 8.91067 | 47.24559 | -1.925.016 | 7.30861 | -23.23339 | 42.05865 |
| 12 | Polygon | 7.39984 | 3.04648 | 8.39879 | -18.8744 | -1.43.313 | 7.83277 | 67.88318 | 31.81125 |
| 13 | Polygon | 4.62131 | 0.78304 | 0.94267 | 4.61129 | -1.619.305 | 2.39202 | -0.38236 | 30.69409 |
| 14 | Polygon | 0.89420 | 0.59905 | 0.7667 | 0.91144 | -1.292.055 | 2.58123 | 3.21759 | 18.0034 |
| 15 | Polygon | 2.49801 | 0.70664 | 0.81796 | 0.81496 | -0.161.207 | 2.51877 | 6.98983 | 30.05972 |
| 16 | Polygon | 61.35228 | 4.87322 | 5.51157 | 18.79364 | -18.1.512 | 7.49064 | -4.21553 | 56.58650 |
| 17 | Polygon | 87.05932 | 0.62174 | 0.10560 | 87.17159 | -15.174.358 | 7.11384 | 25.82038 | 31.10897 |
| 18 | Polygon | 57.89081 | 3.49455 | 3.92741 | 23.15591 | -24.14949 | 7.02698 | 15.62567 | 39.48869 |
| 19 | Polygon | 21.82200 | 3.26071 | 0.93121 | -10.267.52 | -10.230.242 | 7.00145 | 41.07291 | 42.12775 |
| 20 | Polygon | 0.71581 | 0.31762 | 0.92006 | 1.171.312 | -9.602.041 | 7.30934 | -25.15636 | 42.37176 |
| 21 | Polygon | 71.87347 | 3.56208 | 0.48030 | 8.61108 | -167.707.22 | 6.85753 | 27.79367 | 42.37846 |
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| 27 | Polygon | 36.22082 | 3.73595 | 0.94652 | 3.74029 | -0.160.069 | 5.71579 | 6.52632 | 42.15366 |
| 29 | Polygon | 9.81561 | 3.40792 | 0.46452 | -31.127.21 | 4.46.269 | 0.63740 | 40.09259 | 40.10074 |

Multiple Regression Analysis Results for Sinkholes 1984-1989 and Forest Class
## Multiple Regression Analysis Results for Sinkholes 1984-1989

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## Multiple Regression Analysis Results for Sinkholes 2004-2010 and Agriculture Class

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Multiple Regression Analysis Results for Sinkholes 1984-1989 and Agriculture Class.
Multiple Regression Analysis Results for Sinkholes 1989-1993 and Forest Class

Multiple Regression Analysis Results for Sinkholes 1989-1993 and Agriculture Class
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Multiple Regression Analysis Results for Sinkholes 1989-1993 and Urban Class

Multiple Regression Analysis Results for Sinkholes 1993-1999 and Forest Class
Multiple Regression Analysis Results for Sinkholes 1993-1999 and Agriculture Class

Multiple Regression Analysis Results for Sinkholes 1993-1999 and Urban Class
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Multiple Regression Analysis Results for Sinkholes 1999-2007 and Urban Class
APPENDIX III: CLASSIFICATION ACCURACY ASSESSMENT RESULTS

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|          | User     | .845 | .994 | .913 | 1.00 | .931 | .932 | .936 |
|          | Kappa per Class | .803 | .956 | .953 | .955 | .903 | .921 |
| Totals   | Overall Accuracy | .819 | .963 | .938 | .932 | .911 | .933 | .916 |
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APPENDIX IV: FIELD GROUNDTRUTHING OF EXTRACTED SAMPLES FROM CLASSIFICATION

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<th>LATITUDE</th>
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<tr>
<td>56</td>
<td>Forest</td>
<td>77° 59’20.15”W</td>
<td>39° 29’42.27”N</td>
<td>Forest near Cropland</td>
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<td>57</td>
<td>Urban</td>
<td>77° 58’4.17”W</td>
<td>39° 27’28.07”N</td>
<td>Martinsburg</td>
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<td>58</td>
<td>Urban</td>
<td>$77^\circ 58'48.81&quot;W$</td>
<td>$39^\circ 26'22.46&quot;N$</td>
<td>Factory in Martinsburg</td>
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<td>59</td>
<td>Urban</td>
<td>$77^\circ 57'20.56&quot;W$</td>
<td>$39^\circ 28'17.84&quot;N$</td>
<td>Office Complex Martinsburg</td>
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<td>60</td>
<td>Urban</td>
<td>$77^\circ 58'48.71&quot;W$</td>
<td>$39^\circ 28'34.01&quot;N$</td>
<td>Martinsburg Hospital</td>
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<td>2nd Coordinate</td>
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<td>61</td>
<td>Urban</td>
<td>77° 58'55.25&quot;W</td>
<td>39° 27'33.02&quot;N</td>
<td>Office Building Martinsburg</td>
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<td>62</td>
<td>Urban</td>
<td>78° 3'10.68&quot;W</td>
<td>39° 20'56.75&quot;N</td>
<td>Resident. area Inwood</td>
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<td>63</td>
<td>Urban</td>
<td>78° 1'50.17&quot;W</td>
<td>39° 21'21.55&quot;N</td>
<td>Resident. area Inwood</td>
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<td>No.</td>
<td>Status</td>
<td>Type</td>
<td>Longitude</td>
<td>Latitude</td>
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<td>64</td>
<td>Urban</td>
<td>78° 1’9.57”W</td>
<td>39° 20’50.48”N</td>
<td>Resident. area</td>
<td>Tarico Heights</td>
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<td>65</td>
<td>Urban</td>
<td>78° 3’22.19”W</td>
<td>39° 19’25.95”N</td>
<td>Resident. area</td>
<td>outside Inwood</td>
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<td>66</td>
<td>Urban</td>
<td>77° 59’44.48”W</td>
<td>39° 25’39.23”N</td>
<td>Resident. area</td>
<td>south of Martinsburg</td>
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<td>Latitude</td>
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<tr>
<td>67</td>
<td>Urban</td>
<td>Factory in Martinsburg</td>
<td>78° 1'29.35”W</td>
<td>39° 24'7.74”N</td>
<td><img src="image" alt="Factory in Martinsburg" /></td>
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<tr>
<td>68</td>
<td>Urban</td>
<td>Airport Building in Martinsburg</td>
<td>77° 58’39.37”W</td>
<td>39° 24’27.18”N</td>
<td><img src="image" alt="Airport Building in Martinsburg" /></td>
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<td>69</td>
<td>Urban</td>
<td>Commerc. Development in Inwood</td>
<td>78° 3’13.65”W</td>
<td>39° 19’56.78”N</td>
<td><img src="image" alt="Commerc. Development in Inwood" /></td>
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<td>70</td>
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<td>77° 57'20.36&quot;W</td>
<td>39° 26'30.48&quot;N</td>
<td>Trailer Park SE of Martinsburg</td>
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<td>71</td>
<td>Sinkhole</td>
<td>78° 1'33.48&quot;W</td>
<td>39° 21'24.28&quot;N</td>
<td>north of Inwood by neighborhood</td>
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<td>72</td>
<td>Sinkhole</td>
<td>78° 0'47.32&quot;W</td>
<td>39° 16'32.24&quot;N</td>
<td>Compound sinks in Agricultural land south of Inwood</td>
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<tr>
<td>73</td>
<td>Sinkhole</td>
<td>78° 0'9.83&quot;W</td>
<td>39° 29'42.55&quot;N</td>
<td>New sinks behind industrial buildings west of Martinsburg</td>
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<tr>
<td></td>
<td>Sinkhole</td>
<td>Lat/Long: 77° 58’13.46”W 39° 30’11.74”N</td>
<td>Description: New sink near interstate</td>
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<tr>
<td>74</td>
<td>Sinkhole</td>
<td>Lat/Long: 77° 57’7.24”W 39° 28’2.49”N</td>
<td>Description: New sink in Martinsburg</td>
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<tr>
<td>75</td>
<td>Sinkhole</td>
<td>Lat/Long: 77° 55’22.18”W 39° 21’58.26”N</td>
<td>Description: Ponded sink edge of forest south of Martinsburg Airport</td>
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<tr>
<td>76</td>
<td>Sinkhole</td>
<td>Lat/Long: 78° 4’32.99”W 39° 25’21.01”N</td>
<td>Description: Sinkhole in forest near Ferrel Ridge Anticline</td>
<td></td>
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<tr>
<td>#</td>
<td>Type</td>
<td>Lat/Long</td>
<td>Location</td>
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<tr>
<td>78</td>
<td>Sinkhole</td>
<td>77° 57'38.48&quot;W, 39° 30'9.25&quot;N</td>
<td>By industrial park north of Martinsburg</td>
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<td>79</td>
<td>Sinkhole</td>
<td>77° 56'37.26&quot;W, 39° 28'0.59&quot;N</td>
<td>In pasture east part of Martinsburg</td>
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<tr>
<td>80</td>
<td>Sinkhole</td>
<td>77° 56'14.59&quot;W, 39° 27'7.19&quot;N</td>
<td>Forested sink in Martinsburg</td>
<td></td>
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<td>81</td>
<td>Sinkhole</td>
<td>77° 59'55.35&quot;W</td>
<td>39° 15'59.04&quot;N</td>
<td>Recent sinkhole activity on agricultural land outside of Inwood</td>
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<td>82</td>
<td>Sinkhole</td>
<td>77° 57'9.45&quot;W</td>
<td>39° 27'59.02&quot;N</td>
<td>Older sinks in Martinsburg</td>
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<td>83</td>
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<td>77° 54'18.77&quot;W</td>
<td>39° 21'34.42&quot;N</td>
<td>Older sinks on edge of forest south of Martinsburg Airport</td>
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<tr>
<td>84</td>
<td>Sinkhole</td>
<td>77° 59'22.4&quot;W</td>
<td>39° 29'41.91&quot;N</td>
<td>Older sinks by forest west of Martinsburg</td>
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<td>Number</td>
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<td>Longitude</td>
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<td>85</td>
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<td>39° 30'22.12&quot;N</td>
<td>77° 58'11.34&quot;W</td>
<td>West of interstate in Martinsburg</td>
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<td>39° 26'46.9&quot;N</td>
<td>77° 56'14.86&quot;W</td>
<td>Newer sink beside trailer park in Martinsburg</td>
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<td>87</td>
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<td>39° 26'7.06&quot;N</td>
<td>77° 54'55.32&quot;W</td>
<td>East of Martinsburg</td>
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<td>88</td>
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<td>39° 21'23.53&quot;N</td>
<td>78° 1'33.5&quot;W</td>
<td>North of Inwood by neighborhood</td>
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<td>Sinkhole</td>
<td>77° 56'30.73”W</td>
<td>39° 18’58.83”N</td>
<td>East of Inwood near Darkesville</td>
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<td>89</td>
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<td>Sinkhole</td>
<td>78° 3’58.43”W</td>
<td>39° 25’25.16”N</td>
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<td>LAND USE CLASS</td>
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<td>Width</td>
<td>Depth</td>
</tr>
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<td>Compound</td>
<td>Agricultural-Pasture</td>
<td>24’7”</td>
<td>11’9”</td>
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<td>36’4”</td>
<td>15’11”</td>
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<td>Agricultural-Pasture</td>
<td>14’5”</td>
<td>6’10”</td>
<td>4’10”</td>
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<td>22’3”</td>
<td>13’5”</td>
<td>Trash Filled; ~7-8’</td>
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