MAPPING URBAN GROWTH AND INVESTIGATING ITS POTENTIAL IMPACT ON SURFACE WATER QUALITY IN CHATTANOOGA, TENNESSEE, USING GIS AND REMOTE SENSING

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A Thesis Submitted to the Faculty of the University of Tennessee at Chattanooga in Partial Fulfillment of the Requirements of the Degree of Master of Science: Environmental Science

The University of Tennessee at Chattanooga
Chattanooga, Tennessee

May 2019
ABSTRACT

Urban development involves the conversion of land cover from pervious to impervious. Impervious surfaces (IS) can have ramifications for urban stormwater and facilitate the movement of pollutants to nearby water bodies. This study investigated the IS changes of the Chattanooga, Tennessee, area using GIS and satellite remote sensing data acquired on 1986 and 2016. A model was developed utilizing the Normalized Difference Vegetation Index (NDVI) and a supervised image classification technique to detect IS growth. IS changes were quantified at watershed and stream riparian scale. The results show a net growth of 45.12 square kilometers of IS, 9.96 square kilometers being within 90 meters of streams. A risk assessment was conducted using riparian zone percent imperviousness to assess the potential of stream impairment due to IS change. The assessment shows an increase in the number of streams that are potentially at risk of impairment due to detected urban growth.
DEDICATION

This is dedicated to the people who created a way for others to help the Earth by spending countless hours looking at it from outer space.
ACKNOWLEDGMENTS

I would like to thank the National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS) for providing the Landsat Imagery at free of cost, the city of Chattanooga Water Quality Office for providing the water quality and watershed boundary data, The University of Tennessee at Chattanooga (UTC) Office of Research and Sponsored Program and the UTC Department of Biology, Geology, and Environmental Science for proving assistantships to conduct this research, and the Geological and Remote Sensing Laboratory at UTC for providing necessary logistics for this study. My special thank and gratitude are due to:

- Dr. Azad, for accepting me under your tutelage and imparting with me as much information and wisdom as you could during my time in this program, for teaching me to think where and why in the world and for helping open my future.
- Dr. Schorr, for jump starting my fascination of statistics, listening to all my random questions and imparting with me your love, curiosity, and desire to protect the waters in our world.
- Dr. Hong, for helping me take the ideas and thoughts in my head and turn it into something comprehensible to the world.
- Rick Blanton and Kyle Jones for being the best friends and colleagues someone could ask for and for listening to my ideas at all hours with patience and humor.
• Andy Carroll, Charlie Mix, Andrew Mindermann and the rest of the IGT Lab for giving the best advice for a up and coming GIS professional and for helping me grow my love of GIS, remote sensing, and the environment around me.

• Dr. Kalafsky, Dr. Li, Dr. McKinney, Dr. Nagle, Dr. Logan and Jay Price for helping a young undergrad learn to love and care about geography, sustainability and the understanding that each person has a role to play to protect our world.

• To my parents and siblings who lovingly made me the person willing and capable to undertake the quest that is higher education that culminated in this work.

• And all the rest of my friends, family, and loved ones for whom none of this would have ever been possible and to you I am eternally grateful.
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LIST OF ABBREVIATIONS

EPB, Electric Power Board
GIS, Geographic Information System
HUC, Hydrologic Unit Code
IBI, Index-based Built-Up Index
IS, Impervious Surface
km, Kilometer
km², Square kilometers
EMS, Electromagnetic Spectrum
EPA, Environmental Protection Agency
LaSRC, Landsat Surface Reflectance Code
LEDAPS, Landsat Ecosystem Disturbance Adaptive Processing System
LULC, Land use and land cover
m, Meter
MODIS, Moderate Resolution Imaging Spectroradiometer
MRLC, Multi-Resolution Land Cover Characteristic
NAIP, National Agricultural Imagery Program
NASA, National Aeronautics and Space Administration
NDBI, Normalized Difference Built-Up Index
NDVI, Normalized Difference Vegetation Index
NIR, Near Infra-Red
NHDplus, National Hydrography Dataset plus

NLCD, National Land Cover Database

OLI, Operational Land Imager

PCC, Pixels Correctly Classified

R, Red

RGB, Red, Green and Blue.

TCT, Tasseled Cap Transformation

TM, Thematic Mapper

TSS, Total Suspended Solids

USGS, United States Geological Survey

UTC, University of Tennessee at Chattanooga
## LIST OF SYMBOLS

- $\Theta$, definition of symbol
- $\rho$, surface reflectance
- $\rho_{\text{NIR}}$, surface reflectance for Near Infra-Red band
- $\rho_R$, surface reflectance for Red band
- $C_E$, sum of the classification class that were incorrectly classified
- $C_T$, amount of a classification class that is correctly classified
- $E_D$, sum of the expected frequencies along the horizontal row in a confusion matrix
- $k$, Cohen’s Kappa-coefficient
- $n$, total subject sample size
- $n_T$, sum of correctly classified subjects
- $O_C$, sum of other classes that were classified as C
- $O_D$, sum of the observed frequencies along the diagonal in a confusion matrix
- $p$, probability value for a statistical test
- $P_E$, chance agreement of a classification
- $P_O$, observed agreement of a classification
- $S$, Wilcoxon matched-pairs signed-ranks test coefficient
- $X_n$, A thirty-meter riparian zone with $n$ determining the proximity of the zone to a stream
CHAPTER 1

INTRODUCTION

1.1 Background

As urban areas continue to densify and expand into their surrounding environment, their new development can alter the nearby landscape dynamics. Often these expanding urban areas already encompass or are encroaching upon nearby surface water resources [1]. Urban areas are often defined by anthropogenically created impervious surfaces such as concrete, asphalt, and metal [2,3]. These spatial relationship between urban areas and water resources have long had the attention of the scientific community, whose work has shown that urban development can impact local surface water resources [4-7].

Nestled along the Tennessee River is the city of Chattanooga, a growing metropolitan area on the southeastern border of Tennessee. The city of Chattanooga has in recent years experienced a steady rate of economic and population growth, which necessitates the effort to be aware of the location of the growth and its relationship to the surrounding water resources. To date, there have not been any formal attempts to quantitatively map urban growth and analyze the development’s relationship to water resources in the Chattanooga, Tennessee, area. The use of satellite imagery to remotely detect historic and present landcover can provide the necessary data needed to create an urban development dataset [8,9]. There are several methods for extracting information from remote sensing data. One of these methods involves the analysis of surface reflection, a calculated value based on the difference between entering and exiting solar radiation. A number of spectral indices, or ratios of reflectance values from different portions of
the electromagnetic spectrum (EMS), have been developed to differentiate between subjects [10-14]. These indices can be applied to imagery data to visualize the location of the desired features. In order to define features within an image, a form of classification is needed to determine class boundaries via value breaks in the data. This study will be the first attempt to quantitatively map urban growth in the Chattanooga, Tennessee, area and analyze the development’s spatial relationship to local water resources. Through the utilization of remotely sensed data and GIS analyses, this research aims to better understand if/how urbanization has impacted the landcover and landscape dynamics of the greater Chattanooga area.

1.2 Objectives

The goal of this study was to investigate the potential impact of urban growth on water quality in and around the city of Chattanooga, Tennessee. This goal was met by conducting three sequential, related objectives.

1. Map net IS change in the study site between January 24, 1986, and November 26, 2016 using satellite imagery from NASA’s Landsat satellite mission.

2. Perform a quantitative analysis of the IS changes obtained in objective 1 in relation to local water resources.

3. Develop a risk assessment model to identify the potential areas of concern for water resource’s quality in the study site due to the proximity and quantity IS growth.
CHAPTER 2
LITERATURE REVIEW

2.1 Population Growth

Global urbanized areas, as of 2014, contain 54% of the global population and are estimated to increase to 66% by 2050. Urbanization levels are not globally uniform; however; in North America, for example, 82% of the population resides in urban areas compared to other continents such as Africa and Asia with 40% and 48%, respectively. Similarly, increases in urbanization are not consistent. The fastest growing areas are in Africa and Asia and are estimated to increase to 56% and 64%, respectively, with more urbanized areas such as Northern America growing at slower rates [15]. While slower than other areas globally, North America, and specifically the continental United States, is still experiencing significant growth both in urban population and urban developed land.

The United States Department of Agriculture (USDA) Natural Resources Conservation Service’s National Resources Inventory (NRI) found that between 1982 and 2012 the amount of developed land in the continental United States (CONUS) increased by 58%, which is equivalent to 42 million acres [16]. The CONUS urban population has also grown at an increasing rate from slightly more than 167 million in 1980 to over 249 million as of 2010 [17]. Growth rates for population and urban lands are also not consistent spatially across CONUS. For example, the United States Environmental Protection Agency (EPA) reported that between 1982 and 2012 its Southeast Region (Region 4) had the largest rate of developed land increase at roughly 92% and
the largest absolute increase in population and developed (urbanized) land with 22 million people and 13 million acres respectively [18].

Tennessee, as part of the EPA Southeast Region, has also been experiencing significant urban population and land growth. Between 1980 and 2010 Tennessee has experienced a 6% growth in its urban population, equating to an increase of slightly more than 1.4 million people living in urban areas since 1980 [17]. Developed land in Tennessee has nearly doubled since 1982, rising from 1,656.4 thousand acres to 3,115.8 thousand by 2012. This growth is mirrored in Hamilton County, Tennessee, whose population growth rate was 16.9% between 1980 and 2010, growing from 287,643 to 336,463. By 2010 the urban population in Hamilton County accounted for 89.9% of the total population. The U.S. Census Bureau estimates that in 2016 the Hamilton County population was 357,738, about 6.3% (21,275 people) increase since 2010 [19].

The unique location of Chattanooga along the Tennessee-Georgia border creates a census challenge due to inter-state commuters from North Georgia and several neighboring municipalities. The 2010 Census reported the population within the Chattanooga city boundary at 167,674, whereas the greater Chattanooga metro that includes a portion of the north Georgia area and surrounding exurbs was reported at 528,143—over three times the population within the municipal limits. The U.S. Census currently estimates the Chattanooga population at 175,462, with the greater Chattanooga metro area at 551,632, increases of 4.06% and 4.04% respectively [17,20,21]. To date, no official studies have investigated urban land cover change in the Chattanooga, Tennessee, area, although conclusions can be drawn for urban land use growth (e.g. increases in number of housing units within the municipal city limits-- as of 2016 there were an estimated 81,897 housing units, a large increase from 69,593 in 1990 [17,20].)
2.2 Impacts of Urbanization

With urbanization continuing to increase, it has been imperative to monitor, manage, and research issues that could be associated with urban growth. An immense quantity of scientific literature has demonstrated the negative impact of urban growth on resources such as agriculture, timber, surface and groundwater resource quality, and energy resources [22-35]. As urban areas continue to grow, sustaining increasing population sizes creates larger demands on surrounding resources including water. The multiplicative demand on water, for instance (drinking, infrastructure, outdoor recreation, tourism, etc.) places a large stress on water resources that may already be exacerbated by climate and other environmental changes. Urbanization’s demand on water resources can be seen with the recent water crisis in Cape Town, South Africa, and Lake Mead near Las Vegas, Nevada [36-38]. It is therefore crucial to monitor and investigate the surrounding water resource health near rapidly urbanizing areas to proactively implement water resource management plans.

2.3 Water Resources

Tennessee contains 909 square miles of water surface area with an estimated length of 60,417 miles of rivers, streams, and creeks [39,40]. Water resources are a large role in the Tennessee economy, being used for commerce, agriculture, power generation, recreation and transportation. The Tennessee Valley Authority as of September 2016 operates 19 hydroelectric dams and several other power plants that require water for steam generation [41]. The economic impact of Tennessee’s waterways is seen by the transportation of over 34 million tons of cargo with a total value of nearly 8.1 billion dollars reported for 2012 [42]. Aside from energy generation and commerce, Tennessee’s water resources provide housing and recreation
attractions for residents and tourists alike. A recent study from the University of Tennessee Institute of Agriculture estimated that the man-made lakes and reservoirs on the Tennessee River in the TVA network generates roughly 11.9 billion dollars in economic impact annually through aquatic recreation, entertainment and waterfront property. This figure roughly equates to an impressive 1 million dollars per shoreline mile [43,44].

Chattanooga has a strong relationship with its surrounding environment, relying on it for utilities, commerce, recreation and tourism. Located upriver from downtown Chattanooga, the TVA operates Chickamauga Dam, generating an average net 119 megawatts a day [45]. Downtown Chattanooga lies directly adjacent to the Tennessee River, and has several major parks and trails following along the riverfront. These parks are often used to host outdoor recreation and entertainment such as music festivals, regattas, and triathlons The parks, along with other attractions such as the 120-million dollar downtown Riverwalk, have earned Chattanooga multiple national awards for best outdoor city [46,47]. The city of Chattanooga reported that tourism alone generated 1 billion dollars for the economy in 2015, with the largest attraction, the city’s Aquarium, being along the Tennessee River [48]. These awards and the revenue generated by tourism reflect the impact that the environment and outdoor attractions on the suitably nicknamed “Scenic City”.

2.4 Economic Growth in Chattanooga

Chattanooga’s population boom is primarily attributed to the rapid economic growth in its six county metropolitan area in southeastern Tennessee and northwestern Georgia [49]. The metropolitan area has been ranked in the top ten metropolitan cities in the Southeast, U.S. for job growth in 2017 (9th) with a national rank of 21st [50]. In 2017, the Chattanooga metro area
added slightly more than 11,200 jobs reducing the region’s unemployment rate to 3.4%, which is the second lowest on record with the lowest record being 3.2% in September of 2017 and a 30% decrease in unemployment since 2016 [51]. Chattanooga is home to several large organizations such as Volkswagen, Unum, Tennessee Valley Authority, Blue Cross Blue Shield, Wacker, and Amazon that are driving the area’s economic growth. These companies employ a significant amount of the local population and have invested large amount of resources into the area, including Volkswagen’s 1-billion-dollar factory or BlueCross’ 300-million-dollar campus on Cameron Hill, located within downtown Chattanooga [52,53]. The economic growth of the city is heavily attributed to the implementation of fiber optic internet by the City’s Electric Power Board (EPB) having 1 gigabit and now 10 gigabytes of service. It was found that within a four-year period between 2011 – 2015 the fiber optic infrastructure generated roughly 1 billion dollars in economic and social benefits. With multiple large corporations continuing to expand, a nationally ranked internet infrastructure, and a supported nickname as the “Scenic City”; Chattanooga economic and social environment is becoming increasingly attractive to startup businesses. The city has also designated a 140-acre portion of the downtown area for startups, small business, nonprofits and government offices called the “Innovation District” [54].

Tennessee’s government is expecting to see its population double in the next fifty years, and to address this growth, the governor has appointed a committee to establish a plan for future water availability [55]. Substantial population growth projections are also mirrored for the metropolitan area population of Chattanooga. The metro area within Tennessee is expected to grow by 40.8% by 2070; adding another 164,010 residents alone [56]. Economic projections for the Chattanooga area are optimistic for continued growth. Local officials and businesses point to recent developments such as nearby Huntsville, Alabama securing a Toyota-Mazda production
plant as opportunities to expand Chattanooga’s burgeoning automobile industry [57]. With continued growth projections for both population and economy, Chattanooga housing is increasing both in size and in cost. U.S. Census Bureau data on Chattanooga’s housing burden percentage, those paying more than 30% of their income on rent, has increased by 11.9% to 47.8% as of 2015. As housing and development continues to grow, some community organizations are beginning to have concerns about these changes [58-60].

2.5 Chattanooga’s Pollution Legacy

Although Chattanooga has received numerous awards recently for outdoor recreation, livability and appeal, the city has an infamous past as being regarded the most polluted in the United States. In 1969 Walter Cronkite, a Consumer News and Business Channel national anchor, reported that Chattanooga is “the nation’s dirtiest city” after revealing federal findings that Chattanooga has the worst air quality out of any city in the U.S. due to the large amounts of loosely regulated industry downtown [61-63].

The city’s legacy with water resource issues is also tied to its industrial history with several large industries being on or nearby local waterways and causing heavy, historic contamination of the local water resources [64]. The most significant example of Chattanooga’s historic impact on local waterways is Chattanooga Creek. This waterway is currently listed as an EPA superfund site and has been since 1995 due to extensive industrial dumping. Since listing, the EPA, along with regional and local agencies and potentially responsible parties, to conduct several projects to clean up and restore the creek. However, Chattanooga Creek is still currently listed as a superfund site and a fish consumption advisory is still in place [65-67]. Other local Chattanooga waterways (e.g. Stringers Branch) have also had issues with historic pollution [68].
While Chattanooga has made great strides towards improving local water resources, excessive pollution still occurs. On January 8th, 2018 more than 1,000 gallons of petroleum-based fuel was spilled into Citico Creek, located near downtown Chattanooga and a tributary to the Tennessee River [69]. Even after the completion of the spill clean-up, local and regional officials are unsure about the full impact of this event [70,71].

Chattanooga’s water quality has been the topic of a few studies in recent years. Schorr et al. [72] conducted an assessment of water quality and aquatic biota in Chattanooga area streams partnering with the municipal Stormwater Management office. Although the assessment recorded water quality for several streams, it did not make any quantitative assessments on relationship between water quality and land use and land cover (LULC). There have been some investigations into relationships between Chattanooga’s water resources and surrounding land cover. Long and Schorr [73] investigated urban land use at the watershed scale in the Chattanooga area and its effects on selected streams. They found that urbanized watersheds were negatively correlated with fish species diversity and biotic integrity and that this negative correlation was related in part to high levels of sedimentation.

2.6 Urbanization and Surface Water Quality

The relationship between urban growth and surface water quality has been investigated in several urban areas [1,74-76]. Urbanization in surface water quality studies is often used an umbrella term for several specific urban LULC types including IS, commercial land use, high density residential land use, and commercial-residential mixed land use. Surface water quality can be characterized through specific parameter measurement differences to historic records and/or to undisturbed location levels in urban growth water quality studies. These spatiotemporal
measurements are then related to surrounding land use types to determine possible land use effects on water quality parameters. There is a significant quantity of literature detailing negative relationships between urban LULC growth and surface water quality; example parameters researched and supporting literature can be found in Table 2.1 below. All parameters listed in Table 2.1 have been found to be adversely affected by the listed land use types; with measured parameter levels all being higher than natural levels, (except dissolved oxygen which is found to be lower). Overall, urbanized watersheds have been found to have significant impacts on surface water resources including degraded water quality, habitat and biota. There has been research and assessments conducted on Chattanooga area water quality and it was concluded that urbanized watershed catchments have had degraded water quality [72,73]. However, there has not been any research investigating the amount of urban growth Chattanooga has experienced and its influence on surface water quality.

2.7 Land Use and Land Cover Change and Urbanization

Urban growth is the change in LULC for and by anthropogenic activities such as residential, commercial and industrial development. Growth is commonly quantified through LULC detection analysis of selected classes such as agricultural, open field, urban, forest, wetland and barren. Quantitatively assessing urban growth requires defining which LULC categories should be considered urban. For the USGS National Land Cover Database [77-79] urban land cover is defined by spatial intensity of developed land which is the percentage of IS per unit area. Other efforts to map urban growth use the amount of detectable IS to measure urban extent [80-83]. IS are defined as being composed of materials such as asphalt, concrete, and metal that slows or inhibits water infiltration to top-soil. These surfaces therefore include
building rooftops, sidewalks, parking lots, and roads, which the amount of land cover composed of IS can then be related to urban growth; as these surfaces account for a wide range of urban associated LULC.

Remote sensing has been established as an effective method for investigating urban growth due to the differing visible and spectral differences between LULC classes [84-88]. Urban growth detection using remote sensing has been used to investigate changes across a range of temporal and spatial scales due to the advantages offered by various remote sensing technologies. Through these investigations, numerous image processing techniques have been developed or utilized to improve LULC research accuracies including: Tasseled Cap Transformation (TCT), Normalized Difference Built-Up Index (NDBI), Index-based Built-Up Index (IBI), Normalized Difference Vegetation Index (NDVI) and supervised classification schemes such as density slicing [11,12,85,89-93]. IS growth has been investigated using remote sensing and is often paired with water quality investigations due to the established relationship between the two variables [94-96].
Table 2.1  Selected water quality variable associations with urbanized land cover types. The relationship is given by the general impact of the land cover on the parameter. A positive (+) or negative (-) symbol shows the parameter concentration response to increases in specified land cover.

<table>
<thead>
<tr>
<th>Water quality variable</th>
<th>Land cover association</th>
<th>Parameter concentration</th>
<th>Literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total suspended solids (TSS)</td>
<td>General Urban, IS</td>
<td>+</td>
<td>[97-99]</td>
</tr>
<tr>
<td>Turbidity</td>
<td>General Urban</td>
<td>+</td>
<td>[99-101]</td>
</tr>
<tr>
<td>Dissolved solids</td>
<td>Commercial</td>
<td>+</td>
<td>[5,99,102]</td>
</tr>
<tr>
<td>Dissolved oxygen (DO)</td>
<td>General Urban, IS, Residential, Commercial</td>
<td>-</td>
<td>[1,103-105]</td>
</tr>
<tr>
<td>Heavy metals</td>
<td>General Urban, Residential, Commercial, Industrial</td>
<td>+</td>
<td>[75,106,107]</td>
</tr>
<tr>
<td>Conductivity</td>
<td>General Urban, IS, Commercial, Residential and Agricultural</td>
<td>+</td>
<td>[73,103,108]</td>
</tr>
<tr>
<td>Temperature</td>
<td>General Urban, IS</td>
<td>+</td>
<td>[108-110]</td>
</tr>
<tr>
<td>pH</td>
<td>General Urban, IS</td>
<td>+</td>
<td>[108,111,112]</td>
</tr>
<tr>
<td>Total nitrogen (TN)</td>
<td>Commercial, Residential and Agricultural</td>
<td>+</td>
<td>[100,103,104]</td>
</tr>
<tr>
<td>Total phosphorus (TP)</td>
<td>Residential</td>
<td>+</td>
<td>[102,103,105]</td>
</tr>
<tr>
<td>Ammonia</td>
<td>General Urban</td>
<td>+</td>
<td>[106,113,114]</td>
</tr>
<tr>
<td><em>E. coli</em></td>
<td>General Urban, IS</td>
<td>+</td>
<td>[108,115,116]</td>
</tr>
<tr>
<td>Algae (chlorophyll)</td>
<td>Urban General, IS</td>
<td>+</td>
<td>[117-119]</td>
</tr>
<tr>
<td>Fecal coliform</td>
<td>General Urban, IS, Commercial, Residential and Agricultural</td>
<td>+</td>
<td>[98,103,115]</td>
</tr>
</tbody>
</table>
2.8 Urban Growth and Riparian Areas

The land immediately surrounding water resources is considered riparian areas. These zones can be described as a range of area adjacent to water resources including areas 100 meters (m) away and further [120]. The conservation and protection of forest riparian land is critical as they act as buffers between the flow of matter from upland areas into hydrologic resources and have a strong influence on the surrounding water resource quality [121]. They are attributed with mitigating the flow of sediment and nutrients from surface and groundwater into adjacent water resources [122], effects on fish assemblages [123] and other physiochemical water quality variables [124,125]. As with other critical habitats LULC development poses a significant threat to riparian areas by compromising the buffer’s ecological integrity and altering buffer areas landscape [105,126]. Research has suggested that vegetated buffers of a minimum of 30m is needed to act as a functioning non-point source pollutant control [127].

Acting as a non-point source pollutant, IS proximity to water resources and the respective riparian buffer have also been found to affect water quality [8,128,129]. Riparian buffer LULC can have a better ability to predict stream surface water quality leading to an increase in research and government attention to understanding and protecting these corridors [130,131]. Other research has found that the composition of riparian land cover has a slightly better ability to predict stream water chemistry than watershed land cover [132]. Threshold percent imperviousness values for stream riparian zones that have been found to begin indicating stream impairment begin at 10% cover [133].
2.9 Mapping Urban Growth

Traditional methods for investigating LULC change has been primarily through in-situ surveying with measurements also conducted via aerial photograph digitization. These methods can provide accurate, detailed information but are limited temporally and spatially due to resources. Remote sensing GIS allow for the mapping and analysis of historical and current LULC across larger areas than traditional methods [134]. Remote sensing data acquisition also have the ability for routine temporal data collection of the same area of interest which allows for stronger change detection analyses [135]. Since remote sensing and GIS acquisition and analysis of LULC data has been established, it presents a more temporal and fiscal affordable option for investigating urbanization.

Acquisition of LULC data is primarily conducted by satellite based optical sensors due to the ability to differentiate different types of LULC classes by their spectral responses in the EMS [136,137]. The partnered USGS and NASA Landsat mission is noteworthy for its extreme use in LULC studies with the Landsat mission starting in 1972 and continued sensor improvements [138]. Data from the Landsat missions have been used for the creation of a National Land Use Classification Dataset (NLCD) by the Multi-Resolution Land Characteristic Consortium (MRLC) to generate an accurate nationwide land cover map every five years.

Optical satellite sensors, including Landsat, have been well established for mapping urban growth, including IS [4,81,139-141]. While optical sensors are the primary data source used for LULC detection, there have been efforts to use active sensor technologies such as Synthetic Aperture RADAR (SAR) or light Detection and Ranging (LiDAR) for urbanization investigations due to the unique physical characteristics of many primary land cover features associated with urban areas such as buildings and roads [142,143]. Studies combining the two
sensing technologies have found that the data fusion can increase model accuracy and information extraction [144,145].

Impervious surface mapping using multispectral remote sensing technologies has been suitably established [4,95,146]. The use of NDVI is common for IS mapping by finding threshold values for water and vegetation in attempt to isolate IS [147-149]. Supervised and unsupervised classification algorithms to extract spectral signature classes that can be assigned LULC values is also commonly used, however traditional classification algorithms can confuse LULC classes such as bare or dry soils, shadowed areas caused by oblique image collection and wetlands due to similar spectral signatures [147]. Spectral mixing techniques such as linear spectral mixing and multiple endmember spectral mixture analysis have been found successful for IS mapping but require significant data collection and processing for accurate results [150-154].

2.10 Analysis Techniques

The use of remote sensing and GIS can be highly beneficial; however, current image processing and geospatial analysis techniques may not be sufficient for accurately characterizing non-linear or complex urban growth relationships or predicting future urban growth [155-159]. Regression models and machine learning in these applications are therefore used to increase modeling accuracy and information extraction and offer predictive modeling capabilities. Regression models have been used to relate historic urban growth to various socioeconomic variables [160,161], changes in multiple water quality parameters [98,162], and predict future urban growth [163,164] is well documented and have been concluded effective. Machine learning is a narrow type of computer artificial intelligence that uses a pre-determined algorithm
to be optimized on training datasets such as the target dataset which it analyzes for algorithm parameter optimization. The result is a trained algorithm for a specific task that can be used for regression or classification analyses either by supervised or unsupervised methods [165-167]. Machine learning based algorithms using support vector machines, decision tree, random decision forest (random forest) and classification and regression tree algorithms have been found to be accurate when used for urban growth studies [157,168,169]. Although found successful for urban growth research, machine learning algorithms often require large datasets for training and validation which can be prohibitive for some research.

2.11 Statement of the Problem and Scope of the Study

A review of relevant literature on this subject matter, described above, indicates that urban growth can have negative impacts on surface water quality and that the greater Chattanooga, Tennessee area has experienced rapid population and economic growth in past the past 30 years [7,17,40,170,171]. The majority of literature on this subject points to the arrival of new business and residents could negatively impact the surrounding environment due to the creation of more urban LULC [172-174]. These new or established developments could cause stress on the nearby water resources. This literature review presents a strong case for researching possible relationships between urban growth and surface water quality in the greater Chattanooga area by using remote sensing, GIS, and data analytics.
CHAPTER 3

STUDY SITE

The study site used for this research are seven USGS Hydrologic Unit Code 12 (HUC-12) watersheds located centrally in Hamilton County, Tennessee as seen in Figure 3.1. The watersheds were chosen because the fate for surface hydrologic resources within them feed into the Tennessee River. Thus, having the potential for material to move from within the HUC-12 watersheds to the Tennessee River. The watersheds chosen are listed in Table 3.1 and can be referenced geographically in Figure 3.1.

Hamilton County is in the southeastern portion of Tennessee, located in the Appalachian Valley and is bisected by the Tennessee River. The county has a total land area of 1,403.8 square kilometers (km²) and a total water area of 86.3 km² [175]. Hamilton County is in the Southern Limestone/Dolomite Valleys and Low Rolling Hills area of the Ridge and Valley ecoregion [176]. The Valley and Ridge region is characterized as composed of Paleozoic (Cambrian to Pennsylvanian), composed of parallel ridges and valleys due to geologic folding and faulting. The study site lies in a complex geologic subregion that is primarily composed of carbonate rock such as limestone and dolomite; however, there is a considerable amount of shale, including Chattanooga shale, sandstone and other rock types [176,177]. Hamilton County’s elevation ranges from 655m to 191m [178].

The effects of watershed characteristics such as geology, topography, soil type, and LULC on surface water quality are well researched and documented. There have been findings that environmental factors such as geology, physiography, soils, climate and hydrology have
been found to affect surface water quality across most of Hamilton County [179]. Since the Tennessee Ridge and Valley ecoregion geology, topography and soil composition has remained unchanged for the past 50 years, spatiotemporal changes in surface water quality will therefore be associated with changes in LULC. This is supported by the USGS National Water-Quality Assessment conclusion that sediment contamination of surface stream water quality is persistent and nutrient loadings in subbasins for the Upper Tennessee River Basin are primarily influenced by land use and streamflow [180].

Table 3.1 The names of the HUC-12 watersheds selected for the study site with the ID used in Figure 3.1

<table>
<thead>
<tr>
<th>HUC-12 Watershed</th>
<th>Location ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nickajack Reservoir Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Reservoir Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Reservoir</td>
<td>G</td>
</tr>
</tbody>
</table>
Figure 3.1 Study site map which shows the seven selected HUC-12 watersheds within Hamilton County
A NASA Landsat satellite image of 1986 and 2016 were used for this study. A scene from Landsat 5 Thematic Mapper imagery acquired on January 24, 1986 was used to represent land cover for 1986, and a scene from Landsat 8 Operational Land Imager imagery acquired November 26, 2016 was used to represent land cover for 2016. Both satellite images in the RGB and NIR spectrums have a spatial resolution of 30m. The true color Landsat 5 TM image for the study site is shown in Figure 4.1 and the Landsat 8 OLI can be seen in Figure 4.2. A view of both Landsat images for the Lower South Chickamauga Creek watershed can be seen in Figure 4.3. Since the two images were collected by different Landsat sensors with a significant temporal gap between acquisition, atmospheric correction was needed to convert both images into the same radiometric scale [181]. The conversion of the image values to represent the surface reflectance requires the correction of atmospheric effects on exiting electromagnetic radiation, which is an important image pre-processing step [182,183]. The Landsat 5 TM scene reflectance values were generated using NASA’s Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software [184]. For the Landsat 8 OLI scene, NASA’s Landsat Surface Reflectance Code (LaSRC) was used to generate values [185].

LEDAPS was developed to correct for atmospheric interference for Landsat 5 TM and 7 Enhanced Thematic Mapper Plus digital value data (level 1 data). The method used for atmospheric correction on Landsat 5 and 7 data was derived from methods used to correct Moderate Resolution Imaging Spectroradiometer (MODIS). Environmental variables considered...
by LEDAPS include water vapor, ozone, geopotential height, aerosol optical thickness, and digital elevation. These variables along with the level 1 data are fed to the Second Simulation of a Satellite Signal in the Solar Spectrum radiative transfer model to generate corrected data. [184,186].

The LaSRC generates atmospherically corrected Landsat 8 OLI data using a different and improved methodology than the LEDAPS. This was accomplished by utilizing the MODIS surface reflectance Collection 6, Landsat 8 OLI aerosol and cirrus bands. The LaSRC also uses improved ancillary datasets for the environmental variables modeled. These new and or improved input data are then used in the Satellite Signal in the Solar Spectrum Vector radiative transfer model, an updated version of the radiative transfer model used in LEDAPS [187]. While the two atmospheric correction methods differ, both produce surface reflectance data; maintaining continuity during cross satellite platform data analysis. The surface reflectance values for these scenes were ordered from the USGS Earth Explorer site. Once processed, surface reflectance data from both models must be further processed by users to remove invalid data values generated by the models.

High resolution, multispectral aerial photographs from the United States National Agricultural Imagery Program (NAIP) collected in 2014 were acquired of the study site for the accuracy assessment portion of the study. NAIP imagery acquired for this study had a spatial resolution of 1m and included RGB and NIR bands. State boundary data was collected from the U.S. Census Bureau’s data server. Hydrologic boundary data were collected from the USGS National Hydrography Dataset Plus (NHDplus) and the city of Chattanooga Water Quality Program. Stream location data were collected from the USGS National Hydrography Dataset Plus and the city of Chattanooga GIS Office.
Figure 4.1 Landsat 5 TM image acquired on January 24, 1986 over the study site
Figure 4.2  Landsat 8 OLI image acquired on November 26, 2016 over the study site
Figure 4.3  Landsat 5 TM image (top) acquired on January 24, 1986 and a Landsat 8 OLI image (bottom) acquired on November 26, 2016 of the Lower South Chickamauga Creek HUC-12 watershed
CHAPTER 5

METHODOLOGY

5.1 Mapping Impervious Surfaces

The methodology used for this objective follows a standardized procedure for image processing presented by John Jensen [188]. The steps, when followed, will take raw image data and return a finished product. The digital image processing steps are, in order:

1. Image retrieval—the collection of the digital image and compiling of all individual bands into a composite layer;

2. Image pre-processing—the data quality assessment (cloud cover over the image, stripping, missing data, statistical evaluations, etc.) and reduction via area of interest selection.

3. Image rectification and restoration—radiometric corrections which are systematic errors that can be in the form of stripping. Scan line corrections or restorations can be performed on non-systematic errors which includes atmospheric corrections (calculating image radiance and or reflectance) and ortho-rectification to correct for topographic errors; geometric corrections are also conducted during this step.

4. Image enhancements—analyses can be performed and include contrast/brightness adjustments, band rationing and indices (such as NDVI), spatial filtering such as moving window, and raster data math such as principal component analysis (PCA).

5. Feature and information extraction—the use of parametric (supervised classification such as maximum likelihood or parallelepiped), non-parametric (unsupervised classification,
6. Image post-processing—the use of spatial filtering and accuracy assessment of the image classification process.

The data used for this objective had most of the image pre-processing and image rectification and restoration steps completed prior to collection. Once the Landsat data and NAIP imagery were collected, necessary bands for each dataset were masked to the study site and stacked to create RGB and NIR composite imagery. The model designed for this objective is based upon the application of NDVI to map IS due to breaks in NDVI values for different land covers, which can be used to isolate IS areas. To assist in land cover isolation the NIR band was used to separately classify water resources and the green band for shadows in both images. The overall model for IS location extraction can be visualized with Equation 1.

\[
IS_{Data} = IS_{NDVI} - Shadow_{Green} - Water_{NIR}
\]

where \(IS_{NDVI}\) represents a NDVI image that has classified IS and vegetated areas, \(Shadow_{Green}\) represents a dataset using the green band of a Landsat sensor that has classified shadows and \(Water_{NIR}\) represents a dataset using the NIR band of a Landsat sensor that has classified surface waterbodies. Subtraction in Equation 1 is used to represent the removal of non-IS surfaces from the classified NDVI dataset via the classified Green and NIR datasets.

Descriptions for the image enhancements, information extraction and image post-processing used to the model are described below. All analyses for this objective was conducted using ArcGIS Pro GIS software [189]. Bar charts and statistical tests applied were conducted in the Jupyter Notebook environment using Python scripting language [190].
5.1.a Image Enhancement

The primary component of the model used for this objective was the implementation of the NDVI. This index, seen in Equation 2, uses the near infrared (NIR) and red (R) portions of the EMS.

\[
\text{NDVI} = \frac{(\rho_{\text{NIR}} - \rho_{\text{R}})}{(\rho_{\text{NIR}} + \rho_{\text{R}})}, \quad (2)
\]

where \(\rho_{\text{NIR}}\) is the surface reflectance value of NIR and \(\rho_{\text{R}}\) is the surface reflectance value of R. NDVI was originally developed to map green vegetation which has a sharp contrast in the amount of absorption of red wavelengths compared to near infrared [191]. Green vegetation has a high absorption of light in the red portion of the EMS while reflecting a significant portion of the NIR portion; this response is driven primarily by the vegetation’s photosynthetic activity [192]. This difference in EMS absorption causes areas of healthy, green vegetation to have large, positive values from NDVI. This index can also be used to map other non-vegetated land covers, primarily water and IS, due to each land cover’s distinct interactions with red and NIR wavelengths [84]. Where IS have close to equal reflection of both red and NIR light, they generate NDVI values close to 0 [11,193]. Negative NDVI values indicate non-vegetated areas often consisting of water [194]. A NDVI was generated for each image, to separate the vegetated and non-vegetated areas [191]. This concept of mapping vegetation to subsequently extract exposed IS has been previously established as an alternative method for estimating IS [9,195]. The Landsat 5 TM NDVI equation can be seen in Equation 3 and the Landsat 8 OLI NDVI equation can be seen in Equation 4.

\[
\text{Landsat 5 TM NDVI} = \frac{(\rho_{\text{B4}} - \rho_{\text{B3}})}{(\rho_{\text{B4}} + \rho_{\text{B3}})}, \quad (3)
\]

where \(\rho_{\text{B4}}\) and \(\rho_{\text{B3}}\) represent the reflectance values of NIR and R, respectively.
Landsat 8 OLI NDVI = \frac{(\rho_{B5} - \rho_{B4})}{(\rho_{B5} + \rho_{B4})}, \quad (4)

Where \(\rho_{B5}\) and \(\rho_{B4}\) represent the reflectance values of NIR and R, respectively. Figure 5.1 shows the NDVI image generated for 1986 and Figure 5.2 shows the NDVI image for 2016. Figure 5.3 shows the NDVI images of both dates for the Lower South Chickamauga Creek watershed.
Figure 5.1  NDVI image of the study site for January 24, 1986
Figure 5.2   NDVI image of the study site for November 26, 2016
Figure 5.3 NDVI image of the Lower South Chickamauga Creek watershed for January 24, 1986 (top) and November 26, 2016 (bottom) of the study site.
5.1.b Image Classification

To classify desired land covers, density slicing classification was performed. This supervised classification method requires the researcher to determine the spectral response range of desired variables from a single layer image. This is conducted by an initial manual or statistical based classification of an image based on the distribution of the pixel values. Then continued re-classification is conducted by adjusting pixel value threshold until the desired landcover has been effectively isolated. Reclassification and verification can be improved using reference location data, which can be colored imagery and/or pre-labeled reference areas.

Density slicing technique was applied on the generated Landsat 5 and Landsat 8 NDVI images to classify the IS and vegetated areas. Density slicing was also used to categorize waterbodies using the NIR band and shadows with the green band for each date. To assist in classification for each date the true color Landsat image was used as a visual reference for each date. Reference polygons were used to assist in determining IS land cover threshold values for both 1986 and 2016. Figure 5.4 and Figure 5.5 show the density slicing reference locations used. Figure 5.6 shows examples of reference polygons for both 1986 and 2016 with the NDVI image and true color image for comparison. During density slicing repeated inspection of these anchor points were conducted to gauge the effectiveness of the used pixel threshold values. Table 5.1 gives the threshold values determined for each class.
Table 5.1  The threshold values for density slicing classification for the 1986 Landsat 5 TM and 2016 Landsat 8 OLI images

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Year</th>
<th>Data</th>
<th>Threshold Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shadows</td>
<td>1986</td>
<td>Green Band</td>
<td>[142, 330]</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>Green Band</td>
<td>[33, 225]</td>
</tr>
<tr>
<td>Vegetation</td>
<td>1986</td>
<td>NDVI</td>
<td>(0.255873, 0.790147)</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>NDVI</td>
<td>(0.385, 0.902)</td>
</tr>
<tr>
<td>Water</td>
<td>1986</td>
<td>NIR Band</td>
<td>[38, 350]</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>NIR Band</td>
<td>[4, 190]</td>
</tr>
<tr>
<td>IS</td>
<td>1986</td>
<td>NDVI</td>
<td>(-0.02992, 0.255873)</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>NDVI</td>
<td>(-0.09, 0.385)</td>
</tr>
</tbody>
</table>
Figure 5.4  NDVI of the study site for January 24, 2016. Red boundaries denote the location of reference areas for density slicing classification.
Figure 5.5 NDVI of the study site for November 26, 2016. Red boundaries denote the location of reference areas for density slicing classification.
Figure 5.6  Density slicing classification reference location comparisons using NDVI and true color images for 1986 and 2016. (A) shows a reference polygon used for the 2016 classification. (B) shows a reference polygon used for the 2016 classification. (C) shows a reference polygon used for 1986 classification.
5.1.c Dataset Compilation

Using raster algebra, the final IS dataset for each date was created by combining the classified NDVI, green band and NIR band datasets using a nested conditional statement executed with the ArcGIS raster calculator tool. The conditional statement isolated each desired land covers from each dataset and returned a single dataset containing all the classified classes. The resulting datasets were then reclassified into a binary impervious surfaces-pervious and other surfaces dataset which is the final IS dataset. The IS dataset is seen in Figure 5.7 for 1986 and Figure 5.8 for 2016.
Figure 5.7  Detected IS for the study site on January 24, 1986 as observed by Landsat 5 TM
Figure 5.8 Detected IS for the study site on November 26, 2016 as observed by Landsat 8 OLI
5.1.d Accuracy Assessment

Zonal statistics was used for the accuracy assessment of the IS model for 2016. This was conducted by digitizing 140 randomly located reference IS areas within the study site. Figure 5.9 shows the locations for the 2016 reference IS areas. Each HUC-12 watershed contains 20 of the digitized reference polygons. Every reference IS polygon covers an area equal to 15m². The NAIP dataset was used as the source of these reference IS polygons. A majority count zonal statistic was applied to the digitized reference polygons overlaying the impervious dataset. This was conducted to determine if the majority of the classified pixels covered by the reference polygons were impervious or pervious. Due to resource constraints, it was not possible to obtain high resolution aerial photography to generate reference polygons to evaluate the 1986 dataset. In this case a true color Landsat 5 TM image was used to obtain the 140 reference polygons. The reference polygons digitized using the NAIP data that contained 100% IS on the Landsat 5 TM image were used for the accuracy assessment. Only 60 polygons digitized with NAIP imagery represented 100% IS cover in 1986. These polygons were then used to assess the accuracy of the 1986 IS dataset following the methods used for the 2016 dataset.
Figure 5.9  Locations of the IS reference sites (truth data) used for calculating Zonal Statistics. Yellow points represent individual polygon locations. The sites were randomly selected on a color orthoimagery (2014 NAIP image) with twenty polygons per watershed. Each site covers an area of 15m$^2$. 

Table: Watershed ID

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nickajack Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Elza Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>
A confusion matrix and Cohen’s Kappa-coefficient (k) were calculated for each date. The Kappa statistic has been shown to be an effective measure of a classification model in remote sensing and other scientific fields, due each ability to evaluate on the interclassifier agreement and remove the bias [196-198]. Kappa statistics evaluated the performance of the IS classification models by calculating the User (Type I error or false positive) and Producer’s accuracy (Type II error or false negative) for each class, the proportion of pixels correctly classified (PCC), and Kappa-coefficient of agreement. The Producer’s accuracy reports the error of omission created by the model, quantifying the amount of each class that have not been correctly classified. The equation for the Producer’s accuracy is shown as Equation 5.

\[
\text{Producer’s Accuracy} = \frac{C_T}{C_T + O_C}
\] (5)

where \(C_T\) is the amount of a class C that is correctly classified, and \(O_C\) is the sum of other classes that were classified as C. The User’s accuracy reports the error of commission which is the amount of other class that have been classified incorrectly. The equation for the User’s accuracy is shown as Equation 6.

\[
\text{User’s Accuracy} = \frac{C_T}{C_T + C_E}
\] (6)

where \(C_E\) is the sum of the class that are incorrectly classified. The PCC is calculated by dividing the total number of correctly classified pixels by the total number of pixels classified. The equation for calculating overall accuracy of a classification model is shown as Equation 7.

\[
PCC = \frac{n_T}{n}
\] (7)

where \(n_T\) is the sum of correctly classified subjects and \(n\) is total subject sample size. The Kappa-coefficient of agreement (k) describes the accuracy of the classification model compared to
random classification on the assumption that some of the pixels could have been classified correctly by chance. The equation for finding the Kappa-coefficient is shown as Equation 8.

\[ K = \frac{P_O - P_E}{1 - P_E} \] (8)

where \( P_O \) is the observed agreement of classification, \( P_E \) is the chance agreement of classification and 1 represents maximum agreement. To calculate \( P_O \) and \( P_E \) Equations 9a and 9b were used.

\[ P_O = \frac{O_D}{n} \] (9a)

\[ P_E = \frac{E_D}{n} \] (9b)

where \( O_D \) is the sum of the observed frequencies along the diagonal in the confusion matrix, \( E_D \) is the sum of expected frequencies along the horizontal and \( n \) is the total number of subjects. To generate the confusion matrix 250 randomly stratified accuracy assessment points were generated for each date. These points were validated using the relevant Landsat image. For 2016, the NAIP imagery from 2014 was also used to assist in accuracy point validation. The location of the assessment points of the confusion matrix generation can be seen in Figure 5.10 for 1986 and 5.11 for 2016.
Figure 5.10  Location of the accuracy assessment points for calculating Kappa Statistics for the 1986 IS
Figure 5.11  Location of the accuracy assessment points for calculating Kappa Statistics for the 2016 IS
5.2 Water Resource Proximity Analysis

To understand the spatial relationship of the IS growth regarding water resources within the study site, IS change per HUC-12 watershed and stream riparian areas was measured. The detected IS datasets were masked by each of the selected HUC-12 watershed boundaries for quantification of the IS change in each HUC-12 watershed. IS area was calculated using the quantity of IS pixels and a conversion factor (30mx30m) to present the values be in km\(^2\).

For the stream analyses, streams within the study site were extracted from the NHDplus dataset and combined with auxiliary data from the city of Chattanooga Water Quality Program. The first stream analysis was performed by creating buffer distances of 30m, 60m, and 90m on both sides of the collected streams. A map showing the stream buffers generated can be seen in Figure 5.12. After the buffers were generated, they were clipped by each of the HUC-12 watersheds to create separate watershed riparian buffer boundaries. The following features were then used to extract IS from both IS datasets. IS area was then calculated in km\(^2\) for each of the buffer features using the quantity of IS pixels and a pixel resolution conversion. The proximity analysis was conducted in ESRI’s ArcGIS Pro GIS environment and bar charts for result reporting were generated using the Python scripting language in the Jupyter notebook environment [190].
Figure 5.12 Stream Buffers generated to represent riparian zones
5.3 Assessing Stream Risk

To assess the probability of stream impairment due to IS change, a model was developed for this study to independently assess streams for their potential risk. It evaluates stream segments to provide further detail regarding sections of streams that may have higher risk due to new or existing development. Additionally, the model accounts for not only the quantity of change but the proximity of change to the stream. During the risk assessment, percent imperviousness was calculated and recorded. The risk assessment was conducted in ESRI’s ArcGIS Pro GIS environment. The bar charts were generated using the Python scripting language in the Jupyter notebook environment [190].

5.3.a Stream Segmentation

To segment the stream dataset, points were generated every 90m along the stream with points also placed at the ends of the stream and at the intersection of stream branching. These points were then used to splice the original stream dataset and act as endpoints for new, unique stream segments. A total of 12,910 stream segments were generated within the study site. Some generated segments were shorter than 90m due to stream branching and/or small stream segment lengths.

5.3.b Riparian Zone Generation

Both IS datasets were converted from pixels to points which represented the centers of the original pixels, allowing for a spatial join, which summarizes and then joins the attributes of features that meet a pre-determined spatial criterion, to be performed for points within 30m, 60m, and 90m of each stream segment. This zone of influence considers all land cover within
these distances from any point along the segment, including the start and end points. The attributes of each IS dataset were then summarized per segment of the stream in the zone.

These results allowed for quantifying and locating the IS growth around each stream segment within the study site. Quantification of the amount of IS development were normalized using the number of points within the zone to account for shorter stream segments. The normalization by area generated a percent imperviousness value per zone of influence surrounding each stream segment. By subtracting the 30m zone results from the 60m zone results and the 60m zone from the 90m zone, the area with each segment can be partitioned into three evenly spaced, 30m wide riparian zones. This relationship between spatial join buffer sizes and riparian zone creation can be seen in Table 5.2. Figure 5.13 visualizes how each segment considers the points within the zone of influence and how the percent imperviousness for the riparian area is generated. The model is based on the understanding that riparian areas up to 150m from the stream can have significant impacts of stream water quality [199]. The proximity of the development is considered to have a stronger impact on the stream than the development occurred farther away [200].

Table 5.2  Riparian buffer interval distance from streams and equivalent stream buffer variables

<table>
<thead>
<tr>
<th>Interval Distance Range from Stream</th>
<th>Variable</th>
<th>Buffe</th>
</tr>
</thead>
<tbody>
<tr>
<td>0m - 30m</td>
<td>X₁</td>
<td>X₂</td>
</tr>
<tr>
<td>30m - 60m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>60m - 90m</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Buffer Distance Range from Stream</th>
<th>Variable</th>
<th>Interval Equivalent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0m - 30m</td>
<td>X</td>
<td>X₁ + X₂ + X₃</td>
</tr>
<tr>
<td>0m - 60m</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>0m - 90m</td>
<td>Z</td>
<td></td>
</tr>
</tbody>
</table>
Figure 5.13 Visual description of how stream segment percent imperviousness was calculated for the stream risk assessment. Assigned color and number ID are used to aid in identifying segment-buffer pairs. An example chart is given to describe the attributes calculated from the segment-buffer pair and the resulting percent imperviousness.

5.3.c Relating IS Development Proximity and Quantity to Risk

A linear weighted model was then developed and applied to each segment to calculate the probability of surface water impairment due to the distance and magnitude of percent impervious in each riparian zone. This model can be seen in Equation 10.

\[
\text{IS proximity risk model} = (W_3 \times X_1) + (W_2 \times X_2) + (W_1 \times X_3)
\]  

(10)
where $X_1$, $X_2$, and $X_3$, represent the percent imperviousness (normalized) within the three separate 30m riparian zones, and $W_1$, $W_2$, and $W_3$, represent the IS-stream influence weight. The values for the IS-stream influence weight are shown as the subscript numeral. The weights were incorporated arbitrarily using the values of 1 – 3, where the value of 3 represents the most influential, 2 represents the moderately influential and 1 represents the least influential. These values reflect that usually the influence of the growth of IS on the stream is inversely related to the distance to the stream. That is, the stream will have more influence from the nearby development. The output of this model indicates which portions of the streams, within the study site, that have an increased probability of being impaired due to the surrounding IS development.
CHAPTER 6
RESULTS AND ANALYSIS

6.1 IS Mapping

6.1.a Accuracy Assessment

Zonal Statistics

According to the results of zonal statistics, the accuracy for the IS classification of 1986 was 88.3%. That is, 53 of the 60 reference polygons were correctly classified as IS. The accuracy for the IS classification of 2016 was 90%. That is, 126 of the 140 reference polygons were correctly classified as IS.

Kappa Statistics

The confusion matrix prepared for 1986 is shown in Table 6.1. The overall accuracy reported by the confusion matrix for 1986 is 90.0%. The Kappa-coefficient calculated is 0.624 showing that the model for 1986 classified 62.4% better than a random classification of the data. The confusion matrix prepared for 2016 is shown in Table 6.2. The overall accuracy reported by the confusion matrix for 2016 is 84.8%. The Kappa-coefficient calculated is 0.545 showing that the model for 2016 performed 54.5% better than a random classification.
Table 6.1  Confusion matrix for the 1986 Landsat 5 TM IS classification

<table>
<thead>
<tr>
<th>Classification</th>
<th>Other</th>
<th>Impervious</th>
<th>Total</th>
<th>User’s Accuracy</th>
<th>Kappa (k)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other</td>
<td>198</td>
<td>12</td>
<td>210</td>
<td>94.3%</td>
<td></td>
</tr>
<tr>
<td>Impervious</td>
<td>13</td>
<td>27</td>
<td>40</td>
<td>67.5%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>211</td>
<td>39</td>
<td>250</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Producer’s Accuracy</td>
<td>90.0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Kappa (k)</td>
<td>0.624</td>
</tr>
</tbody>
</table>

Table 6.2  Confusion matrix for the 2016 Landsat 8 OLI IS classification accuracy

<table>
<thead>
<tr>
<th>Classification</th>
<th>Other</th>
<th>Impervious</th>
<th>Total</th>
<th>User’s Accuracy</th>
<th>Kappa (k)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other</td>
<td>178</td>
<td>16</td>
<td>194</td>
<td>91.7%</td>
<td></td>
</tr>
<tr>
<td>Impervious</td>
<td>22</td>
<td>34</td>
<td>56</td>
<td>60.7%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>200</td>
<td>50</td>
<td>250</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Producer’s Accuracy</td>
<td>84.8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Kappa (k)</td>
<td>0.545</td>
</tr>
</tbody>
</table>

6.2 Water Resource Proximity Analysis

6.2.a HUC-12 Watershed Development

The total HUC-12 IS area calculations performed on this study’s model show that there has been significant growth in the study site as shown in Figure 6.1 and described in Table 6.3. The net growth within the study site was 45.12 km². This growth was not spatially equal in its distribution and occurred heavily in the Lower South Chickamauga Creek watershed with an
increase of 24.3 km² of IS. The Lower South Chickamauga Creek watershed had the largest percent increase in impervious development with a change from 24.2 to 48.5 km² equaling slightly more than a 100% increase in impervious area. The IS datasets for Lower South Chickamauga Creek are shown in Figure 6.2. All but the Chattanooga Creek watershed showed an increase in IS with development being less than 10 km² in each area. Finally, the Chattanooga Creek watershed had a small decrease in IS area, decreasing by 0.01 km².

![Impervious Surface Cover Area in 1986 and 2016](image)

**Figure 6.1** The chart shows a comparison between the IS areas mapped for January 24, 1986, and November 26, 2016 for the different HUC-12 watersheds

**Table 6.3** IS cover area detected using Landsat 5 TM for January 24, 1986 and Landsat 8 OLI for November 26, 2016. Area is broken into the seven HUC-12 watersheds that form the study site

<table>
<thead>
<tr>
<th>IS Data Area in Square Kilometers</th>
<th>1986</th>
<th>2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>HUC Watershed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chattanooga Creek</td>
<td>20.12</td>
<td>20.11</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>7.42</td>
<td>14.24</td>
</tr>
<tr>
<td>Tennessee River - Nickajack Lake Upper</td>
<td>37.93</td>
<td>40.31</td>
</tr>
<tr>
<td>Tennessee River Chickamauga Lake Lower</td>
<td>9.26</td>
<td>13.91</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>24.23</td>
<td>48.48</td>
</tr>
<tr>
<td>North Chickamauga Creek lower</td>
<td>14.63</td>
<td>20.85</td>
</tr>
<tr>
<td>Blue Spring Creek - Chickamauga Lake</td>
<td>6.73</td>
<td>7.54</td>
</tr>
</tbody>
</table>
Figure 6.2 Changes in IS for the Lower South Chickamauga Creek watershed from January 24, 1986 to November 26, 2016
6.2.b Stream Riparian Development

The IS growth measured shows that there has been significant IS growth near selected streams in the study site. The results of this analysis can be seen in Table 6.4. In 1986, IS cover accounted for 14.9% of the total area within 30m of streams, increased to 18.1% by 2016. Compared to the change within 90m of streams, where in 1986, IS cover occupied 15.2%, increased to 20.9% by 2016. The net growth of IS within 90m of streams was 9.96 km². The total increase of IS within the first 30m was 2.04 km², with an increase of 3.43 km² between 30m and 60m, and 4.49 km² between 60m and 90m of streams. The average change in IS area for the 30m, 60m and 90m buffers in each HUC-12 watershed was 0.29, 0.49, and 0.64 km² respectively. IS development within 90m of streams accounted for 22% of the total IS development detected. Changes in IS extent within the stream riparian areas within the study site is shown in Figure 6.3, which shows the coverage of IS in riparian areas in green and the added extent in 2016 in red.

The North Chickamauga Creek Lower watershed experienced a decrease of 0.024 km² of IS within 30m of streams but reported large increases in IS for the 60m and 90m buffers. The Chattanooga Creek watershed experienced a decrease in IS within 30m and 60m of streams but did experience a small increase within 90m. There was growth for the remaining five watersheds at each buffer distance with similar trends found in the total HUC-12 IS area analysis. The Lower South Chickamauga Creek watershed showed the largest growth of IS development in each of the three distance zones. It experienced an increase of 1.35 km² within 30m of streams, 3.29 within 60m, and 5.63m within 90m. This equated to being 66.3%, 60.1% and 56.4% of the total IS development regarding each buffer distance. A portion of the Lower South Chickamauga Creek IS change in relation to stream buffers is shown in Figure 6.4.
Table 6.4  IS growth within buffers of streams within the study site for 1986 and 2016. IS

IS area in square kilometers within stream riparian zones

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td></td>
<td>1.49</td>
<td>1.32</td>
<td>3.18</td>
<td>3.07</td>
<td>4.89</td>
<td>4.91</td>
</tr>
<tr>
<td>Spring Creek</td>
<td></td>
<td>0.47</td>
<td>0.89</td>
<td>1.00</td>
<td>1.90</td>
<td>1.57</td>
<td>2.98</td>
</tr>
<tr>
<td>Tennessee River - Nickajack Upper</td>
<td></td>
<td>2.59</td>
<td>2.74</td>
<td>5.42</td>
<td>5.72</td>
<td>8.07</td>
<td>8.84</td>
</tr>
<tr>
<td>Tennessee River Chickamauga Lake Lower</td>
<td></td>
<td>0.40</td>
<td>0.70</td>
<td>0.77</td>
<td>1.41</td>
<td>1.13</td>
<td>2.14</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td></td>
<td>2.16</td>
<td>3.52</td>
<td>3.99</td>
<td>7.28</td>
<td>5.71</td>
<td>11.34</td>
</tr>
<tr>
<td>North Chickamauga Creek lower</td>
<td></td>
<td>1.54</td>
<td>1.52</td>
<td>2.99</td>
<td>3.39</td>
<td>4.42</td>
<td>5.46</td>
</tr>
<tr>
<td>Blue Spring Creek - Chickamauga Lake</td>
<td></td>
<td>0.27</td>
<td>0.28</td>
<td>0.55</td>
<td>0.60</td>
<td>0.91</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Impervious surface cover change near streams between 1986 and 2016

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nokomak Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Figure 6.3  IS growth, from January 24, 1986 to November 26, 2016, within 90 meters of stream segments
Figure 6.4  IS growth, from January 24, 1986 to November 26, 2016, within 30, 60, and 90 meters of stream segments in the Lower South Chickamauga Creek watershed
6.3 Riparian Development and Risk Analysis

6.3.a Riparian Percent Imperviousness

For the 1986 dataset, the first two 30m riparian interval zones on average were 15.2% covered by IS with the third interval having an average of 15.5%. In the 2016 dataset, the average percent impervious cover for all the 30m riparian zones had increased to 17.9%, 20.1%, and 21.6% respectively, with the amount of growth increasing for further riparian zones.

Descriptive statistics for the riparian development analysis can be seen in Table 6.5. A visual description of the distributions of percent imperviousness for each zone in 1986 and 2016 can be seen below in Figure 6.5 with outliers being visualized as plus symbols above the top whisker. The distributions also show that the two further riparian zones show increases in the second and third quartiles compared to 1986. Maps showing the percent imperviousness for each riparian zone can be found in Appendix A.

Table 6.5 Descriptive statistics for the percent imperviousness within the first three separate 30m riparian zones for stream segments for January 24, 1986 and November 26, 2016

<table>
<thead>
<tr>
<th>Interval</th>
<th>Year</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Min.</td>
</tr>
<tr>
<td>0m - 30m</td>
<td>1986</td>
<td>15.2%</td>
<td>27.4%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>17.9%</td>
<td>29.8%</td>
<td>0.0%</td>
</tr>
<tr>
<td>30m - 60m</td>
<td>1986</td>
<td>15.2%</td>
<td>24.1%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>20.1%</td>
<td>27.7%</td>
<td>0.0%</td>
</tr>
<tr>
<td>60m - 90m</td>
<td>1986</td>
<td>15.5%</td>
<td>23.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td>2016</td>
<td>21.6%</td>
<td>27.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>
Figure 6.5  Boxplot graph of the percent imperviousness values for each of the three 30m, riparian zones

6.3.b Stream Risk Assessment

The range in values for the stream impairment risk model was 0 through 6, allowing for different levels of probable risk to be assigned. Table 6.6 below shows the levels of risk related to the equivalent range in risk model values. The basis for these levels originated from the amount of development that must be present to achieve this score. For a stream segment to be assigned the lowest value (0.0) there must be 0% imperviousness in all three riparian zones while the maximum value (6.0) requires 100% imperviousness in all three riparian zones. Therefore, a score between 0 and 1 shows segments with little to no risk of impairment related to IS development. A score between 5 and 6 shows areas that have little or no pervious surfaces in their riparian zones. A map showing the risk of streams due to IS development for 1986 and 2016, are shown in Figure 6.6 and 6.7 and respectively. The change in stream risk within the Lower South Chickamauga watershed is shown in Figure 6.8.
Table 6.6  Model scores for potential stream risk assessments due to riparian imperviousness

<table>
<thead>
<tr>
<th>Risk of Impairment</th>
<th>Model Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0 &lt; 1</td>
</tr>
<tr>
<td>Very Low</td>
<td>⩾ 1 &lt; 2</td>
</tr>
<tr>
<td>Low</td>
<td>⩾ 2 &lt; 3</td>
</tr>
<tr>
<td>Medium</td>
<td>⩾ 3 &lt; 4</td>
</tr>
<tr>
<td>High</td>
<td>⩾ 4 &lt; 5</td>
</tr>
<tr>
<td>Very High</td>
<td>⩾ 5 &lt; 6</td>
</tr>
<tr>
<td>Extreme</td>
<td>6</td>
</tr>
</tbody>
</table>
Figure 6.6  Risk of stream impairment model scores for January 24, 1986. Each segment is visualized by their respective risk score.
Figure 6.7  Risk of stream impairment model scores for November 26, 2016. Each segment is visualized by their respective risk score.
Figure 6.8 Comparisons between the potential risk of stream impairment model scores for January 24, 1986 and November 26, 2016 of the Lower South Chickamauga Creek
The average score per stream segment was 0.92 and 1.06 for 1986 and 2016, respectively. Statistics describing the distribution of the model’s results are shown below in Table 6.7. For both dates, 75% of the model scores were below 2, a classification of low risk of impairment. Table 6.8 gives the quantity of segments with each level of risk, the total length of segments for each level of risk, and the change in quantities between 1986 and 2016. The distributions of risk scores for both dates are visualized in boxplots (Figure 6.10).

Table 6.7  
Statistics of potential risk assessment of stream segments due to riparian imperviousness

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min.</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1986</td>
<td>0.92</td>
<td>1.45</td>
<td>0</td>
<td>0</td>
<td>0.15</td>
<td>1.22</td>
<td>6</td>
</tr>
<tr>
<td>2016</td>
<td>1.06</td>
<td>1.47</td>
<td>0</td>
<td>0</td>
<td>0.33</td>
<td>1.57</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 6.8  
Stream impairment risk model score counts and approximate total stream lengths per score for each date. Counts represent the number of segments within that class.

<table>
<thead>
<tr>
<th>Risk of Impairment</th>
<th>1986 (km)</th>
<th>2016 (km)</th>
<th>Change (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>8155 (634)</td>
<td>7168 (550)</td>
<td>-987 (84)</td>
</tr>
<tr>
<td>Very Low</td>
<td>1883 (148)</td>
<td>2108 (169)</td>
<td>+225 (21)</td>
</tr>
<tr>
<td>Low</td>
<td>1012 (77)</td>
<td>1278 (100)</td>
<td>+266 (23)</td>
</tr>
<tr>
<td>Medium</td>
<td>737 (58)</td>
<td>812 (63)</td>
<td>+75 (5)</td>
</tr>
<tr>
<td>High</td>
<td>506 (36)</td>
<td>593 (45)</td>
<td>+87 (9)</td>
</tr>
<tr>
<td>Very High</td>
<td>374 (27)</td>
<td>505 (38)</td>
<td>+131 (11)</td>
</tr>
<tr>
<td>Extreme</td>
<td>243 (17)</td>
<td>446 (32)</td>
<td>+203 (15)</td>
</tr>
</tbody>
</table>
Figure 6.9  Boxplot shows the distribution of the January 24, 1986 and November 26, 2016 stream impairment risk models’ results.
CHAPTER 7
DISCUSSION

7.1 IS Mapping

7.1.a IS Cover Change

The results of this study indicated that there has been an overall increase in the net IS development between January 24, 1986 to November 26, 2016 within the study site, with growth being unequal across the seven HUC-12 watersheds. In total, slightly more than 6% of the total study site’s surface cover changed to IS between January 24, 1986 and November 26, 2016. The total IS cover percentage increased from 16% to 22% in the study site. This amount of IS growth fits the substantial growth in population, housing units, and economic activity in the area, as other research has found that increases in population can be related to proportionally larger increases in IS [201]. The larger proportional increase in IS area could be viewed as the result of residential and commercial development driven by the population growth. The contribution of both population and economic growth to IS growth are considered for the EPA’s IS Growth Model [202]. The results are further supported by this since the three primary contributors to IS cover are buildings, roads, and parking lots, listed in order of contribution [203].

7.1.b IS Classification Accuracy

The results of the confusion matrix accuracy assessments show that the classification of impervious and non-impervious surfaces using the model developed in this study was reasonably successful. The confusion matrices did show that the classification model had a better
performance in 1986 than that of 2016. The values of Kappa statistic ranging from 0.41 to 0.6, and from 0.61 to 0.80 can be interpreted to represent moderate and substantial agreement for a classification, respectively [204]. According to this interpretation, the accuracy of the classification model for 1986 dataset can be described as substantial. Similarly, on the other hand, the accuracy of the classification model for 2016 dataset can be described as moderate. The model’s classification accuracy for pervious surfaces for both dates are much higher than impervious surfaces, which could result from the assignment of points using the random stratification method, which placed a much larger number of accuracy assessment points for assessing the pervious surfaces. The lower quantity of assessment points in impervious surfaces could, therefore, be more heavily affected by outlying classification errors. Differences in the User’s Accuracy and Producer’s Accuracy show the variation of different types of errors that the classification model experienced for each class. Having a higher Producer’s Accuracy shows that the model was more likely to have more false positives and less false negatives. On the other hand, a higher User’s Accuracy indicates the presence of the opposites. In this study, for IS classification, both dates showed a higher Producer’s Accuracy. This result indicates that the model had a difficulty to differentiate between subject’s spectral response effectively and classified some non-urban IS as urban IS. The main source of confusion is believed to be from open dry soils.

The zonal statistics accuracy assessment showed that both dates had a similar performance in IS classification, 88.3% for 1986 and 90% for 2016 regarding the ability of the model to correctly classify moderately sized areas of urban IS.
7.1.c Environmental Influences on IS Classification

The accuracy assessment results for both datasets are at an acceptable level with regards to the effectiveness of the data and environmental conditions at the time of data acquisition. Moderate scale resolution sensors, such as the Landsat TM and OLI, have been utilized for IS mapping, however, a consensus has been found that with data of this scale it is not an effective ability to detect smaller areas of IS [95]. This study found that pixels determined as being IS are those where the majority to entirety of the land cover is impervious.

Environmental factors at the time of image acquisition are believed to have been an influence for both IS dataset generation. Water, shade, and dry soil have been found to be difficult for many classification models due to the spectral confusion [205]. Shadows, which are present in both images, can be caused by the angle of the sun and/or sensor. The effect of shadowed areas was accounted for in the model and is not believed to have had any significant effect on the results of the study. For the 2016 image, a strong drought affected the study site by producing an increased amount of dry soils, river recession, and wildfires [206]. For the 1986 image, several clear-cut areas were seen in the study site exposing large areas of dry soil. The evaluation of the obtained IS data shows the presence of some dry and compacted soil, which were classified as IS. This probably stems from the conflicting spectral response of dry soil and IS (in some case). However, it is believed that detection of dry soils as IS in some case did not contribute to a major portion of detected areas [207-209].

The effects of noise and errors from the data, model, and environmental systems are also believed to have an influence on the results. The estimated area of IS for both dates is believed to be conservative, even with the detection of dry soil as it is inferred through the increase in housing units and population in the study site. There has been a net growth of suburban areas
between 1986 and 2016 much of which is believed to have not been detected by this model. Based on visual inspection of the true color images. Suburban land cover can include IS such as roofs, drive-ways, and sidewalks. Although attempts were made to detect IS in sub-urban areas with the aid of true color images it was not possible to accurately detect them due to sensor’s coarser spatial resolution and erroneous detection of dry soil [207,210].

7.2 Water Resource Proximity to Impervious Surfaces

The accuracy of the proximity of the IS development to streams accuracy is dependent on the accuracy of the detected IS and the positional accuracy of the stream data. Since the locations of the streams are assumed to be accurate due to the U.S. National Map accuracy standards met by the NHDplus dataset [211]. Errors from the IS detection portion of this study are believed to be the cause of the detected decrease in IS with 30m of streams in the Chattanooga Creek and North Chickamauga Creek Lower watersheds and within 60m of streams for the Chattanooga Creek watersheds. The results of the IS growth near streams also show that the growth is unequal across HUC-12 watersheds, thereby signifying that some may have increased impairment. With a total IS growth of 36.63 km² within 90m of streams, the Lower South Chickamauga watershed experienced the largest amount of growth of 11.34 km², having 30.9% of the growth. This finding parallels with the finding that the Lower South Chickamauga watershed experienced the largest amount of overall IS growth. Having the largest portion of IS development within the watershed and near the streams suggests that the Lower South Chickamauga watershed surface water quality could have the most noticeable, significant impairment relative to the other watersheds within the study site.
Differences in percent imperviousness between the three riparian zones show an average increase for all three zones with the increase being larger the further the zone is from the stream. Shifts in second and third quartile percent imperviousness in the 2016 dataset compared to the 1986 dataset support the conclusion that in 2016 stream riparian zones had experienced increases in IS development. The largest increases in the farthest zone suggests that the growth has begun to develop closer to streams. Increases in anthropogenic development and activity closer to streams increases the risk of potential impairment of stream surface water quality and riparian habitat [128]. Large portions of stream riparian zones are still present and not heavily disturbed within the study site driving the need for local policy action for riparian zone protection that could help mitigate increases in potential stream impairment.

7.3 Impairment Risk due to IS Development

The potential risk of stream impairment increased from January 24, 1986 to November 26, 2016. The results of the Wilcoxon rank paired sum show that that the distribution was different between the 1986 and 2016 model scores. Although the test did not show which direction the distributions are different. The increase in the total number of stream segments at risk being impaired suggested that stream surface water quality health in November 26, 2016 was at a higher risk than it was in January 24, 1986. Segments with extreme risk of impairment experienced the third largest increase between the two datasets. The increase in average risk can be attributed to the increase of risk for 7.64% of stream segments, where 987 stream segments have experienced increases in risk. This is coupled with the 27.75% of segments that have maintained risk of impairment since 1986. These findings show that there is a moderate
proportion of streams within the study site that could have significant impairment due to long-term exposure or rapid introduction to urban development.

The risk model developed in this research showed that the location of the potentially impaired stream water quality due to impervious surface development are within the immediate riparian areas. Initially, it was planned to assess the water quality within the study site using *in-situ* methods and collect datasets with historic water quality information for the purpose of investigating potential changes in stream water quality. However, due to time constraints and resource limitations, these efforts were not fully conducted. The work that was completed are discussed in the future research section of this paper.
CHAPTER 8
CONCLUSIONS

Hamilton County has experienced large population and economic growth in the past 30 years and contains numerous stream networks that drain into the Tennessee River. Chattanooga is the primary city within Hamilton county, sitting along the Tennessee–Georgia border, and contains a large portion of the county’s population and economic activity. This study was the first attempt to utilize remote sensing and GIS to map historical and current impervious surface (IS) of the greater Chattanooga area to determine its net spatial growth across seven HUC-12 watersheds and their relationship to streams. IS cover was used to represent areas of anthropogenic development, specifically urban and suburban areas. Utilizing the multispectral acquired by the USGS Landsat satellite sensor program for multispectral imagery, IS detection was conducted using NDVI and density slicing technique. This study found that there had been an increase in IS within the study site with significant growth occurring near many of the streams. The IS change detected showed that the overall growth was not equal spatially. Most of the IS development occurred in the Lower South Chickamauga Creek watershed. It was found that dry soil from transitioning land cover or drought created artifacts during classification. Areas of suburban development are not believed to be fully mapped due to the spectral dominance of the pervious surfaces such as tree cover.

The results of the stream analysis show that there is an overall increase in percent imperviousness surface growth in the first three 30m stream riparian zones in the study site. The largest increase in percent imperviousness of stream riparian zone occurred between 60m to 90m
from streams, indicating that urban growth is beginning to encroach on critical, immediate riparian zones. The model for potential risk of stream surface water quality impairment reflects that there is an increase in risk for some portions of streams due to riparian IS development. The HUC-12 watersheds in the study site directly feed into the Tennessee River, thereby increasing the possible impact of the land cover change for areas downstream of the study site. This study also found decreases in pervious surfaces in stream riparian zones signaling a decrease in buffer capacity for filtering impaired surface and ground water. IS development detected within the watersheds could be the sources of potential new or continued surface water quality degradation. This study can conclude that there has been an increase of at least 45.12 km² of IS cover in the seven HUC-12 watersheds within the greater Chattanooga, Tennessee, area and 9.96 km² of IS cover growth within proximity to streams between 1986 and 2016 causing concerns for the local stream and river surface water quality.
CHAPTER 9

FUTURE RESEARCH

9.1 Looking Foreword

The primary goals of this research were to map urban growth in the Chattanooga, Tennessee, area, to determine the growth’s spatial relationship with surrounding water resources, and to assess whether the growth could have had a potential impact on these resources. The next step for continuing this research would be to investigate any possible IS related changes in surface water quality within the study site. The goal for this investigation is to detect if there have been any changes in water quality over time and where these changes occurred. If changes have occurred, the relationship between the water quality changes and urban growth could be analyzed using methods such as hydrodynamic or numerical models. The relationship testing could be able to determine if the detected IS growth has impacted the Chattanooga water resources, regarding its quantity and proximity to surface water resources. Additionally, changes in water quality at sampling points could be analyzed to see if there is any relationship to support the probable stream risk assessment. This relationship between risk score and water quality change could be performed between individual water quality parameters or via a water quality index score. Researching possible changes in water quality, measured via \textit{in-situ} methods, could be related to the stream risk assessment conducted in this study. This analysis could act as a validation to determine if the streams were and are at risk and the accuracy of the risk assessment.
9.2 Chattanooga’s Municipal Water Quality Data

Water quality data were obtained from the City of for the Citico Creek and Friar Branch stream watersheds within the Chattanooga area. Citico Creek watershed is located within the Tennessee River – Nickajack Lake Upper HUC-12 watershed, while Friar Branch watershed is in the Lower South Chickamauga Creek HUC-12 watershed. The details describing the raw datasets collected from the City can be seen in Table 9.1. The City’s water quality datasets contain several physiochemical parameters collected over large temporal range but couldn’t be readily used for this study because of: (1) difference in variables collected between the two watersheds, (2) inconsistency of sampling frequencies, and (3) insufficient samples.

The locations of the sample sites can be seen in Figure 9.1 which shows the part of the watersheds the office sampled and where they reside in relationship to the HUC-12 watersheds used in this study. The green points in location map represent sampling locations conducted by the city of Chattanooga Office of Water Quality. For Citico Creek, sample sites are located primarily in the central and southern portions of the watershed with no sampling occurring in the northern portion of the watershed or at the outflow. For Friar Branch sampling occurs mainly in the central and eastern portions of the watershed. The northern portion of the watershed is not truly sampled.
Table 9.1 The raw city water quality dataset collected of Friar Branch and Citico Creek

<table>
<thead>
<tr>
<th></th>
<th>Friar Branch</th>
<th>Citico Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Locations</td>
<td>8</td>
<td>16</td>
</tr>
<tr>
<td>Total Number of Samples</td>
<td>472</td>
<td>648</td>
</tr>
<tr>
<td>Sampling Location GPS</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Parameters Measured

- Odor
- Clarity
- Floating Solids
- Color
- Suspended Solids
- Sheen
- Foam
- Temperature (°C)
- pH
- Conductivity
- DO
- Turbidity NTU
- Flow
- Volume
- E. Coli
- TSS
- Precipitation w/in 72 hours of sample
- Notes Taken at Sample Site

- Odor
- Clarity
- Floating Solids
- Color
- Suspended Solids
- Sheen
- Foam
- Temperature (°C)
- pH
- Conductivity
- DO
- Flow
- Volume
- E. Coli
- TSS
- Precipitation w/in 72 hours of sample
- Notes Taken at Sample Site
Figure 9.1  Sampling locations of the city of Chattanooga Water Quality Measurements in the Citico Creek and Friar Branch watersheds
9.3 Preliminary Dataset Cleaning

A preliminary dataset cleaning was conducted in efforts to create a smaller, more manageable dataset that could be used for future research. The dataset cleaning was conducted using the python library Pandas in the Jupyter Notebook environment [190,212]. Details of the resulting datasets can be seen in Table 9.2. Variables that were recorded either qualitatively or had no clear recording system were removed from the original dataset including color, odor and on-site notes. Further, sample records that had no values for attributes besides location and time were removed from the datasets. During the cleaning process several sampling locations were found to have the same GPS location but were denoted as duplicates although there was no duplicated record. These records were re-labeled to be included with the rest of the records that share the same site. Although turbidity is a common water quality variable studied in the surface water quality–urbanization research nexus, it was not included since Citico Creek did not have the parameter and comparisons between the two datasets could not be made. The removal of records and the re-labeling of site locations reduced the total number of records and sample locations shown in Table 9.2.
Table 9.2  Filtered city water quality dataset for Friar Branch and Citico Creek

<table>
<thead>
<tr>
<th></th>
<th>Friar Branch</th>
<th>Citico Creek</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling Locations</td>
<td>8</td>
<td>16</td>
</tr>
<tr>
<td>Total Number of Samples</td>
<td>349</td>
<td>636</td>
</tr>
<tr>
<td>Sampling Location GPS Location</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Parameters Selected

1. Temperature (°C)
2. pH
3. Conductivity
4. DO
5. E. Coli
6. TSS
7. Precipitation w/in 72 hours of sample

Parameters Generated

1. Uniform sampling location ID
2. Watershed ID
3. Year
4. Month
5. Season
9.4 Dataset Limitations and Recommendations

After the initial cleaning the datasets still showed some limitations for the analysis. Only 135 records (21%) for Citico Creek contained a record of each of the selected attributes, while 334 records (95%) in Friar Branch had a record for each attribute. For all the samples taken for both locations it was found that there was no set interval of sampling, as the year to year sample quantity was not consistent. Further, the records year to year did not have a consistent seasonal sampling interval with the dataset having skewing heavily towards samples being taken in the Summer rather than any other season. Table 9.3 shows the number of samples recorded per year per watershed. Additionally, the locations of the sample sites for both watersheds do not allow for a total capture of the water quality as several areas of streams are not represented. As previously mentioned, there are several portions of the watersheds that are not represented by the sampling locations. Figure 9.2 and 9.3 show the locations of the City’s sampling locations alongside the 2016 risk assessment scores calculated by this study. In both watersheds’ locations areas with stream segments having a high or greater possible risk of impairment have not been sampled. Recommendations for the Water Quality office on improving these datasets for reporting and research purposes, based on the limitations found, would be to set a standard sampling interval and requirements for water quality sampling including a minimum required parameter collection and to begin collecting turbidity in Citico Creek.
Table 9.3  The number of samples taken per year per watershed by the City Water Quality Office for Friar Branch and Citico Creek watersheds

<table>
<thead>
<tr>
<th>Year</th>
<th>Watershed</th>
<th>Number of Samples Taken</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Citico Creek</td>
<td>270</td>
</tr>
<tr>
<td>2001</td>
<td>Citico Creek</td>
<td>78</td>
</tr>
<tr>
<td>2002</td>
<td>Citico Creek</td>
<td>13</td>
</tr>
<tr>
<td>2003</td>
<td>Citico Creek</td>
<td>91</td>
</tr>
<tr>
<td>2005</td>
<td>Citico Creek</td>
<td>11</td>
</tr>
<tr>
<td>2012</td>
<td>Friar Branch</td>
<td>40</td>
</tr>
<tr>
<td>2013</td>
<td>Friar Branch</td>
<td>121</td>
</tr>
<tr>
<td>2014</td>
<td>Citico Creek</td>
<td>112</td>
</tr>
<tr>
<td></td>
<td>Friar Branch</td>
<td>98</td>
</tr>
<tr>
<td>2015</td>
<td>Citico Creek</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>Friar Branch</td>
<td>58</td>
</tr>
<tr>
<td>2016</td>
<td>Citico Creek</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Friar Branch</td>
<td>24</td>
</tr>
<tr>
<td>2017</td>
<td>Citico Creek</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Friar Branch</td>
<td>8</td>
</tr>
</tbody>
</table>
Figure 9.2  Potential risk of stream impairment due to IS growth as of 2016 in the Citico Creek Watershed along with the sampling locations the city of Chattanooga Water Quality measurements
Figure 9.3  Potential risk of stream impairment due to IS growth as of 2016 in the Friar Branch Watershed along with the sampling locations the city of Chattanooga Water Quality measurements
9.5 Using the Dataset

Although the water quality datasets need improvements, they can still be used to conduct future research for some parts of the study site. The datasets could be used to determine if there are any significant water quality differences between the two watersheds. Further, within each watershed, differences between sampling points could be determined and used to locate where the most change occurred. These differences could then be related to the closest stream segment and conclude the validity of the stream risk assessment conducted in this study. The City’s datasets contain several individual water quality parameters that modeling could be conducted to determine the response of the parameters to changes in IS at different riparian distances. Since both datasets are complex in their composition, the use of non-linear or non-parametric analysis methods would be useful. The water quality datasets are not large enough to be used for deep learning methods effectively, but a shallow ANN could offer the analytical power needed to detect non-linear relationships between IS growth and water quality in the datasets.

9.6 Improvements to Impervious Surface Dataset

The IS detection model performed with reasonable accuracy (as assessed by the zonal and Kappa statistics accuracy assessments). However, the model could be enhanced and refined, as the current dataset is not believed to represent all IS cover within the study site. The use of additional image enhancement and information extraction techniques are, therefore, should be explored for future research. In some cases, dry soil provided significant challenge to separate then from IS. The use of the Tasseled Cap Transformation (TCT) could be worth exploring for accurately detecting and classifying these areas [90,213]. This image enhancement technique has also been found to be useful for detecting IS areas which could be utilized for improving the IS
dataset created in this study [214]. The use of machine learning or supervised classification
techniques such as support vector models, decision tree and maximum likelihood have been
found successful for mapping LULC change [215]. These methods have also been found to be
capable of successfully classify IS areas [8,216,217]. These could also be useful for IS mapping.
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APPENDIX A

RIPARIAN PERCENT IMPERVIOUSNES MAPS
Percent impervious cover within 30 meters of streams in 1986.

Percent IS within 30m of streams in 1986. Streams are visualized in 90m segments for percent IS.
Percent impervious cover within 30 meters of streams in 2016.

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nickajack Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek-Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake-Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Percent IS within 30m of streams in 2016. Streams are visualized in 90m segments for percent IS.
Percent impervious cover between 30 and 60 meters of streams in 1986

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-McDugan Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Percent IS between 30m and 60m of streams in 1986 Streams are visualized in 90m segments for percent IS.
Percent impervious cover between 30 and 60 meters of streams in 2016.

### Watershed ID

<table>
<thead>
<tr>
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<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Spring Creek</td>
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</tr>
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<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nickajack Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Streams are visualized in 90m segments for percent IS.

Percent IS between 30m and 0m of streams in 2016. Streams are visualized in 90m segments for percent IS.
Percent impervious cover between 60 and 90 meters of streams in 1986.

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
<td>B</td>
</tr>
<tr>
<td>Lower South Chickamauga Creek</td>
<td>C</td>
</tr>
<tr>
<td>Tennessee River-Nickajack Lake Upper</td>
<td>D</td>
</tr>
<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Percent IS between 60m and 90m of streams in 1986. Streams are visualized in 90m segments for percent IS.
Percent impervious cover between 60 and 90 meters of streams in 2016

<table>
<thead>
<tr>
<th>Watershed</th>
<th>ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chattanooga Creek</td>
<td>A</td>
</tr>
<tr>
<td>Spring Creek</td>
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<td>Lower South Chickamauga Creek</td>
<td>C</td>
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<tr>
<td>Tennessee River-Nickajack Lake Upper</td>
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<tr>
<td>North Chickamauga Creek Lower</td>
<td>E</td>
</tr>
<tr>
<td>Tennessee River-Chickamauga Lake Lower</td>
<td>F</td>
</tr>
<tr>
<td>Blue Spring Creek-Chickamauga Lake</td>
<td>G</td>
</tr>
</tbody>
</table>

Percent IS between 60m and 90m of streams in 1986 Streams are visualized in 90m segments for percent IS.
VITA

Jonah Hall was born in Chattanooga, Tennessee, to the parents of Jaime and Matthew Kerns and Rob and Sarah Hall. He is the first of five children, having two younger sisters and two younger brothers. He began his high school education at the Chattanooga Center for the Creative Arts and finished his diploma in 2014 duel enrolled at Middle College Highschool and Chattanooga State Community College. Afterwards, he attended the University of Tennessee at Knoxville pursuing an interdisciplinary degree in sustainability and worked for the University’s Recycling Office acting as their special project coordinator and data manager. Through his work with the University of Tennessee Recycling staff and his coursework he became interested in GIS and data analytics concerning urban sustainability. Jonah completed a Bachelor of Arts degree in December of 2016 in Interdisciplinary Studies: Sustainability with a minor in Geography. Immediately after graduation Jonah accepted a dual graduate research and teaching assistantship at the University of Tennessee at Chattanooga in the Environmental Science Program. Jonah graduated with a Master of Science degree in Environmental Science in May 2019.