THE EFFECTS OF IMPERVIOUS SURFACES AND FORESTS ON WATER QUALITY IN A SOUTHERN APPALACHIAN HEADWATER CATCHMENT: A GEOSPATIAL MODELING APPROACH

A Thesis
by
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ABSTRACT

The Effects of Impervious Surfaces and Forests on Water Quality in a Southern Appalachian Headwater Catchment: A Geospatial Modeling Approach

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Water quality of stream and river systems is affected by the land cover compositions that are present within their watersheds and riparian corridors. Research in recent decades has demonstrated that impervious surfaces such as roads, rooftops, and parking lots can exert significant stress on the health of riverine systems. Impervious surfaces prevent groundwater infiltration, reduce aquifer recharge, increase surface runoff and contaminant transport, deprive surrounding vegetation of aeration, and increase the temperature of stormwater runoff. Forests serve to enhance water quality and to ameliorate the negative effects of human altered land covers through mechanisms such as absorption of stormwater runoff, filtration of pollutants and sediments, increasing groundwater infiltration and aquifer recharge, stabilization of streambanks, providing cooling effects through shading of stream ecotones, and promotion of healthy riparian habitats for flora and fauna.

This thesis research was undertaken with the goal of examining the effects that impervious surfaces and forests exert on stream system water quality. The research was conducted in the headwaters of the New River in Watauga County, North Carolina in order to provide a study area of origin streams within a nested watershed assemblage which provided a variety of sub-watersheds with varying land cover proportions for comparison. Water quality variables, collected through an ambient water quality monitoring program, of specific conductivity, chloride, nitrate, and sulfate were examined over an eight month study period. The results of this research demonstrated that the effects of impervious surfaces and forests on stream water quality are clearly identifiable. Correlation analysis and linear regression testing provided robust evidence to support the central hypothesis of the research: *there is a statistically significant relationship between land cover and water quality in the headwater stream systems of the Upper South Fork watershed of the New River, with impervious surfaces exerting a negative influence and forest land covers exerting a positive influence on water quality*.

The influences of spatial scale on these effects was examined through investigation of water quality datasets and calculations of the total percentage impervious area (TPIA) and total percentage forest area (TPFA) for the Upper South Fork watershed, in six sub-watersheds within the Upper South Fork, and riparian buffer distances of 25 m, 50 m, 100 m, and 150 m. The TPIA at the 100 m buffer distance was found to exert the strongest negative effects on water quality, and TPFA at the 50 m buffer was found to exert the strongest positive effect. Nearly all spatial arrangements of land cover composition were found to have statistically significant relationships with water quality.

Limiting the amount of impervious surfaces that occur within 100 meters of streams and establishing a 50 meter forested stream buffer zone would serve to protect stream water quality from the effects of non-point source pollution. In the context of population growth and increasing urban development continuing into the 21st century, preservation and restoration of forested riparian buffers and the elimination of impervious surfaces within them should be a primary concern for the general public, the scientific community, and public-policy decision makers.

DEDICATION

I dedicate this thesis to my wife, Lisa, without whom this research and many other wonderful things would never have been possible, and to my son, Logan, who helped me finally grow up. Also to my parents, Nick and Pat Coffey, who patiently, lovingly, supportively waited a very long time for the growing up part.

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I offer my warmest regards and thanks to the students, faculty, and staff of the Department of Geography and Planning at Appalachian State University.

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CHAPTER ONE

Introduction

1.1 Background

Research has indicated that the water quality of stream and river systems is affected by the land cover types that occur within their watersheds and riparian corridors. In recent decades it has been demonstrated that impervious surfaces such as roads, rooftops, sidewalks, patios, and parking lots, exert significant stress on stream system health. Impervious surfaces prevent groundwater infiltration, reduce aquifer recharge, increase surface runoff and contaminant transport, deprive surrounding vegetation of aeration, and increase the temperature of stormwater runoff. Forests, on the other hand, serve to protect water quality and to ameliorate the negative effects of human altered land covers through mechanisms such as absorption of stormwater runoff, filtration and removal of pollutants and sediments, increasing groundwater infiltration and aquifer recharge, stabilization of streambanks, providing cooling effects through shading of streams, and promotion of healthy riparian habitats for flora and fauna.

This thesis research was undertaken with the goal of examining the relationship between land cover composition, in this case impervious surfaces and forests, and stream system water quality. The research was conducted in the headwaters of the New River in Watauga County, North Carolina (Figure 1) in order to provide a study area of origin streams within a nested watershed assemblage which provided a variety of land cover proportions for comparison.

Many residents and visitors consider the High Country area surrounding Boone and Blowing Rock, North Carolina to be one of the most beautiful places on Earth. The headwaters of the Upper

South Fork watershed of the New River are located in the High Country. This headwaters catchment, which will be referred to as the Upper South Fork throughout this thesis, is filled with an abundance of lush, verdant forest, miles of clear, rocky, bubbling mountain streams, and a rich assemblage of mountain flora and fauna. Permanent residents, seasonal residents, tourists, and visitors alike enjoy this beautiful mountain environment.

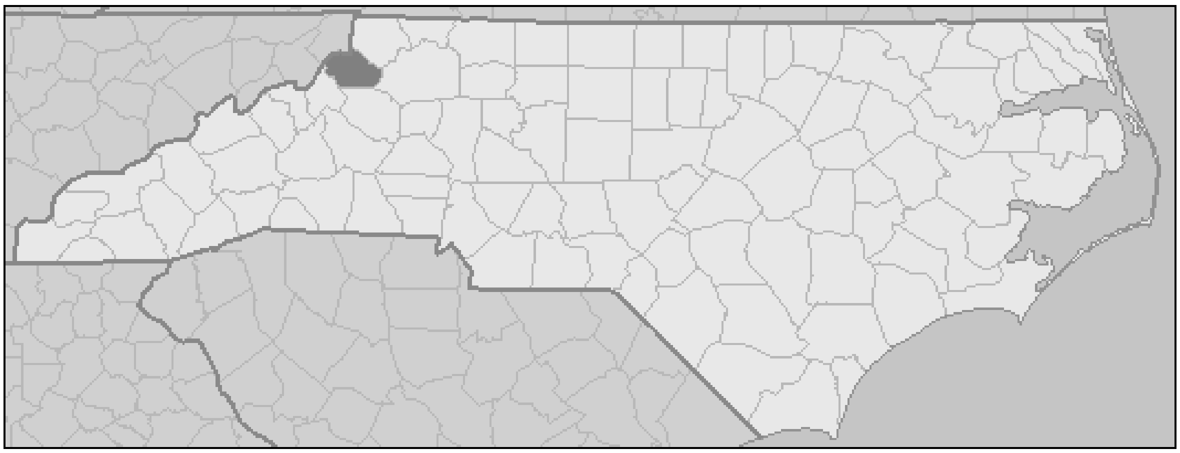


Figure 1. Watauga County, North Carolina: location of Upper South Fork watershed of the New River.

Despite this natural beauty and nearly pristine mountain environment, the traditional land cover composition has changed as a result of human development patterns, with anecdotal evidence indicating that a marked increase in development has occurred over the past several decades. As a result, the natural resources of the Upper South Fork, particularly its water resources, are increasingly threatened. Although the areas around Boone and Blowing Rock have not experienced significant growth in terms of industrial development, the region's beauty and natural amenities have resulted in a thriving second-home market, with a large percentage of the new development in the area attributable to luxury-home development construction for a substantial in-migrant and seasonal population. In addition, Appalachian State University, the regional healthcare system, and light commercial and retail development all vie for control of the limited buildable land resources in these restricted mountain valleys. These formerly forested areas have seen a marked increase in the amount of impervious surfaces as a result of development, and a corresponding reduction in areas of forest land cover. These development driven land cover alterations potentially represent a significant threat to the water quality of the headwaters of the Upper South Fork.

Since the majority of surface water extraction for human use occurs in large river systems downstream from headwater catchments such as the Upper South Fork, these larger drainage basins have traditionally received the greater portion of attention regarding scientific inquiry and public-policy decisions. The issue of water quality in upland headwater stream systems has only recently begun to receive a similar degree of attention. The prevalence of research focused on larger downstream rivers may be due in part to some of the difficulties inherent in headwater stream research. Headwater stream systems are often located in mountainous areas with high topographic relief. These rugged terrains present researchers with site access difficulties not encountered in areas of low topographic relief. Headwater streams can also be quite dangerous during peak streamflow and stormflow conditions which occur during and after precipitation events, as well as seasonally due to snowmelt. Another difficulty of headwater stream research is the lack of reliable, pre-existing geospatial and water quality data for many of these areas. Due to the rugged topography and remote locations of many headwater systems, these areas are often poorly represented by relevant data domains. On those occasions when data sources and information are located by researchers, they are often outdated and of poor resolution, both spatially and temporally. Since description, analysis, and evaluation of headwater stream systems requires suitable water quality data, research in these areas is further confounded by the lack of good quality, temporally comprehensive water quality data for many of these systems. As a result, research projects focused on headwater systems are often required to generate their own primary data, which can prove difficult not only due to the previously mentioned reasons, but also due to the difficulty in installing and maintaining monitoring equipment in these remote streams.

1.2 Research design and statement of hypothesis

This thesis research project consisted of several distinct but interrelated research components including: development of a geospatial database for the Upper South Fork Watershed; geographic information systems (GIS) visualization, analysis, and modeling procedures; establishment of a long-term ambient water quality monitoring program, complete with databases, field and laboratory methods and guidelines; and multiple statistical analyses for the testing of the central hypothesis regarding the relationship between land cover and water quality in the study area. In order to evaluate the relationship between land cover characteristics and water quality at various spatial scales, such as individual sub-watersheds and riparian corridors of various widths, and to assess the health of the headwater streams in the Upper South Fork New River watershed of Watauga County, NC, this thesis research project was designed with several goals:

1. Creation of highly accurate, high resolution digital terrain models (DTMs) of the study area from bare earth light detection and ranging (LiDAR) data. These DTMs included a terrain dataset and digital elevation models (DEMs) generated using a repeatable, semi-automated workflow.

2. Creation of an optimal drainage network pattern and delineations of the sub-watersheds within the study area through development of a repeatable hydrographic modeling framework.

3. Generation of high resolution (1 meter) land cover classification datasets, focused on classification and area calculations at select scales, including watershed, sub-watersheds, and riparian buffers, for impervious surfaces and forest land covers, using a repeatable, semi-automated methodology for similar land cover extractions.

4. Establishment of a long-term ambient water quality monitoring program, complete with the development of data management applications, guidelines for continued operations, and strategic planning of future monitoring phases and strategies.

5. Environmental modeling of the relationship between land cover and water quality in the study area, emphasizing whether land cover characteristics at select scales exert positive or negative influences on water quality parameters.

A review of these primary objectives indicated that the research goals were somewhat hierarchical in nature, inasmuch as the results of the first four goals serve as inputs for the fifth objective. The fifth objective was identified as providing the central hypothesis of this thesis research project, and was tested using descriptive and inferential statistical analyses. The central hypothesis of this thesis research can be summarized as:

> *There is a statistically significant relationship between land cover and water quality in the headwater stream systems of the Upper South Fork watershed of the New River, with impervious surfaces exerting a negative influence and forest land covers exerting a positive influence on water quality.*

This central hypothesis acted as a focusing theme for the other research components and provided a testable hypothesis as the culmination of the research design framework. This research design allowed the development, analysis, and discussion of each of the individual research components while still retaining emphasis on the primary objective of testing the central hypothesis regarding the relationship between land cover composition and water quality in the Upper South Fork. In order to test this hypothesis a diagnostic framework was established. Statistical analysis procedures, including descriptive statistics, correlation analysis, and linear regression, were conducted using land cover composition data generated by this research along with water quality data collected from a newly established water quality monitoring program for the Upper South Fork.

In addition to the creation of the water quality database, another goal of this research was the creation of a new database of geographic and geospatial information for the study area. The contents of the database included terrain, hydrographic, land cover, thematic information, statistical testing results, and other datasets at very high resolutions. The many geographic information system procedures, input layers, and output layers produced during the course of this research represent a rich library of geospatial data. Development of this database represents new methodological and research design approaches to integrated hydrographic and environmental modeling. Some of the derived datasets included terrain datasets and digital elevation models generated from 2004 bare earth LiDAR at a 5 meter nominal post spacing; high resolution digital drainage network representations, watershed, and sub-watershed delineations generated from hydrographic modeling procedures; forest land cover classifications from 2010 “leaf-on” 1 meter aerial photography source imagery and ancillary data layers; and impervious surface classifications from 2009 “leaf-off” 6 inch aerial photography and ancillary data layers. This geodatabase can be integrated with the water quality monitoring database to allow spatial querying of information, examinations of change over time in both water quality and land cover, and many other inquiries regarding issues and interrelationships of terrain characteristics, hydrology, land cover, and water quality within the Upper South Fork.

1.3 Study area description

The headwaters of the Upper South Fork (Figure 2) are located in the northern mountains of western North Carolina near the towns of Boone and Blowing Rock. Boone, with a 2009 population of 14,138 (Town of Boone 2011), is located at 36°12’41” N and 81°40’7” W at an altitude of approximately 3,330 feet, and Blowing Rock, with a population of approximately 1,425 (Town of Blowing Rock 2011), is located at 36°7’47” N and 81°40’21” W at an altitude of roughly 4,000 feet. The entire area is situated in the Blue Ridge Mountain Province of the Southern Appalachian Mountain range in North Carolina. The topography of the study area can be described as primarily mountainous, rugged terrain with an average slope of 27 %. The exception to this rugged topography within the study area occurs in the area containing the central business district of the Boone, which is also home to Appalachian State University and the regional healthcare systems’ facilities. Howard’s Knob (elevation 1,340 meters) to the northwest and Appalachian Ski Mountain (elevation 1,219 meters) in the southwest of the Upper South Fork represent two of the largest mountain peaks in the 232 square kilometer study area. Rugged erosional mountain valley landscapes comprise the majority of the remainder of the study area's topography. Marked declines in elevation can be observed across the southern, southwestern, and southeastern boundaries outside of the study area. These rapid drop-offs represent the eastern escarpment of the Blue Ridge Mountains in this location, with the study area's high elevation mountainous terrain dropping rapidly off into the foothills and valleys bellow. The land cover of the Upper South Fork is still predominantly forest (Coffey and Colby 2010a), with lesser amounts of agricultural and pastoral land covers present, and a rapidly increasing amount of developed land and impervious surfaces.

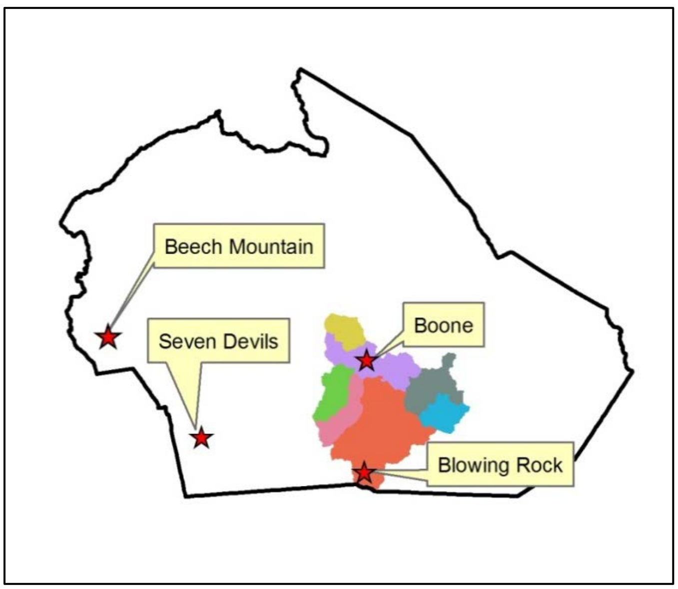


Figure 2: Study Area in Watauga County, NC, with individual sub-watersheds represented by different colors and incorporated towns labeled.

The general climate of the area can be classified as a humid, temperate climatic zone. Spring and summer typically experience the greatest amounts of precipitation, and fall the least (State Climate Office of North Carolina 2009). Flood events often occur in late summer and early fall, and are usually directly related to periods of peak precipitation. These flood events vary locally due to individual sub-watershed characteristics, as well as local hydroclimatic and land-use differences. Yearly precipitation averages between 100 and 140 centimeters of rainfall annually, with average snowfall in this portion of the northern mountains averaging approximately 100 centimeters per year (Kocin et al., 1995). Average winter low temperatures are approximately -3˚ C , with January and February typically being the coldest months. The average summer high temperature is approximately 25° C, with July and August being the hottest months (USGS 2008, State Climate Office of North Carolina 2009).

The geology of the northern North Carolina mountain region can be characterized as a complex heterogeneous fractured rock complex, which has experienced periods of intense metamorphism, faulting, folding, and igneous intrusion. The regolith, the saprilitic transition zone, and the fractured bedrock are the three principal components that comprise the groundwater system. The thickness of the regolith varies from none to a depth of greater than 150 feet, with much local variation. It consists primarily of a mixture of clay, soil, residuum, saprolite, alluvium, and collovium, ranging in dimension to the size of large boulders (Daniel and Dahlen 2002). The base of this heterogeneous regolith is characterized by a transition zone of saprolite grading into bedrock, which primarily consists of metamorphic and igneous rock types that vary from felsic to ultramafic. The regolith allows groundwater to percolate into the storage areas within the fractured bedrock, while the transition zone provides the area where the majority of horizontal groundwater movement occurs. Since the regolith and bedrock are connected, the aquifer systems in the regions are classified as unconfined. Also, since the transmission zone is an area of relatively rapid groundwater movement and since the unconfined aquifers of the region are relatively shallow, there is a great potential for contamination of these groundwater sources by surface activities such as land cover change and pollution discharge from both point and non-point sources (Harden et al. 2009).

CHAPTER TWO

Literature Review

2.1 Headwater stream systems

Recent decades have witnessed an increase in the amount of research regarding headwater stream systems. Some of this resurgent interest is likely due to the rising awareness of the important roles of headwater streams for issues such as downstream water quality, biological diversity and richness, and other ecological parameters. The introduction of a relatively small amount of contaminant in headwater streams has a much greater effect than it would in a larger river system, where the greater water volume and discharge are more capable of diluting pollutants. It has also been demonstrated that the water quality of headwater streams has a significant impact on the water quality of downstream systems. The cumulative effect of contaminant transport by the numerous headwater stream discharges into downstream riverine systems has significant consequences for downstream water quality (Bolstad and Swank 1997; Arnold and Gibbons 1996).

Bolstad and Swank (1997) conducted research at the Coweeta Hydrologic Laboratory in western North Carolina to examine the effects of land-use change along successively greater hierarchical order streams on local water quality in a nearly pristine headwater catchment system. The researchers explored the question of whether or not land-use change within a local watershed would result in a cumulatively negative impact on the higher order streams; essentially, whether or not land-use change surrounding headwater streams would cause cumulative loss of water quality downstream. They discovered that there was a distinct, cumulative change in downstream water quality which displayed a statistically significant relationship with human development and land conversion activities upstream. Their research indicated that the increase in deforestation and building activity upstream was a significant factor in the impairment of downstream water quality during stormflow condition, although similar results were not observed during streamflow and baseflow conditions.

Morse et al. (2003) examined 20 headwater catchments in Maine in order to determine the relationship between impervious surface coverage and water quality. The researchers examined stream insect populations (Benthos) as well as chemical and physical indicators including temperature, pH, conductivity, dissolved oxygen, total Nitrogen, total Phosphorous, and total suspended solids. Total Percentage Impervious Area (TPIA) for the study catchments ranged from 1%-31%. A threshold of 6% TPIA was identified as significant, with an abrupt decline in Benthos taxonomic richness occurring beyond this level. Physical and chemical water quality indicators exhibited a linear, inversely-proportional relationship to TPIA, with water quality degrading rapidly as TPIA increased above this 6% threshold value.

Additionally, the surrounding LULC characteristics of headwater stream systems play an especially important role in the water quality of these streams. Although this relationship is not fully understood, it reinforces the importance of protecting not only the headwater streams themselves, but also the quality of their surrounding environment. In their review of research regarding the role of landscape indicators for the assessment of water quality, Gergel et al. (2002) examined the importance of upland LULC in headwater stream systems for downstream water quality. They noted the degradation of downstream water quality that occurs as a result of upstream land use conversion from its natural state to human use. Their research review indicated that human impacted land use can be reliably used as a water quality predictor, rather than analyzing individual land use components separately (residential, urban, agricultural, grazing land, and so on).

Clinton and Vose (2005) conducted research into headwater stream water quality in a study area which contained a land cover composition scenario opposite that of most headwater stream study environments: They examined the water quality of a stream which had headwaters originating in an urban landscape then flowing through forest land covers of a National Forest and an undisturbed forested reference site. Water quality was sampled at multiple locations for over one year and tested for several water quality indicator variables including chloride, nitrate, sulfate, pH, conductivity, and total suspended solids (TSS). Water quality was generally found to be higher at the downstream forested site than at the urban headwater sites. Water quality response to discharge fluctuations was also higher at the urban headwaters than in the forest or reference sites.

2.2 Land cover, impervious surfaces, and water quality

The impact of LULC has been a consistent focus of water quality studies, with TPIA emerging in recent decades as a key indicator in many studies. Dow and Zampella (2000) utilized the single LULC of *Altered Land Use* in their research, defined as land covers such as Urban, Residential, Agricultural, Grazing Land, and other human impacted LULCs. Conway (2007) further narrowed the relationship between human impacted land uses and water quality, examining both *Altered Land Use* and TPIA as key stressors of water quality in order to determine which LULC category exerted the strongest influence on water quality. Conway's research indicated that TPIA exerts a very significant influence on water quality, with a threshold of approximately 2.4% - 5.1% TPIA within a catchment resulting in stream water quality impairment. Conway suggested that despite the importance of TPIA for water quality determination, *Altered Land Use* may be a better indicator for future research due to the difficulties in determining accurate TPIA measurements as well as the significant correlation demonstrated between *Altered Land Use* and water quality.

Lenat and Crawford (1994) conducted a study into the relationship between impervious surfaces in urban areas and water quality. They concluded that suspended sediment yield was highest in impervious areas during stormflow and moderate flow events, and lowest during low flow conditions. In their examination of the impact of urban landscape patterns on stream systems, Alberti et al. (2007) compared a wide assortment of landscape metrics such as edge density, contagion, and connectivity, as well as traditional LULC classes and TPIA. They determined that there was a significant relationship between TPIA and water quality, with a much stronger correlation in this relationship than was observed with other landscape metrics. Burns et al. (2005) conducted a study in the Croton River basin of New York, USA, examining the effects of TPIA on runoff generation. Their research concluded that TPIA had a variable effect on runoff, with the most significant relationship evident in runoff generation during wet season storm events.

It has been demonstrated by numerous studies that land-use conversion from more natural or vegetated covers to urban use has a direct correlation with an increase in water quality stressors and an increased vulnerability to degradation within stream systems (Beach 2002; Bolstad and Swank 1997; Chang 2003; Gilvear et al. 2002; Lenat and Crawford 1993; Northington and Hershey 2006; Reynard et al. 2001; Stohlgren et al. 1998; Sudduth et al. 2007; Todd et al. 2007). In their analysis of the impacts of land-use change and changing climate on the characteristics of a local hydrologic system, Todd et al. (2007) analyzed the local stressors affecting basin water quality conditions in the area around Indianapolis, Indiana. They separated baseflow from streamflow, and attempted to create a hydrological modeling system wherein these variables could be predicted based upon local change in climate and land-use. The primary aim of their project was to construct a research methodology that could be applied to different geographic areas receiving differential hydrologic, climatological, and land-use change variable input over a specific temporal period. From the results of their research the authors concluded that continued rapid population growth and climate change contribute significantly to the deterioration of water quality, and represent a very real threat to the future quality of water resources in urbanizing areas. It has been demonstrated that forested areas exert significant influence in preserving and protecting the water quality of adjacent streams from the stressors introduced by increased TPIA and other human land use conversions within riparian buffer zones or a watershed (Arnold and Gibbons 1996; Maillard and Santos 2008; Alberti et al. 2007; Li et al. 2009; Gergel et al. 2002; Allan and Johnson 1997).

Spatial scale also seems to play an important role in the relationship between the percentage of forest land cover (TPFA) within an area and the water quality of local streams, with various buffer widths indicating a strong explanatory value for variance in area water quality indicator values. Tran et al. (2010) found that forest land cover correlated significantly with improved water quality, particularly at the 200 meter riparian buffer zone scale. The research of Sliva and Williams (2001) produced similar results, with the proportion of forest land cover at the 100 meter buffer scale demonstrating a significant correlation with water quality. A detailed analysis of the optimal width of forested riparian buffer zones was undertaken by Sparovek et al. (2002). The authors concluded that 52 meters is the optimal forested riparian buffer zone width for reducing sediment yield while minimizing the buffer width to allow for agriculture and forestry to take place in adjacent areas. Their research was notable for its inclusion of econometrics and potential public policy impacts of issues surrounding forested riparian buffers, water quality, and commercial concerns.

Recent years have witnessed widespread and often severe droughts in many parts of North Carolina, the United States, and the World. Droughts are often attributable, at least in large part, to land cover change and changing climatic conditions. Drought and the water quality degradation that generally accompanies it will continue to be of major concern as population growth and land-use conversions continue to rise dramatically. Band et al. (2004) performed a research project in order to assess the effects of droughts on the water supplies and hydrology of the Catawba River Basin, which serves as a major drinking water source as well as source of hydroelectric power and nuclear cooling water in the Piedmont region of North Carolina. Many of the Catawba's headwater stream systems originate in areas similar to the Upper South Fork, which are witnessing rapid land cover conversion, deforestation, and introduction of impervious surfaces. Their research indicates that land-use change and hydroclimatic conditions had the greatest effect on the basin in terms of susceptibility to drought.

The past century in particular has seen exponential growth in human population, industrial activity and resultant pollution, and human withdrawal of water supplies (Beach, 2002).

2.3 Thresholds of impervious surfaces coverage

There has been a growing amount of research regarding the significant impact of impervious surfaces on water quality, and an emerging indication that certain thresholds of TPIA exist at which water quality conditions in an area reach increasing levels of impairment. Schueler (1994) presented some relatively early research into the topic of impervious coverage percentages, and suggested that a 10% - 20% TPIA threshold exists for watersheds, beyond which streams become impaired. Arnold and Gibbons (1996) conducted a review of the existing scientific literature, white papers, and policy briefs related to the importance of impervious surface coverage for water quality assessment and planning purposes. The authors examined various studies which indicated that a 10% threshold of TPIA exerts a negative impact on stream water quality, with a 30% threshold of TPIA representing a "breaking point" of irreversible damage to riparian systems. Beach (2002) described similar thresholds.

The influence that impervious surfaces as measured by TPIA exert on water quality has been found to be a reliable, rapid index variable for stream system water quality assessment. Some research has indicated that a one-acre impervious surface such as a parking lot (or a portion of one) produces 16 times more runoff than a one-acre grassy land cover such as a meadow or pasture (Beach 2002). In the research of Morse et al. (2003) regarding 20 headwater catchments in Maine, a 6% threshold of TPIA within a watershed was identified as a significant threshold value beyond which water quality indicator variables including physical, chemical, and biological components were found to rapidly decrease in quality. The researchers found that this relationship exhibited a nearly linear, inversely-proportional relationship, with increasing TPIA corresponding with increasing water quality degradation. Ourso and Frenzel (2003) conducted a study for the USGS involving 5 watersheds in

Alaska and found threshold response levels as low as 4.4 - 5.8% TPIA. Conway's research (2007) found even lower levels TPIA thresholds of 2.4% - 5.1% resulting in water quality impairment of area streams.

2.4. Water quality variable selection

Within the research domain of water quality indicator variable selection recent research has indicated that a lesser number of key indicator variables can be used to assess the health of a stream system than had been traditionally employed. Li et al. (2009) conducted a study in the Han River basin of China to examine the impact of LULC on a wide variety of water quality variables. They examined 17 physical and chemical indicators, and determined that approximately eight of these correlated most significantly with LULC: temperature, pH, conductivity, turbidity, suspended particulate matter, dissolved oxygen, nitrate, and phosphates.   Other research has indicated that pH, conductivity, turbidity, nitrate, chloride, sulfate, and phosphates can be utilized as key water quality indicator variables for rapid assessment of stream system health (Tran et al. 2010; Maillard and Santos 2008; Lee 2009; Tong and Chen 2002; Morse et al., 2003; Jones et al., 2001; Gergel et al., 2002; Lenat and Crawford, 1994).

Two separate research projects were undertaken in New Jersey, USA to examine the relationship between LULC and only two key water quality indicators, pH and conductivity (Dow and Zampella 2000; Conway 2007). Dow and Zampella utilized pH and conductivity as water quality variables along with a single LULC for their study, *Altered Land Use*, which consisted of Urban, Residential, and Agricultural LULC. They concluded that there was a linear relationship between both pH and conductivity with *Altered Land Use*, with simple regression models indicating that *Altered Land Use* explained 48% of the variability in pH and 56% of the variability in conductivity, with 79% of variability explained by a combined regression model of pH and conductivity. Conway concluded that pH and conductivity could be used as key indicator values for rapid water quality assessment and to examine the effects of land cover change on water quality.

2.5. Statistical analysis of water quality

An important concern in water quality analyses regards the selection of appropriate statistical exploration, presentation, and analytical methods. Given the spatial autocorrelation and non-independence of sampling site issues that often accompany research into water quality and land use, the selection of appropriate statistical techniques is especially important (King 2005; Griffith 2002; Hunsaker and Levine 1995). Descriptive statistics are one of the most common methods for presenting water quality data in a manner that can be readily interpreted. Li and Migliaccio (2011) stress the importance of presenting the common data measures most often used in descriptive statistical description as the primary step in any water quality analysis. Among measures of central tendency, the median value of water quality variables is often used in order to remove the undesirable effects of outliers on water quality datasets. The mean value is still a useful measure of central tendency, along with mode, but can be skewed by the existence of outliers. The distribution, or normality of water quality datasets is also very important, along with statistical indices of variation such as range, variance, and standard deviation.

In order to determine the presence, strength, and significance of relationships between water quality variables and LULC variables, correlation and regression analyses are often undertaken. Correlation provides a measure of the strength of the relationship between a pair of variables, the correlation coefficient or *r* value, along with a measure of the significance of that relationship, the *p* value. The *r* value also indicates whether a relationship is a positive one or a negative one, with positive relationships having a range between 0 and 1, and a negative relationship having a range of 0 through -1. An *r* value of 0 indicates that no relationship exists between the variables. The lower the *p* value (which ranges from 0 to 1), the greater the significance of the relationship. The *p* value is inversely proportional to the percentage significance value that is sometimes presented. Regression testing provides a measure of the explanatory value of an independent variable (or array of variables in the case of multiple regression), such as specific conductivity, for the value of an independent variable such as total percentage impervious area within a watershed. This regression value is denoted by *R squared*, and indicates greater explanatory power the closer the value is to 1. Logarithmic transformations are also often undertaken with water quality data, since these transformations help the data fit the inherent assumptions of regression analysis such as normality of distribution (Li and Migliaccio 2011).

Correlation analyses, most often using the parametric Pearson's product-moment correlation coefficient, are found in many studies regarding the effects of LULC on water quality. Research projects examining water quality with other parameters or influencing variables also frequently utilize correlation analysis as one of their primary statistical tools. Alberti et al. (2007) employed correlation in their examination of the relationship between water quality and selected landscape metrics. In a similar study, Lee et al (2009) used correlation in a landscape ecological approach to LULC composition and its effects on water quality. Correlation analysis of the relationship between geological makeup within the riparian zone and its effects on water quality was conducted by Smart et al. (2007) along the Dee River in Scotland. Their research was notable for using similar research methodologies and statistical testing procedures for examinations of water quality effects generated by a category other than LULC. King et al. (2005) used correlation analysis to examine the effects of LULC composition and percentages on water quality, and Li et al. (2009) used correlation analysis in a similar manner but with a focus on LULC composition within the 100 meter riparian buffer zone.

Regression analysis, both linear and multiple, is frequently used to provide greater explanatory power for the relationships between water quality and LULC. Sponseller et al. (2001) used regression analysis to relate land cover composition to water quality in a group of watersheds in Virginia, and Sliva and Williams (2001) utilized a similar methodology for their research in Ontario.

Sparovek (2002) employed regression to help determine the optimal width for riparian forest buffers in research conducted in Brazil. A variety of buffer widths were examined for their role in preserving water quality as well as the relative value of this land for commercial purposes, with a riparian forest buffer width of approximately 50 meters emerging as the most significant. Maillard and Santos (2008) also utilized regression in their research regarding land cover and water quality in Brazil, and used multiple regression in order to help establish the relative importance of various LULC compositions regarding their explanatory value for water quality. Dow and Zampella (2000) employed both linear and multiple regression in research they conducted in New Jersey regarding the impacts of LULC change over time on specific conductivity and pH levels. Todd et al. (2007) also employed regression for their examination of LULC change over time effects on water quality in watersheds near Indianapolis, Indiana. The usefulness of log transforming water quality prior to regression is presented by Jones et al. (2001), who employed log transformations in order to produce more accurate regression results from their analysis regarding landscape metrics and water quality. Other water quality research projects that utilized regression analysis were conducted by Alberti et al. (2007), Morse et al. (2003), Baker et al. (2006), and Hunsaker and Levine (2005).

2.6. Spatial scales: watersheds and riparian buffer zones

Issues of scale, from riparian buffer zone to catchment scale, and their implications for water quality and LULC studies, have represented another research domain for numerous projects in the recent past. Landscape metrics and their effects on water quality have gained popularity in recent years, emerging from the growing field of landscape ecology. Contradictory results have been found in many of the studies involving landscape metrics and water quality, however, indicating that further research is warranted to establish a more definitive relationship between water quality indicator variables and landscape metric indices. One possible reason is that the examination of landscape metrics at various study scales in relation to water quality has produced differing findings is that many of these investigations seem to have been undertaken in areas of divergent environmental and geographical characteristics. There has been little research regarding their application to areas of equivalent environmental and geographical characteristics, such as topographic relief, elevation, geology, development patterns, LULC proportions, soil types, magnitude of stream orders, and climatic conditions, which could help clarify the role that landscape metrics may play in explaining the effects of land cover on water quality.

More definitive results regarding the relationship between water quality and land cover composition at various scales have been achieved through examinations of land cover at buffer and watershed scales. A watershed can be basically defined as an element of the landscape that represents a single drainage basin with a single outlet point (NCDWQ 2007b). Watersheds may contain multiple smaller watersheds, termed sub-watersheds, resulting in a "nested" arrangement. A "buffer zone" or simply "buffer" refers to the riparian zone as measured from the stream centerline to the outer edge of the buffer. Therefore, a 50 meter buffer would measure 50 meters from the stream centerline to the outer edge of each side of the stream, resulting in a 100 meter overall width buffer from edge to edge (as seen from above with the stream in the center of this riparian buffer zone). This terminology for watershed and buffer distinctions will be used throughout this thesis.

Tran et al. (2010) compared the effects of watershed scale LULC on water quality contrasted with LULC within a 200 meter riparian buffer zone. Their research concluded that watershed scale LULC did not correlate significantly with water quality variables, whereas the riparian buffer LULC displayed significant correlation. Sponseller et al. (2001) conducted research into the relationship between water quality and LULC at five different spatial scales: the entire catchment, a 30 meter riparian buffer, and three upstream corridors, or segments, of 200 meters, 1000 meters, and 2000 meters. The authors found that water chemistry was most strongly correlated to LULC at the catchment scale, whereas temperature and other physical measures were most strongly correlated at the riparian buffer and upstream segment scales. Benthos taxonomic richness was found to be most significantly correlated at the 30 m riparian buffer and the 200 m upstream segment scales. Sliva and

Williams (2001) examined the issue of scale in three adjacent watersheds in southern Ontario, utilizing two different scales, catchment level and a 100 meter riparian buffer. Overall, catchment scale LULC exerted the greatest effect on water quality, but the proportion of urban land use within the riparian buffer also had a significant effect. Seasonal variation was also observed to play a role in the strength of these relationships.

Maillard and Santos (2008) examined the relationship between LULC and water quality while modeling non-point source pollution effects in a Brazilian watershed. Their research concluded that there were significant relationships between LULC and water quality at the 90m riparian buffer scale, but no significant relationships were found at greater buffer widths. Li et al. (2009) examined the relationship between water quality and LULC in the Han River Basin China at the 100 m riparian buffer scale, very close to the 90m buffer conclusions of Maillard and Santos (2008). Li et al. (2009) concluded that there were significant correlations between LULC composition at the 100 m buffer and two of the water quality variables, specific conductivity and nitrate. Further research, with varying results regarding the explanatory significance of watershed and buffer scales for water quality, has been conducted by Sparovek et al. (2002), Lee et al. (2009), Xiao and Ji (2007), Alberti et al. (2007), Smart et al. (2001), King et al. (2005), Jones et al. (2001), Griffith (2002), Strayer et al. (2003), Hunsaker and Levine (1995), and Allan and Johnson (1997).

2.7. GIScience, remote sensing, and digital image processing

Issues from the field of GIScience, such as those relating to spatial and temporal resolution, land cover classification, digital terrain model generation, topographic normalization, and other remote sensing considerations, represent another important research area for the study of headwater stream systems. Accurate representation of terrain, hydrography, hydrology, and land cover composition is often a significant challenge for research in predominantly mountainous headwater stream systems.

Baker et al. (2006) compared the results of manual and automated hydrologic modeling operations involving drainage network extraction and watershed delineation. The researchers used 10 different automated delineation techniques with distinct parameterizations, in four different physiographic provinces (Appalachian Plateau, Appalachian Mountain, Piedmont, and Coastal Plain). Their research indicated that unenhanced delineations, those that involved no "stream-burning" or other topographic enhancement procedures, resulted in errors greater than 25% compared to those generated by manual delineation techniques when compared to reference imagery and ground-truth observations. The use of topographic enhancement techniques such as "stream burning" with automated delineation was of particular usefulness for error reduction in the Appalachian Mountain and Appalachian Plateau regions. Binh and Thuy (2008) conducted an accuracy assessment of various interpolation algorithms for the generation of digital elevation models (DEMs) in areas of differing topographic relief in Vietnam. Their research concluded that mountainous areas were best represented by DEMs generated via spline interpolation, with spline regularized operations producing slightly better results than tension spline. Inverse distance weighted interpolation algorithms produced less accurate DEMs than spline, with kriging algorithms producing the least accurate terrain representations in mountainous regions. Colby and Dobson (2010) performed a study examining the role of data sources as well as spatial resolution of DEMs in modeling flood extent in the Coastal Plain and Mountain provinces of North Carolina. Their research indicated that hydraulic modeling results from derived DEMs were highly variable based upon the data source and resolution in both regions, with the coarser resolution data (30 meters) being completely unsuitable for hydraulic modeling in the mountains of Western North Carolina.

Remote sensing imagery acquisition, processing, and classification applications are of great use in detecting land-use change (Rogan and Chen, 2004; Seto et al., 2002), and are of particular importance due to the fine temporal resolution studies of hydrologic response to land-use change that analyses undertaken with these applications can provide. Flood events and drought events can be examined within a much shorter time scale than was previously possible. Imagery from many of the newer satellite systems can now be accessed within weeks or months of processing, and some of these sensor platforms can be diverted as needed to study areas of special interest. Lunetta et al. (2002) examined land cover change detection techniques within the Neuse River Basin using Landsat imagery. The researchers compared the accuracy of different classification techniques in detecting land-use change, with particular focus on their applicability for hydrologic studies. Rogan and Chen (2004) discussed the important role of increasingly available remote sensing data on land-use change analysis for future assessments, likewise noting the value of the quick temporal availability, detail, and scalability of remote sensing data. They stressed the greater integration between remote sensing and GIS applications that are currently available as well, and the great potential for future detailed hydrologic response studies utilizing these technologies.

Griffith (2002) presents a literature review of remote sensing applications for water quality research, stressing the importance of spatial scale as well as the usefulness of Normalized Difference Vegetation Index (NDVI) and vegetative phonological metrics for these types of studies. Griffith notes that the classification of impervious surfaces from remotely sensed imagery has become increasingly important in light of the important role that TPIA plays in water quality. For additional research regarding these topics, Bishop and Shroder (2004) have written a comprehensive textbook, *Geographic Information Science and Mountain Geomorphology*, detailing many issues regarding GIScience, remote sensing, and digital image processing in mountainous environments.

Miller et al. (2009) utilized the *Feature Analyst* software from Visual Learning Systems (VLS 2008) to perform a binary land cover classification (impervious and pervious) in Wake County, NC. They assessed the accuracy of the software by classifying 111 unmosaicked 33 centimeter aerial photographs, using a single training set from three of these 111 images. Utilizing this methodology, they were able to achieve a 95% accuracy rate in classifying impervious surfaces, with an overall accuracy of 92% and a kappa statistic of 0.85. They noted that other researchers have achieved similar accuracy results using *Feature Analyst* to examine other imagery types, such as Quickbird imagery and 1 meter digital orthophotos. Vanderzanden and Morrison (2005) conducted research into the usefulness of Feature Analyst for classification of forest land covers. Their report details numerous strategies for effective land cover extraction, particularly when extracting forest land covers from high resolution remotely sensed imagery. Vanderzanden and Morrison achieved high levels of accuracy utilizing Feature Analyst for forest land cover extraction, and provide helpful documentation regarding their input representation pattern for optimal forest extraction. An additional resource for land cover classifications with Feature Analyst is found in the report by Mauger (2006) for the US Fish and Wildlife Service regarding impervious surface extraction in the Lower Kenai Peninsula. Mauger reported difficulties in extracting impervious surfaces in areas of dense forest canopy coverage. Mauger used ancillary data layers such as road networks to augment missing areas of impervious surfaces from image classification processes.

CHAPTER THREE

Geospatial Modeling and Database Development

3.1. Digital terrain modeling

Elevation surfaces for GIS analysis, environmental modeling, and other tasks are usually provided as digital terrain models (DTMs). These DTMs must accurately represent the topography of the area they represent, and should have the finest spatial resolution possible for the creation of robust environmental, hydrologic, and hydrographic models. There are several different types of DTMs commonly used for terrain representation; Triangulated Irregular Networks (TINs) and Digital Elevation Models (DEMs) have traditionally been used for hydrologic and hydrographic modeling. A limitation of TINs within ESRI's ArcGIS 9.3 software suite is the inability of the software to process more than roughly 5 to 10 million points within a single dataset, depending on the geoprocessing operation and other processing variables. With the advent of very-high resolution LiDAR data, even a relatively small study area can consist of a very high number of points far surpassing this limitation. For example, the Upper South Fork watershed which is the study area for this research consists of approximately 10 million bare earth LiDAR points. ESRI has overcome this problem by creating a new type of DTM, the *terrain dataset*.

ESRI describes the terrain dataset as "a multiresolution, TIN-based surface built from measurements stored as features in a geodatabase" (ESRI 2011). Rather than storing the terrain surface as a TIN or DEM, the terrain dataset utilizes the original point-elevation data to generate a TIN-like surface "on-the-fly." This elevation data representation is scalable, and allows for very fast rendering and a hierarchy of resolution-levels that can be user-specified. One of the chief advantages of the terrain dataset is the extremely large amounts of data that can be stored within one. Tens of millions of points can be processed in a file geodatabase environment and billions of points can be used in an ArcSDE environment (ESRI 2011). Additionally, raster DEMs can be easily generated from the terrain dataset using the *TERRAIN TO RASTER* tool in the ArcToolbox.

3.1.1. Methods

The terrain dataset data model was used for this research in order to generate a series of seamless digital terrain models including terrain datasets and DEMs encompassing the entire study area and immediately adjacent areas. A flowchart of these steps is presented in Figure 3. Hydrographic modeling, the next component of this research, required that areas adjacent to the immediate study area be included in order to ensure that watersheds were properly delineated and drainage networks were properly represented. If a digital terrain model were created that didn't include all the possible hydrographic and terrain components of the study watershed (ridgelines, known streams, catchments, etc.) a poorly fitting model could result. This would corrupt all further analyses and derived geospatial products generated from these erroneous terrain and hydrographic models.

The North Carolina Floodplain Mapping Project (NCFMP) maintains LiDAR data for the entire state. This data is provided in 10,000 foot by 10,000 foot tiles, using the North Carolina State Plane FIPS 3200 projection, based on NAD 1983 and the NAVD 1988 vertical datum. A methodology developed by Kevin White, a former graduate student in the Department of Geography and Planning at Appalachian State University, was adopted for use in this thesis research for identifying, acquiring, and processing the twenty five tiles of bare earth LiDAR data which represented the study area (White 2009). The 25 tiles were arranged in a square five x five matrix to allow for adequate representation of the Upper South Fork watershed and areas immediately adjacent to the watershed's boundaries. The area represented by these tiles measured 15.24 kilometers per side, for a total area of approximately 232 square kilometers (57,328 acres; 23, 200 hectares; or 90 square miles).

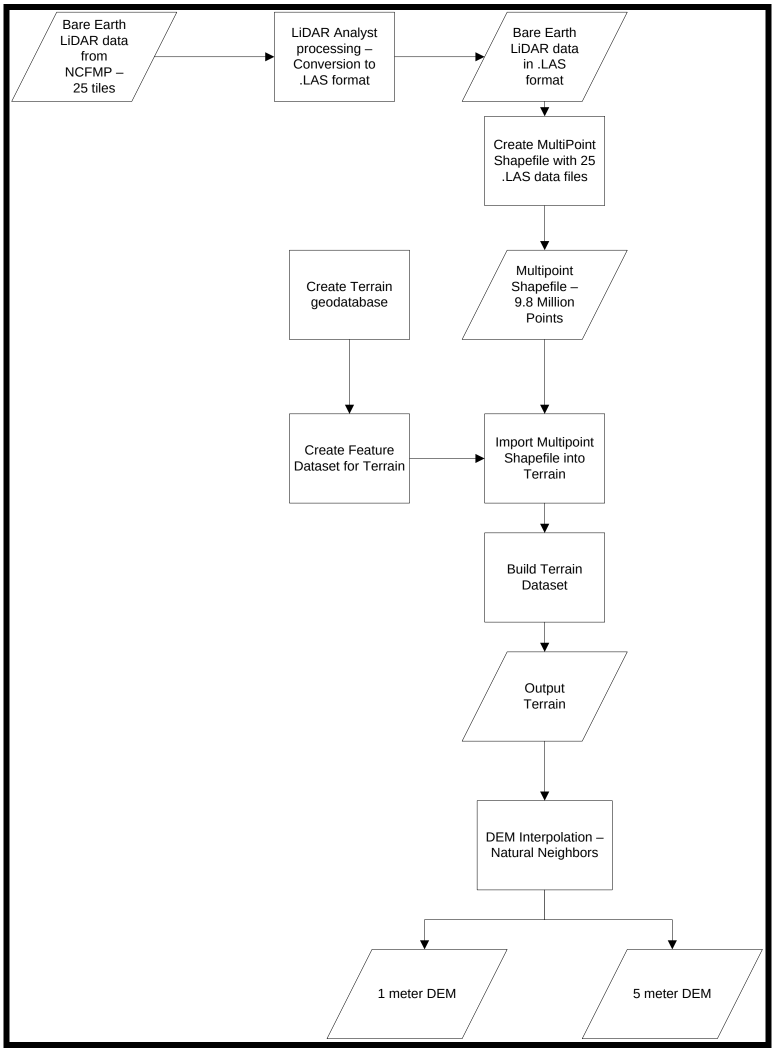


Figure 3. Flowchart of steps involved in creation of terrain dataset and digital terrain models from bare earth LiDAR data.

The tiles for the study area were first identified using a NC Elevation Grid Layer with unique identification numbers assigned to each tile. Twenty-five tiles, in a 5 by 5 matrix were identified as belonging to the Upper South Fork New River watershed study area. The LiDAR data contained in these files was stored in a .TXT format. ArcGIS is capable of converting these files to a suitable format for processing within ArcGIS, but prior research indicated that superior results were obtained by converting these .TXT files to the industry-standard .LAS format (White 2009). LiDAR ANALYST, from Visual Learning Systems (VLS 2008), was used to convert the files from .TXT to .LAS format. This software preserved all geospatial referencing from the source data, as well as calculating offsets for the conversion process. Missing georeferencing information can be defined during the import/conversion process, so all data for this project were converted to the single georeferencing system described above.

Once the bare earth data had been converted into .LAS format, ArcGIS 9.3 was used to convert the data to a Multipoint Shapefile via the *3D ANALYST > CONVERSION > FROM FILE > LAS TO MULTIPOINT* tool of ArcToolbox. This multipoint shapefile consisted of nearly 10 million points, and covered an area of approximately 232 square kilometers. The *POINT FILE INFORMATION* tool was used to calculate the average point spacing, also referred to as nominal post spacing, for each tile. The average point spacing for the overall study area was calculated to be 16.5 feet or 5.1 meters.

A terrain dataset was then constructed. A new file geodatabase was created to house the terrain, and a new feature dataset was created within this geodatabase. The multipoint shapefile that had been previously created was imported into this feature class. Since no breaklines or other topographic features were to be used in this terrain dataset, no other features were imported. The *Terrain Wizard* was then initiated, and the new terrain was created using the average point spacing of 16.5 feet.

Digital elevation models were generated from the terrain dataset. The natural neighbors DEM interpolation algorithm was used for the final products based on prior research (Coffey and Colby 2010b) and the recommendations of ESRI (2011b). Natural neighbors interpolation utilizes the Voronoi neighbors of each cell's center to determine the z, or elevation, value for the cell. Natural neighbors is a more computationally intensive interpolation algorithm, but produces a smoother , more realistic surface than DEMs produced from the linear interpolation method. Other interpolation methods such as inverse distance weighted, kriging, spline, and others are available in the ArcToolbox and through ArcObjects. However, ArcGIS 9.3 consistently failed to generate DEMs from the terrain's multipoint shapefile using these interpolation methods, most likely due to the large number of points, approximately 10 million, which made up the study area's multipoint shapefile of bare earth LiDAR returns. Also, these interpolation methods are not directly accessible via the toolbox or scripting for DEM generation from terrain datasets. It was determined that natural neighbors would, therefore, be the most suitable DEM interpolation algorithm for this thesis research.

In order to carry out accurate hydrographic modeling, 1 meter, 1.2 meter, and 5 meter spatial resolution DEMs were created. The 1 m DEM was of particular usefulness in representing stream sinuosity, since many of these headwater streams are quite small and deeply incised, particularly in the areas of highest topographic relief where the stream channels are often only 2 to 5 meters in width. The 5 m DEM was considered to be a more accurate representation of the elevation surface depicted by the source data, and was used for rapid display and visualization purposes. The 5 m DEM would be most appropriate for geoprocessing operations such as slope calculations, geomorphometric analyses, and other geographic information system operations. The 1 m DEM was used for hydrographic modeling and other GIS operations in order to better represent stream sinuosity and to establish a uniform 1 meter scale for analyses and modeling throughout the thesis research. The 1.2 m DEM was created in order to replicate a portion of the accuracy assessment methodology that the North Carolina Stream Mapping Program had utilized when evaluating the NC Streamlines hydrographic dataset.

3.1.2. Results and Discussion

Creation and storage of the entire area as a single terrain dataset allowed for the creation of multiple DEMs and hydrographic models for the entire study area. The new terrain dataset of the study area, which consisted of approximate 10 million bare earth LiDAR points, was successfully created within the new geodatabase. A high level of detail was observable in the terrain dataset, which closely resembled a TIN with significantly enhanced redraw and computational processing times. Screenshots of this new terrain dataset are shown in Figures 4 and 5. DEMs (1 m, 1.2 m, and 5 m) were generated from the Terrain Datasets using the *TERRAIN TO RASTER* tool in ArcGIS 9.3, and created using the natural neighbors DEM interpolation algorith, in addition to a 1.2 m DEM created using linear interpolation.

Results from the accuracy assessment of the derived drainage network extractions and watershed delineation procedures outlined in the next section quantitatively reinforce the high accuracy indicated by visual comparison of the DEMs with aerial photography and existing topographic data. The 5 meter and 1 meter DEMs are presented in Figures 6 through 10. There is not a high degree of visually detectable difference in the two resolutions in these depictions, but the increased resolution of the 1 meter DEM was found to produce superior hydrographic modeling results and demonstrated more complex spatial detailing at smaller scales for drainage pattern representation.

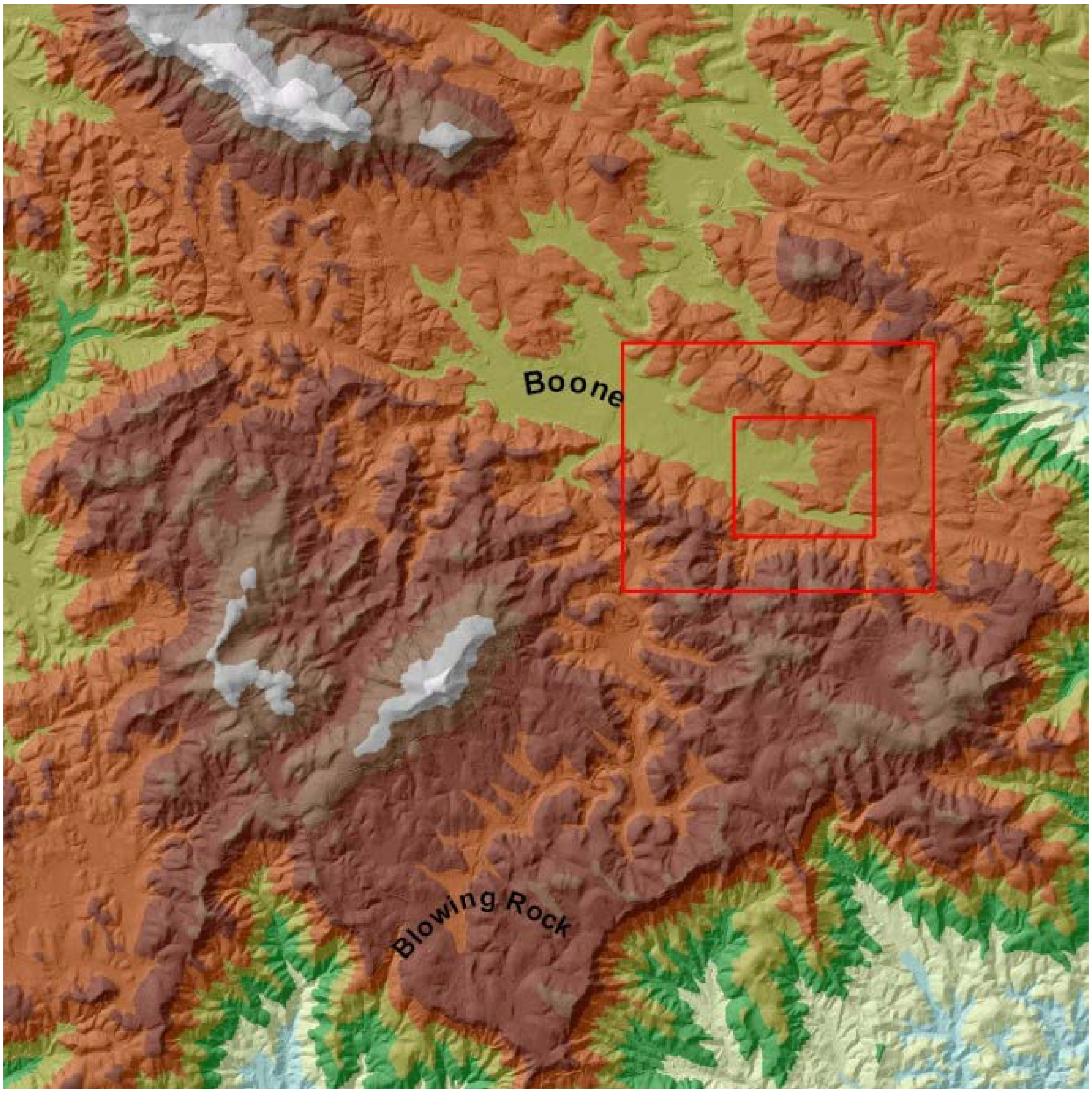


Figure 4. Terrain dataset of entire study area, including 25 bare earth LiDAR tiles from the NCSMP. Study area measures approximately 15,240 meters by 15,240 meters.

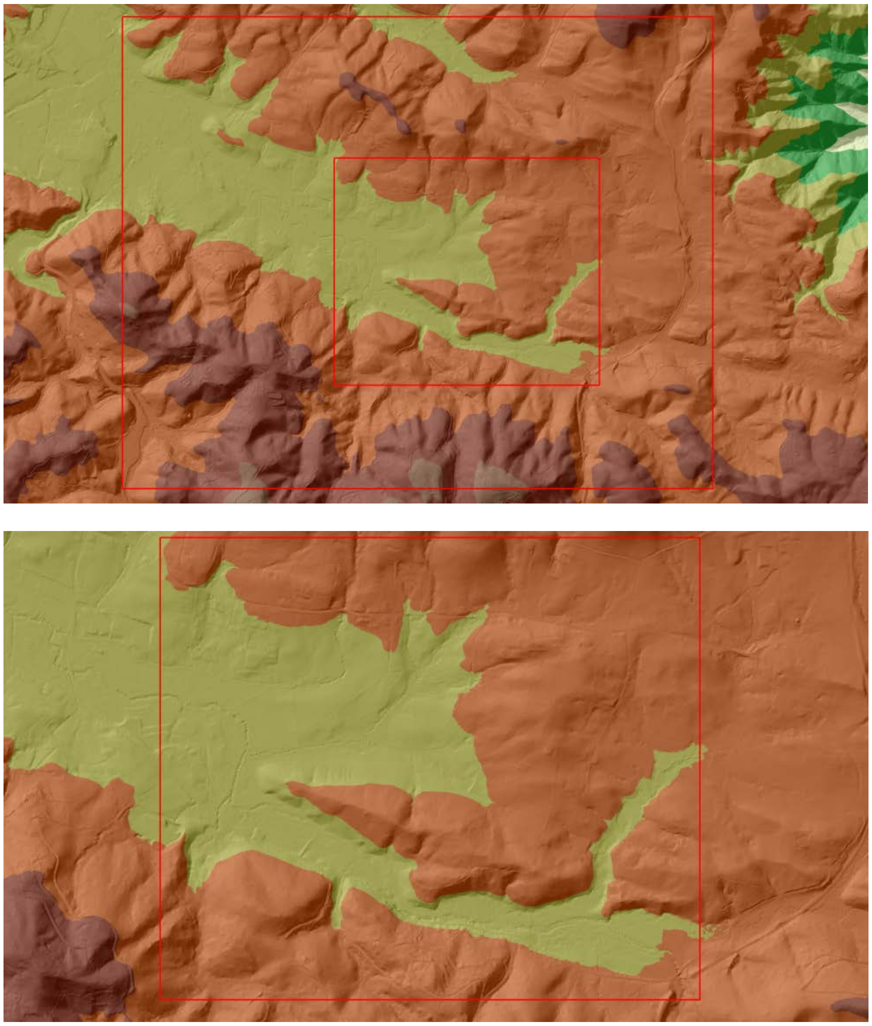


Figure 5. Large scale insets of study area from Figure 4 demonstrate increased resolution and representation of elevation and surface features.

The 1 m DEMs proved to be extremely useful for hydrographic modeling due to their finer cellsize than the 5 m DEMs. The 1 m cellsize permitted enhanced stream representation, with greater precision in accurately representing stream centerlines in comparison to reference imagery in both visual, qualitative assessments as well as quantitative evaluations. Additionally, enhanced hydrographic modeling output from the 1 m DEM served as superior raster input data for conversion to vector features such as vector drainage lines and watershed boundaries. Another advantage of the 1 m DEM resulted from the identical resolution of the aerial photography used for the land cover classifications, allowing for high analytical precision utilizing both of these datasets. This high level of spatial resolution and detail will aid future research into areas such as land cover composition on certain slope ranges and hillsides, forest and impervious area calculations in floodplains, and large-scale human alterations to natural slopes, terraces, ridges, hydrographic features, land cover, and other aspects of the landscape.

The 1.2 m DEMs were utilized in the following research phase, *Hydrographic Modeling*, in an attempt to replicate the accuracy assessment methodology used by the North Carolina Stream Mapping Program. They were not used in subsequent operations, however, since the 1 m DEM was selected due to the spatial resolution it shared with land cover classification imagery datasets and the 5 m DEM was considered to be more consistent with standard GIS practices regarding the spatial resolution of derived products with regards to the resolution of source data. The 5 m DEMs are the most similar in spatial extent to the 5.1 m nominal post spacing of the bare earth LiDAR source data, and therfore arguably better represent the actual terrain. As a general rule in GIScience, a derived product such as a DEM should not have a finer resolution than its source data. However, this is not always the case, particularly in situations where the accuracy of derived products, such as the drainage networks and watershed delineations of this research, is of paramount concern. It is not the intention of this researcher to assert that a DEM of finer resolution than its source data can be presented as a more accurate product than a DEM of similar resolution to its source data.

The higher resolution, 1 m DEM used for hydrographic modeling in this research was created with the goal of representing the study area's hydrography, and was not considered to be more accurate than the 5 m DEM in representing elevation. The improvements in representation of hydrography that were accomplished by this research demonstrated the utility of the higher resolution 1 m DEM. In modeling operations where the 1 m DEM was not necessary, the 5 m DEM was used. This DEM provided a great savings in storage requirements and geoprocessing speed due to its smaller size of 35 megabytes compared to the 886 MB filesize of the 1 m DEM. Very complex geoprocessing procedures and models can be especially computationally intensive when working with the nearly 1 gigabyte 1 m DEM. It should be stressed that 5 m is still a very high spatial resolution compared to the majority of currently available topographic and remotely sensed imagery data. Spatial analysis can be undertaken with a great deal of precision using 5 m spatial resolution data.

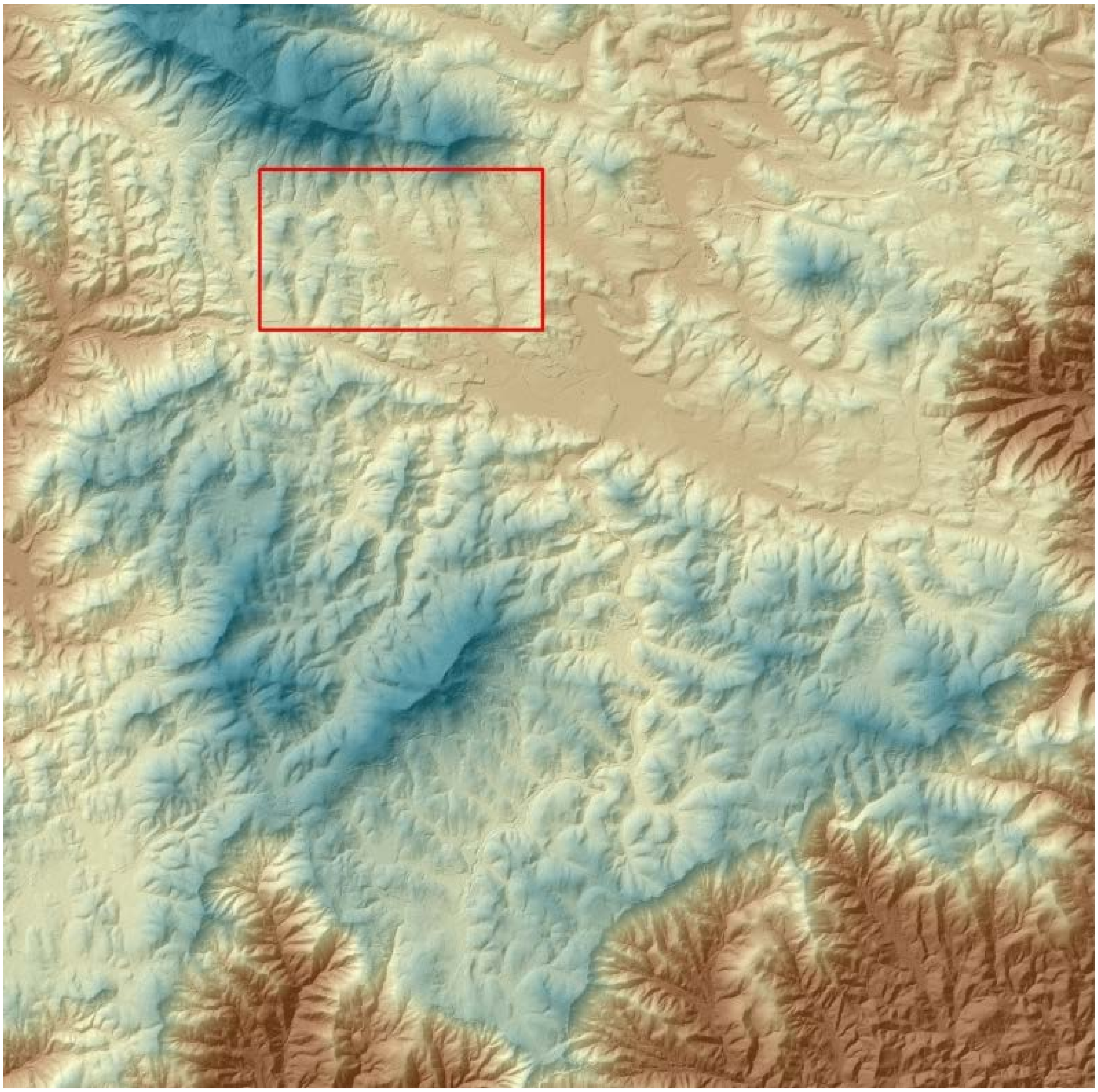


Figure 6. Five meter DEM of Upper South Fork study area.

Figure 7. Five meter DEM inset from Figure 6, featuring the Appalachian State University campus in Boone, NC.

Figure 8. One meter DEM inset from Figure 6, featuring the Appalachian State University campus in Boone, NC.

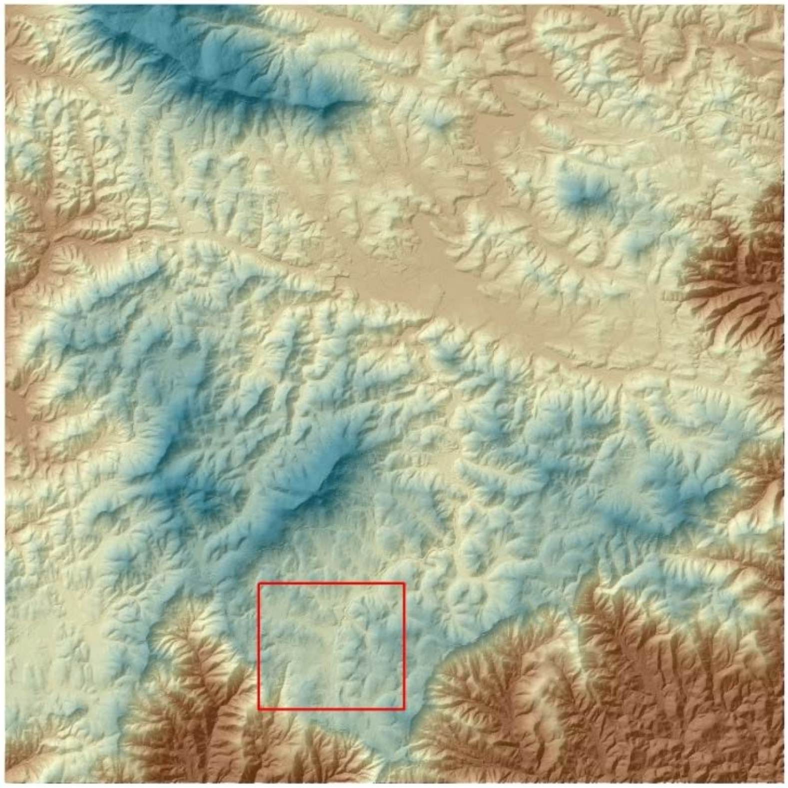


Figure 9. One meter DEM of the Upper South Fork study area.

Figure 10. One meter DEM inset from Figure 9, featuring the location of the city of Blowing Rock.

3.2. Hydrographic Modeling

Hydrographic modeling was undertaken to provide a highly accurate, high resolution digital representation of the surface hydrology of the Upper South Fork watershed and its sub-watersheds. The products derived from this operation were of great importance for testing the central hypothesis regarding the relationship between land cover and water quality. The hydrographic modeling results were of particular importance for examining issues of scales, such as the influence of riparian buffer zones and individual watersheds, since the generation of multiple stream buffers and the derived land cover area classification values for the variable buffer distances and watersheds was highly dependent upon accurate hydrographic modeling results. If the derived drainage pattern was erroneous, errors in land cover area would be compounded during the stream buffer and land cover area calculation operations. The location of watershed outlet points was also of critical importance, not only for determining placement of water quality instruments, but for establishment of a logical watershed structure and hierarchy within the system.

The hydrographic modeling operations were undertaken with the following primary goals:

1. Creation of a comprehensive database of hydrographic information for the study area, with particular emphasis on optimal digital drainage network generation and watershed delineations.

2. Development of a semi-automated, repeatable hydrographic modeling methodology, with particular utility in areas of rugged topography.

3. To compare the hydrographic modeling results using DEMs of several spatial resolutions generated from the terrain dataset with two different interpolation algorithms, natural neighbors and linear, and three different DEM reconditioning, or stream burning, approaches: DEM reconditioning with the North Carolina Stream Mapping Program (NCSMP) drainage lines, reconditioning with the National Hydrography Dataset (NHD) drainage lines, and no DEM reconditioning.

4. A comparison of the hydrographic modeling results of step 3 with those created using readily available source data consisting of a 10 meter DEM from the USGS and the NHD drainage lines for DEM reconditioning in order to assess the results of a methodology that can be

utilized in study areas without access to high resolution LiDAR elevation data and high quality hydrographic source data such as that of the NCSMP.

5. To improve upon the high quality digital drainage network produced by the NCSMP. Prior research (Coffey and Colby 2010b) had revealed significant errors in this dataset regarding erroneous representation of first and second Strahler order streams that did not actually exist.

Since this hydrographic modeling procedure was undertaken using the most current and highest resolution source data available, the outputs were intended to represent a significant improvement in digital hydrographic representation of the study area when compared with previously existing information.

3.2.1. Drainage pattern and watershed boundary delineation

Hydrographic modeling was undertaken using the ArcHydro extension (Maidment 2002) of ArcGIS 9.3. ArcHydro is a powerful suite of hydrologic and hydrographic modeling tools that offers the advantages of a tightly-coupled modeling application that operates within ArcGIS. The architecture and deployment environment of ArcHydro improves the processing capabilities of ArcGIS, reduces the errors that frequently accompany multiple import/export operations, and provides a single graphical user interface (GUI) for the end user. The drainage network extraction and watershed delineation modules of ArcHydro, which were used for this research, are particularly robust. ArcHydro uses a series of processing steps to produce a hydrographic model of a study area. These processing steps are presented in Figure 11. Details of each of these operations are well documented by Maidment (2002). Discussions of some of the more important steps are included as necessary in the following sections.

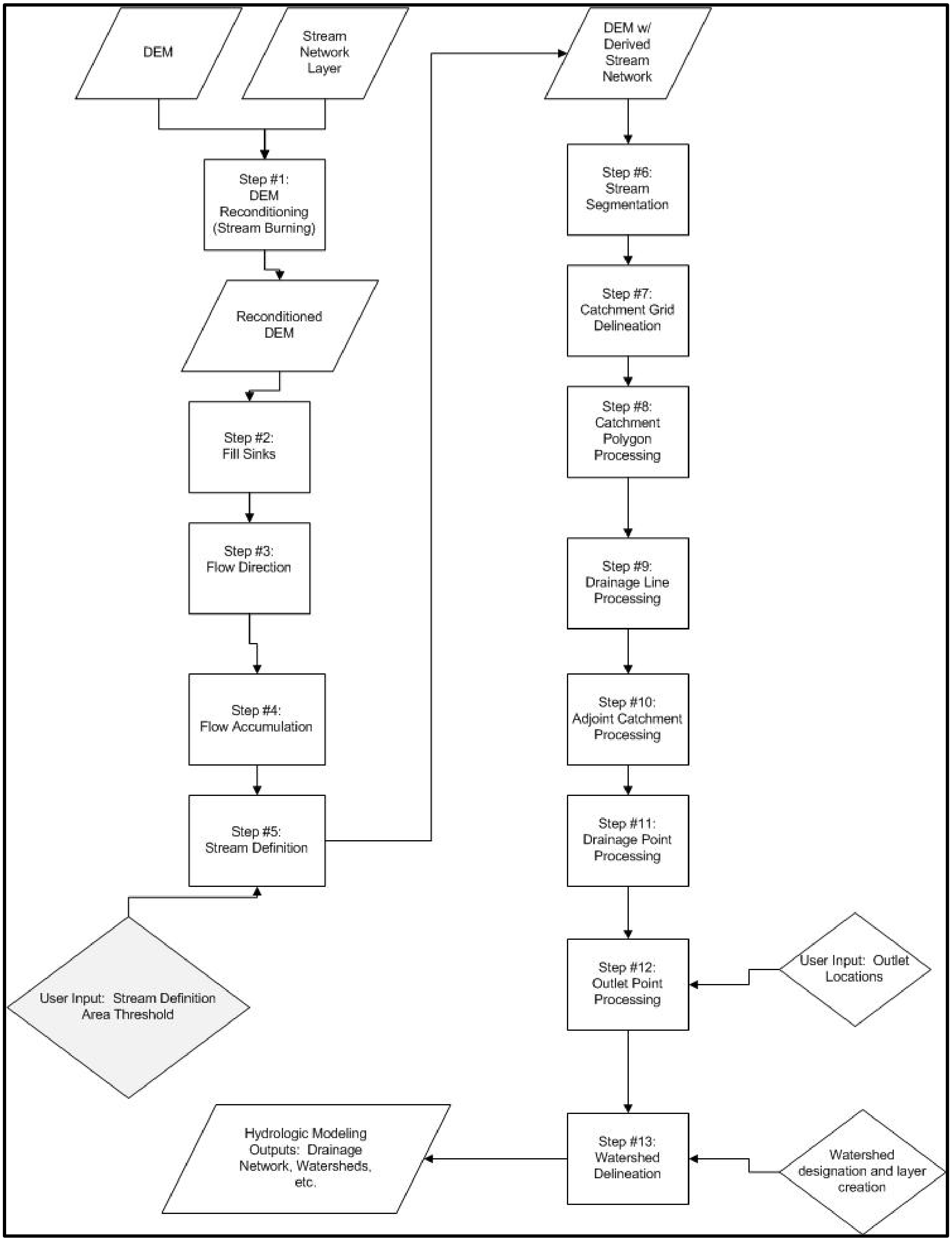


Figure 11. Flowchart of hydrographic modeling steps.

Source data for the hydrographic modeling consisted of DEMs derived from the digital terrain modeling portion of this research at 1 m, 1.2 m, and 5 m spatial resolutions; a mosaicked DEM from the USGS at 10 m resolution; a digital drainage pattern file for the study area obtained from the NCSMP (NCSMP 2010); and a drainage pattern from the NHD (USGS 2010). The NCSMP drainage pattern is occasionally referred to in the literature and this paper as the *NC Streamlines*. The DEMs were used as the source DEM inputs for each of the distinct ArcHydro modeling iterations, and the NC Streamlines and NHD hydrography datasets were used as the input stream networks for DEM reconditioning. DEM reconditioning is a GIS operation wherein a drainage network is "burned-in" to the base DEM. This procedure improves the output of drainage network extractions in areas of low-relief and locations where hydrologic obstructions such as bridges, culverts, and roads act as dams during the modeling operation. The damming effect of these obstructions is due to the fact that the DTM is constructed from the LiDAR point data with inherent limitations regarding 2.5 dimensional digital representation of a 3 dimensional environment. LiDAR cannot penetrate solid objects, therefore bridges, culverts, and roads act as dams for the lower elevation stream channels that pass beneath them and are not represented by the LiDAR data. Another source of error in DEMs generated from LiDAR is a result of the elevation errors among individual points. These errors occur as a result of the accuracy tolerances of the aircraft-mounted LiDAR instrumentation. DEM reconditioning overlays the input stream network on the base layer DEM and subtracts a default or user-defined elevation value from the z-value of the DEM's cells which underlay the stream layer. This effectively incises the stream into the DEM and helps to remove hydrologic obstructions without the extremely laborious process of manually editing individual cells' elevation z-values.

Watershed delineation was undertaken via the final two steps of ArcHydro processes for this research, *OUTLET POINT PROCESSING* and *WATERSHED DELINEATION.* Seven water quality monitoring instruments were available for this research, and it had been determined that the study area would be divided into a primary watershed, the Upper South Fork, and six nested sub-watersheds: Boone Creek, East Fork, Flannery Fork, Goshen Creek, Middle Fork, and Winkler Creek. Members of the Water Resources Planning Committee (WRPC) at Appalachian State University had previously established several drainage outlet points for a preliminary delineation of sub-watersheds, which were used as a planning basis for establishment of the final watershed delineation and water quality monitoring program. A synoptic survey was undertaken on June 25, 2010 to canvas the proposed watersheds and outlet points to determine their suitability for monitoring equipment installation and to assess whether or not the derived watersheds would represent a logical drainage network pattern and catchment arrangement. After reviewing the results of the synoptic survey analysis, seven final drainage outlet locations were established. These outlets were used as input parameters for *OUTLET POINT PROCESSING*, and the seven watersheds were delineated in the final step from these outlet points.

It should be noted that the primary watershed of the study, the Upper South Fork New River watershed, is generally designated as *Upper South Fork* in this text and accompanying figures and tables. Occasionally, however, it is referred to as *State Farm* due to the location of the water quality instrument at the watershed's outlet point in close proximity to ASU property off of State Farm Road in Boone. All of the other watersheds (Boone Creek, East Fork, Flannery Fork, Goshen Creek, Middle Fork, and Winkler Creek) are actually sub-watersheds of the main Upper South Fork watershed and are described as being "nested" sub-watersheds within the larger watershed. In addition, the Goshen Creek watershed is nested within the East Fork watershed. All land cover and area calculation figures throughout this paper assume that the larger watershed in a nested relationship contains the land of the smaller, nested sub-watersheds; in other words, area and land cover values given for East Fork will include the values of Goshen Creek, and Upper South Fork's values contain the values of all the sub-watersheds.

Research by Coffey and Colby (2010a) had previously uncovered errors in the NC Streamlines digital drainage pattern dataset within the Upper South Fork New River study area. A visual examination of the NC Streamlines together with a 6 inch aerial photograph of Watauga County from 2009 indicated that the majority of first order streams and a portion of the second order streams in the NC Streamlines dataset did not actually exist as streams on the ground. Not only were there no perennial streams in these locations, but no indicators of the presence of ephemeral streams were found. A comparison of the underlying topography and slope from the DEMs indicated that ditches, gullies, and erosional features were associated with these erroneous stream segments. It was hypothesized that these erroneous headwater stream segments had been generated as a result of using a commonly used low flow accumulation threshold of 6 acres or 0.024 square kilometers (NCSMP 2010). The 6 acre flow accumulation threshold utilized by the NCSMP likely produced accurate results for the remainder of North Carolina due to smoother topography. The high topographic relief of the Upper South Fork study area, however, required a larger flow accumulation threshold in order to produce an accurate drainage network delineation. After a long series of heuristic tests to establish the optimal flow accumulation threshold for accurate drainage pattern representation, an optimal flow accumulation threshold of 0.072 km^2 (18 acres) was selected. Based on the results of previous research (Coffey and Colby 2010a) regarding optimal DEM interpolation algorithms and the recommendations of ESRI (ESRI 2011b) the 1 m DEM generated with natural neighbors interpolation was used for these modeling iterations. The NC Streamlines dataset was used for DEM reconditioning, and the 0.072 km^2 flow accumulation threshold was used as the input parameter for step #5, *STREAM DEFINITION*, of the ArcHydro processing of these procedures.

The initial analysis phase of hydrographic modeling was undertaken in order to assess the modeling output of DEMs generated from the terrain dataset in conjunction with various DEM reconditioning strategies, and to compare these results with those obtained from the 10 m USGS DEM which had been reconditioned using the NHD drainage lines. In order to compare these results with those obtained by the NCSMP, the 1.2 m DEMs were used in an attempt to replicate the source data and methodology used by the NCSMP, which used 4 foot spatial resolution DEMs during their accuracy assessments. This initial hydrographic analysis modeling phase consisted of 7 individual ArcHydro processing routines, each using a different combination of the DEMS and reconditioning techniques.

3.2.2. Evaluation of digital elevation models and drainage pattern delineation

Once the initial phase of hydrographic modeling involving the attempted replication of the NCSMP methodology had been completed, a series of evaluation procedures was undertaken in order to determine the positional accuracy of the derived drainage patterns. Thirty five random points were generated on the original NCSMP Streamlines using the *CREATE RANDOM POINTS* tool of ArcGIS. These points were then individually relocated to the stream centerlines of a 2009 6 inch aerial photograph of the study area. The *NEAR* function of ArcGIS was then employed to calculate the distance from each random point to each of the derived streamlines from the seven ArcHydro iterations. Descriptive statistics of the results of this operation are presented in Table 1. These results represent hydrographic modeling goals #3 and #4 from page 36, and indicate that despite some small variation in accuracy from hydrographic modeling outputs using 1.2 m DEMs from natural neighbor and linear interpolation methods, the two methods each produced highly accurate results. Additionally, it was demonstrated that use of commonly available 10 m DEMs and the NHD from the USGS can produce accurate results in areas without high quality LiDAR and drainage network datasets such as that of the NCSMP.

Table 1. Descriptive statistics of derived drainage line distances from reference stream centerline.

Hydrographic dataset used for DEM reconditioning	1.2m DEM - Natural Neighbors Interpolation			1.2m DEM - Linear Interpolation			USGS 10m DEM
	NCSMP	NHD	None	NCSMP	NHD	None	NHD
Mean	1.2	7.7	16.1	1.3	7.8	13.4	7.4
Median	0.4	4.6	5.2	0.4	4.7	5.0	4.9
Range	21.3	39.6	110.5	21.9	42.1	55.0	29.0

sample size of random points is 35

all dimensions are in meters

0.073 km^2 stream definition threshold used for all derived drainage networks

The second phase of the hydrographic modeling operations involved the creation of an optimal drainage network pattern and delineation of the seven watersheds from the 1 meter DEM. Qualitative assessment of these hydrographic modeling outputs indicated that highly accurate results had been achieved. Images of each of the watersheds are presented in Figure 12. Descriptive statistics which describe a selection of the hydrographic and physical characteristics of the watersheds are presented in Table 2. Additional images demonstrating the observable differences in the extent of the original NC Streamlines compared to the extent of the derived drainage lines from this research are presented in Figures 13 through 16.

Figure 12. Individual subwatersheds of the Upper South Fork watershed of the New River with derived drainage lines. Clockwise from top left: the Upper South Fork watershed (labeled as State Farm for the water quality monitoring station location), Boone Creek sub-watershed, East Fork sub-watershed, and Flannery Fork sub-watershed.

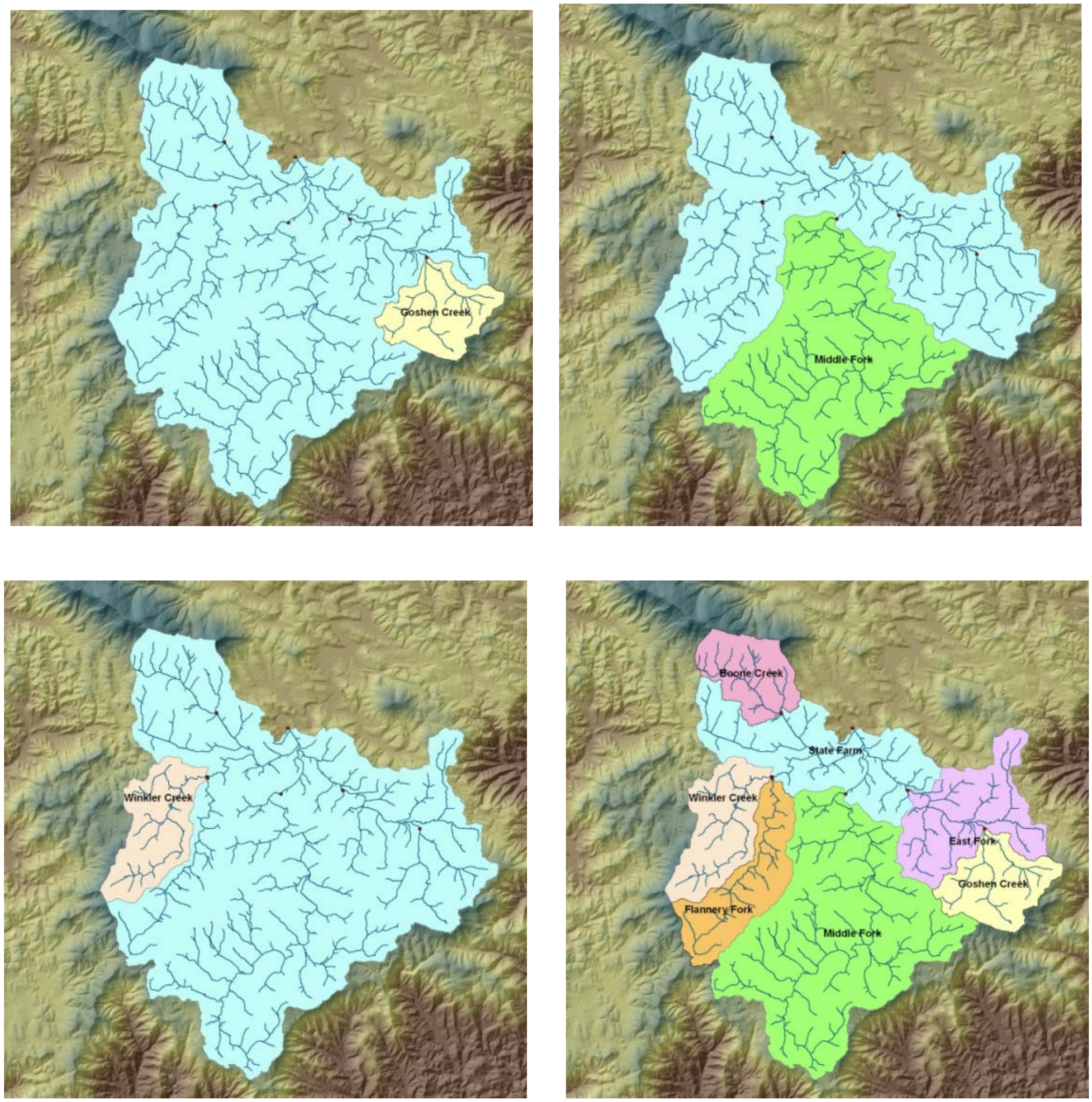


Figure 12 (cont.). Individual subwatersheds of the Upper South Fork watershed of the New River with derived drainage lines. Clockwise from top left: Goshen Creek sub-watershed, Middle Fork sub-watershed, Winkler Creek sub-watershed, and all sub-watersheds.

Table 2. Descriptive statistics by watershed of physical characteristics.

Watershed	Total Area (square meters)	Total Area (square kilometers)	Total Drainage Length (m)	Drainage Length (m)	Drainage Density	Minimum Elevation (m)	Maximum Elevation (m)	Average Elevation (m)	Elevation Range
Boone Creek	5,297,159	5.3	14,238.0	14.2	2.7	960	1426	1193	466
East Fork	15,942,323	15.94	42,485.2	42.5	2.7	949	1258	1103	309
Flannery	7,377,134	7.38	18,315.5	18.3	2.5	990	1389	1190	399
Goshen Creek	6,014,764	6.01	14,059.8	14.1	2.3	974	1258	1116	284
Middle Fork	30,677,282	30.68	76,057.2	76.1	2.5	956	1389	1173	433
State Farm	79,549,505	79.55	203,194.0	203.2	2.6	941	1426	1184	485
Winkler Creek	6,993,984	6.99	16,708.9	16.7	2.4	989	1332	1161	343

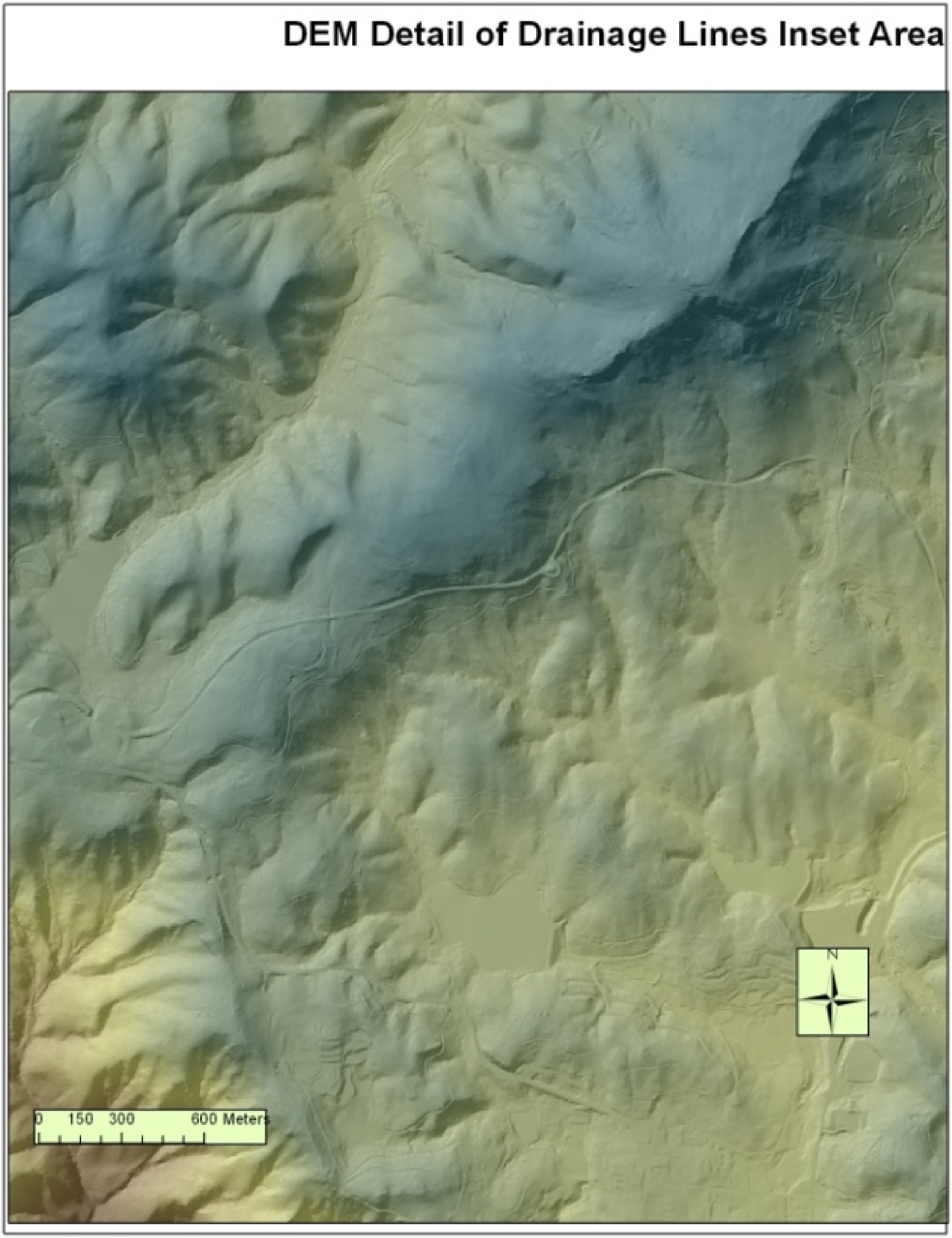


Figure 13. Five meter DEM of area near Blowing Rock generated from natural neighbors interpolation of terrain dataset derived from bare earth LiDAR. No hydrography features are displayed in this image. Surface and elevational features are clearly visible.

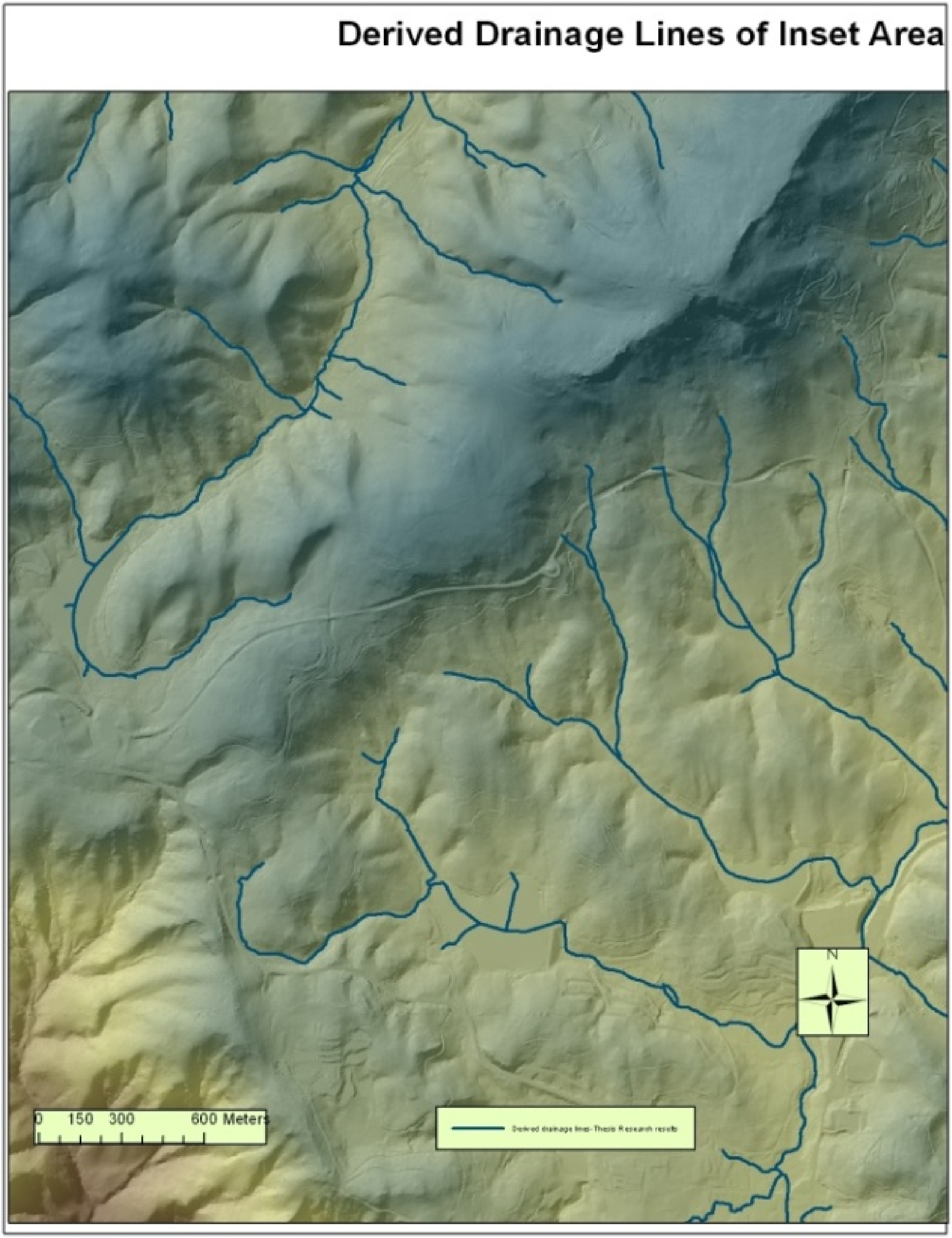


Figure 14. Derived drainage lines from this research (dark blue) from hydrographic modeling results, using 0.072 km^2 flow accumulation threshold, draped over 5 m DEM.

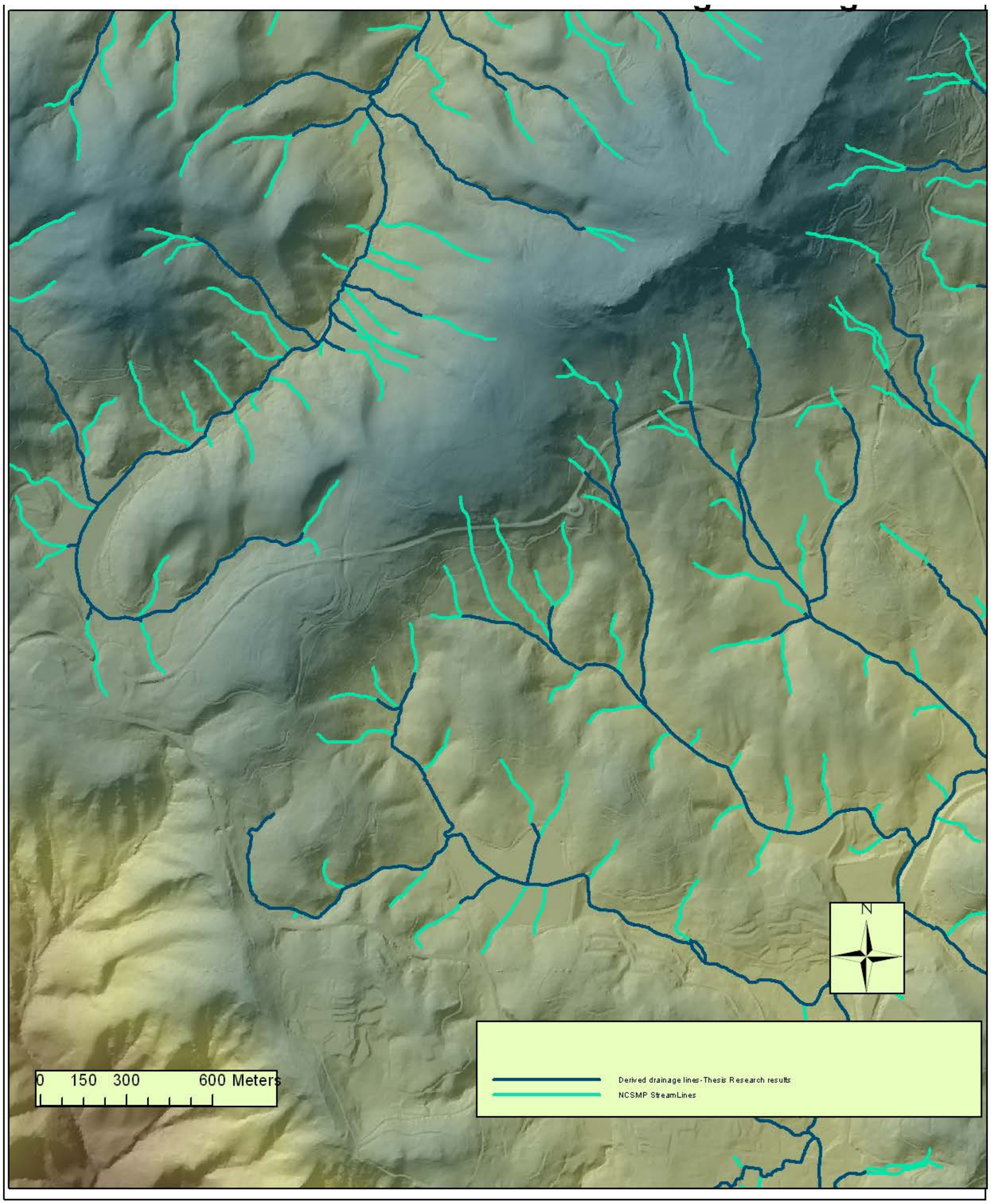


Figure 15. Derived drainage lines from this research (dark blue) with NCSMP drainage lines (light blue) displayed with 5 m DEM. Surface features such as gullies which contributed to generation of erroneous headwater segments of NCSMP are observable.

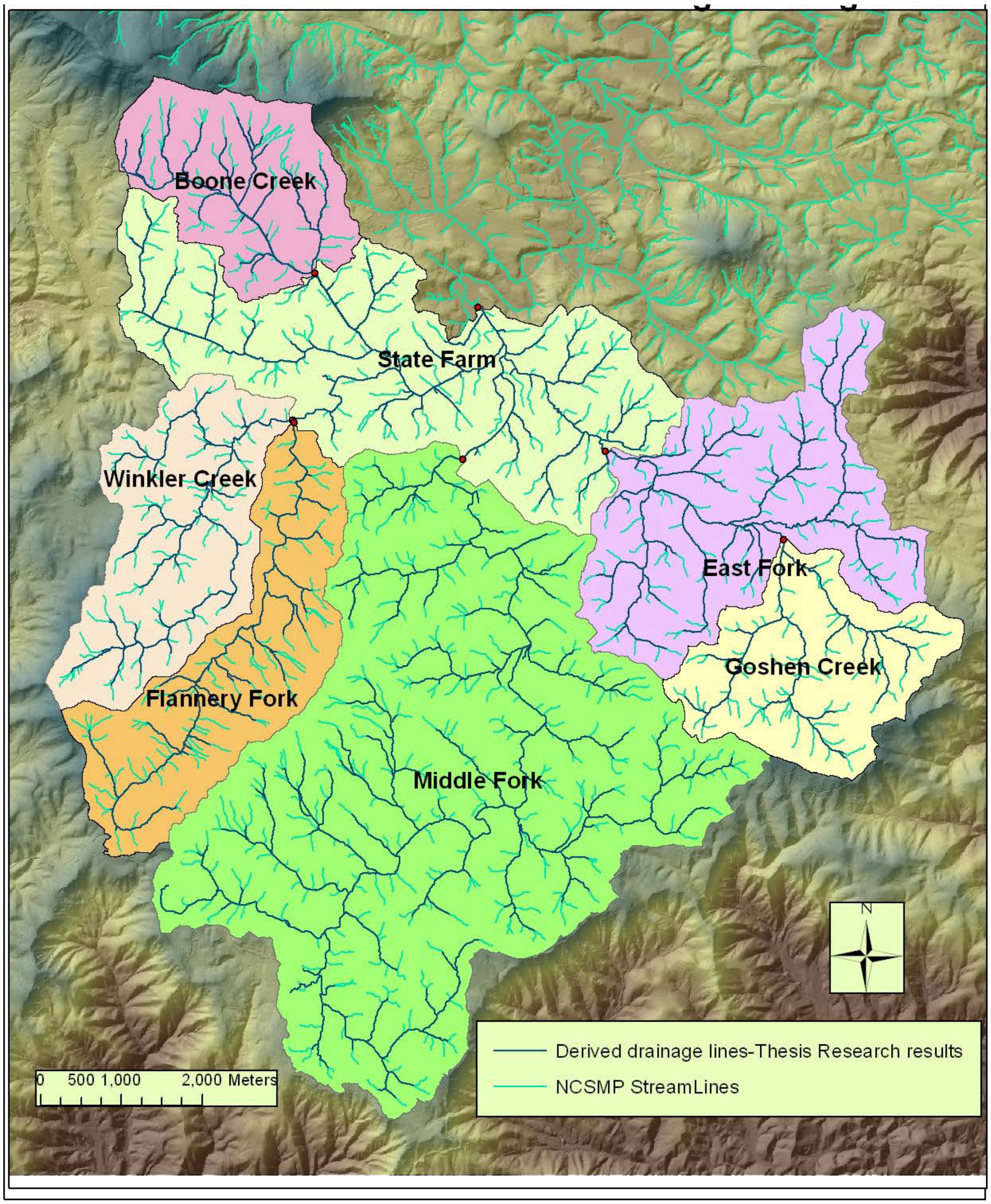


Figure 16. Map of results of hydrographic modeling. Watershed delineations are represented, along with derived drainage lines from this research (dark blue) and NCSMP streamlines (light blue). The "State Farm" label refers to the entire Upper South Fork watershed, and is not intended to only represent the cream colored area in the northern portion of the map. The other six sub-watersheds are nested within the Upper South Fork watershed. The Goshen Creek sub-watershed is nested within the East Fork sub-watershed.

3.2.3. Evaluation of optimal drainage pattern delineation

A series of evaluations were undertaken to test the accuracy of the derived drainage lines from this research in comparison with the NC Streamlines, and to determine how well the hydrographic modeling results represented ground truth as represented by a reference image. Due to the difficulties inherent in field verifying watershed boundaries, the evaluations were designed to measure the correspondence of the derived drainage pattern with the actual streams of the study area. A 6 inch aerial photograph of Watauga County from 2009 was used as the ground truth reference imagery. The conceptual design of the evaluation procedure consisted of several primary components:

1. Determination of the extent of erroneously represented headwater stream segments in NC Streamlines from NCSMP through binary testing of stream presence vs. non-presence at random points.

2. Removal of erroneous headwater stream segments. Evaluation of presence vs. non-presence of the streams in remaining, higher order stream segments through Boolean testing of random points.

3. Determination of the representational accuracy of newly derived drainage lines from this research from ArcHydro processing and increased flow accumulation threshold threshold through Boolean testing of stream presence vs. non-presence at random points.

4. Evaluation of positional precision of derived drainage lines from this research by statistical analysis of distance, via ArcGIS *NEAR* function, between derived drainage lines from this research and actual stream centerlines established by manipulation of randomly generated points to the centerlines of streams visible in reference image.

To test the hypothesis that the NC Streamlines misrepresented non-existent headwater stream segments, the initial task consisted of extracting first order streams from the NC Streamlines dataset and evaluating the presence or non-presence of these first order streams by ground-truthing them with the aerial photograph. An ArcMap document was created and two data layers were added: the air photo and the NC Streamlines. The *STREAM ORDER* tool of the *HYDROLOGY* toolset in *SPATIAL*

ANALYST was used to establish the Strahler stream order of the stream network. First order streams were then extracted as a distinct layer, and are presented in Figure _. One hundred random points were generated on these first order segments using *DATA MANAGEMENT >FEATURE CLASS > CREATE RANDOM POINTS*. These points were then compared to the air photo visually in isolation from one another in order to assign a Boolean value based on '*stream presence vs. non-stream presence*' at the location of each random point. Out of 77 points that were not obscured by vegetation, 0 points were found to have a stream present at that location. All of the first order stream segments of the NC Streamlines were considered to be erroneous as a result. These results are presented in Table 3.

Table 3. Evaluation of NCSMP first order (Strahler) stream segments. Boolean test for presence/non-presence of NCSMP streamline at location of reference image stream.

Total Points	100
Points obscured by vegetation	23
Visible Points	**77**
Stream present at point	0
No Stream present at point	77
Percentage stream present	**0%**
Percentage no stream present	**100%**

The first order stream segments extracted from the base NC Streamlines data layer were removed from the NC Streamlines layer, and one hundred random points were generated on a stream layer derived from the remaining NC Streamlines dataset consisting of higher order streams. The percentage of stream segments represented in the NC Streamlines derived drainage network with the first order stream segments removed that were present in non-obscured random reference points was 72%, as presented in Table 4. However, 28% of random samples showed no presence of a stream at that location, indicating that additional stream segments of higher Strahler order were misrepresented by the NC Streamlines.

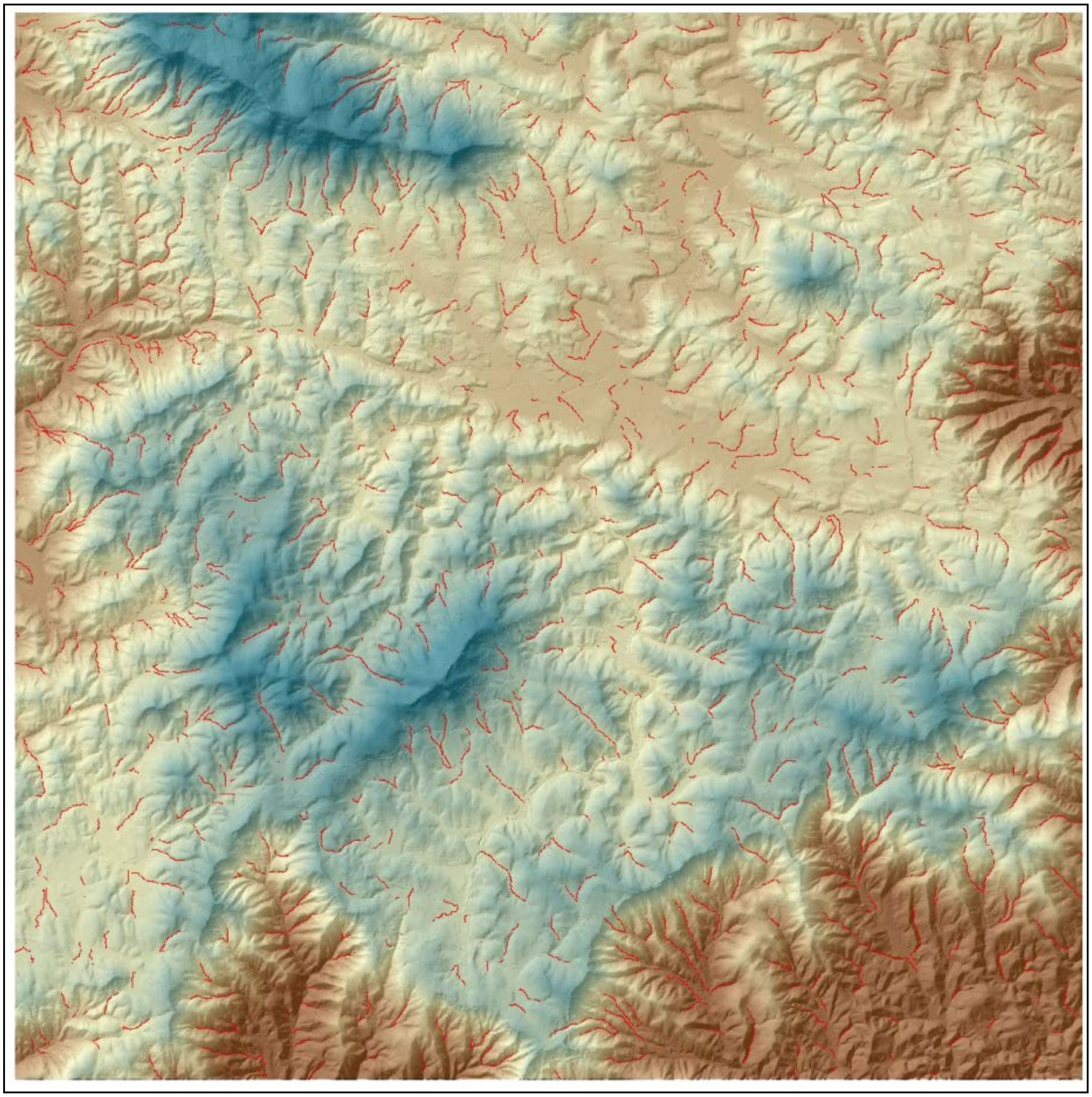


Figure 17. First Strahler order stream segments (red) draped over 5 m DEM.

Table 4. Evaluation of NCSMP streamlines after removal of first order (Strahler) stream segments. Boolean test for presence/non-presence of NCSMP streamline at location of reference image stream.

Total Points	100
Points obscured by vegetation	29
Visible Points	**71**
Stream present at point	51
No Stream present at point	20
Percentage stream present	**72%**
Percentage no stream present	**28%**

The next evaluation procedure was undertaken to determine the accuracy level of the derived drainage lines from this thesis research in regards to their actual existence on the ground as represented on the reference photograph. One hundred random points were generated on the derived drainage lines (Figure 18). The derived drainage lines layer was then removed, and each point's location was examined on the reference photograph to determine the Boolean value for stream presence. These results are presented in Table 5.

Table 5. Evaluation of drainage lines derived for this thesis research from 1 m DEM using 0.072 km2 flow accumulation threshold. Boolean test for presence/non-presence of NCSMP streamline at location of reference image stream.

Total Points	100
Points obscured by vegetation	34
Visible Points	**66**
Stream present at point	63
No Stream present at point	3
Percentage stream present	**95%**
Percentage no stream present	**5%**

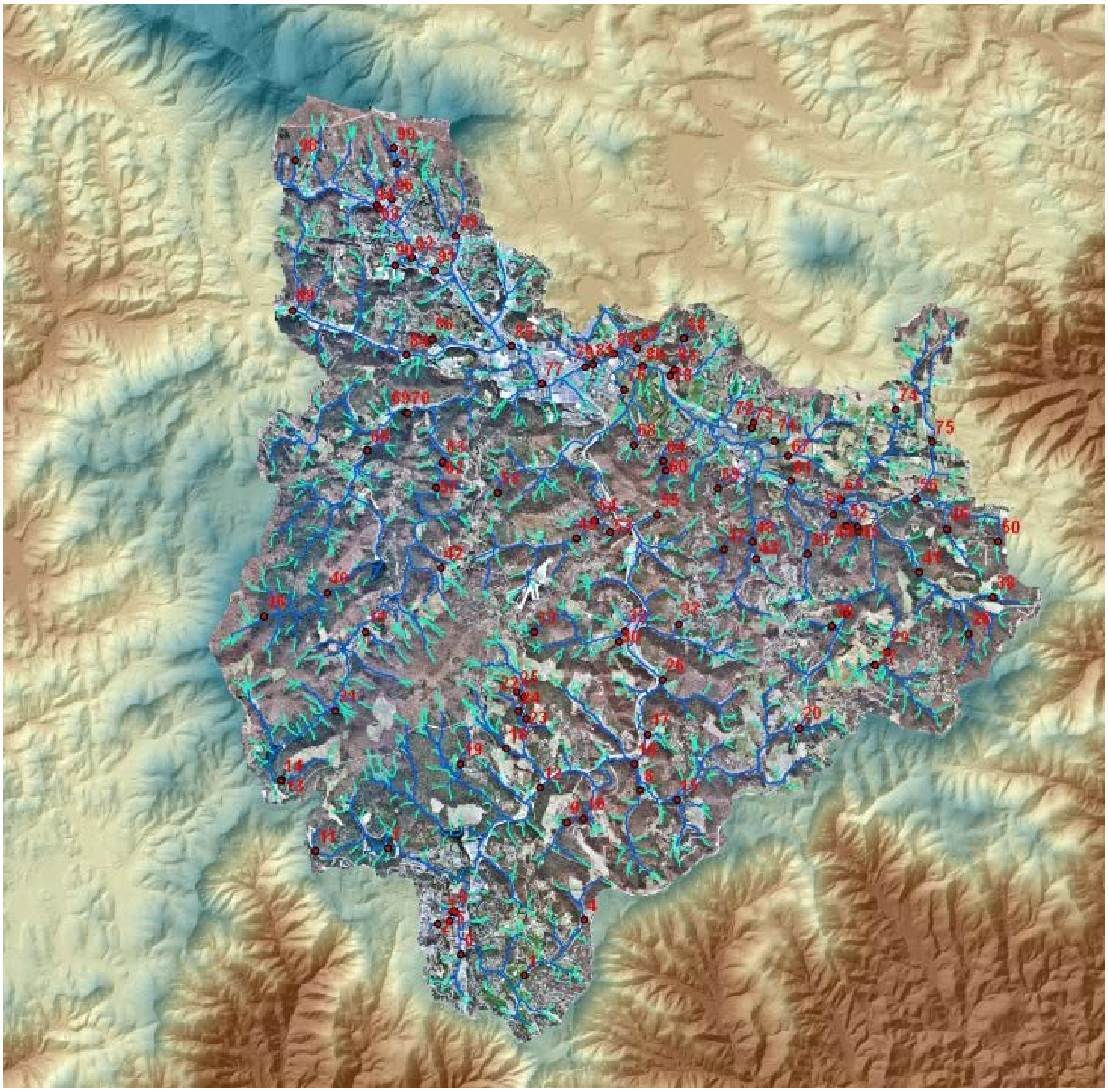


Figure 18. Imagery used for evaluation and accuracy assessment of NCSMP streamlines with first Strahler order streams removed. 6 inch aerial photograph of the Upper South Fork is draped over the 5 m DEM. Random points have been generated along the drainage lines.

The final evaluation procedure involved testing the positional accuracy of the derived drainage lines from this research. The aerial photograph, the NC Streamlines, and the derived drainage lines were all added to a new ArcMap document. Fifty random points were generated on the NC Streamlines in order to populate these sampling points in close proximity to the actual ground-truth streams, and are illustrated below in Figure 19. The placement of each point relative to the stream centerline as represented in the aerial photograph was then reviewed, and, if necessary, the point was manually relocated to ensure that it was located on the exact stream centerline of the air photo. Points that did not exist on actual streams on the ground were removed, as well as points obscured by vegetation. The distance from each of the thirty three remaining points to the centerline of the derived drainage network was calculated using *ANALYSIS > PROXIMITY > GENERATE NEAR TABLE* (Figure 20) in the ArcToolbox. Descriptive statistics of the results from this GIS operation are presented in Table 6.

Table 6. Descriptive statistics of GIS *NEAR* operation with 1 m DEM to calculate distance from derived drainage line to reference image stream centerline.

Point ID	Distance (meters)
Mean	0.898
Median	0.889
Range	1.734
StdDeviation	0.449
Skewness	-0.100
Kurtosis	-0.654
N (samples)	33

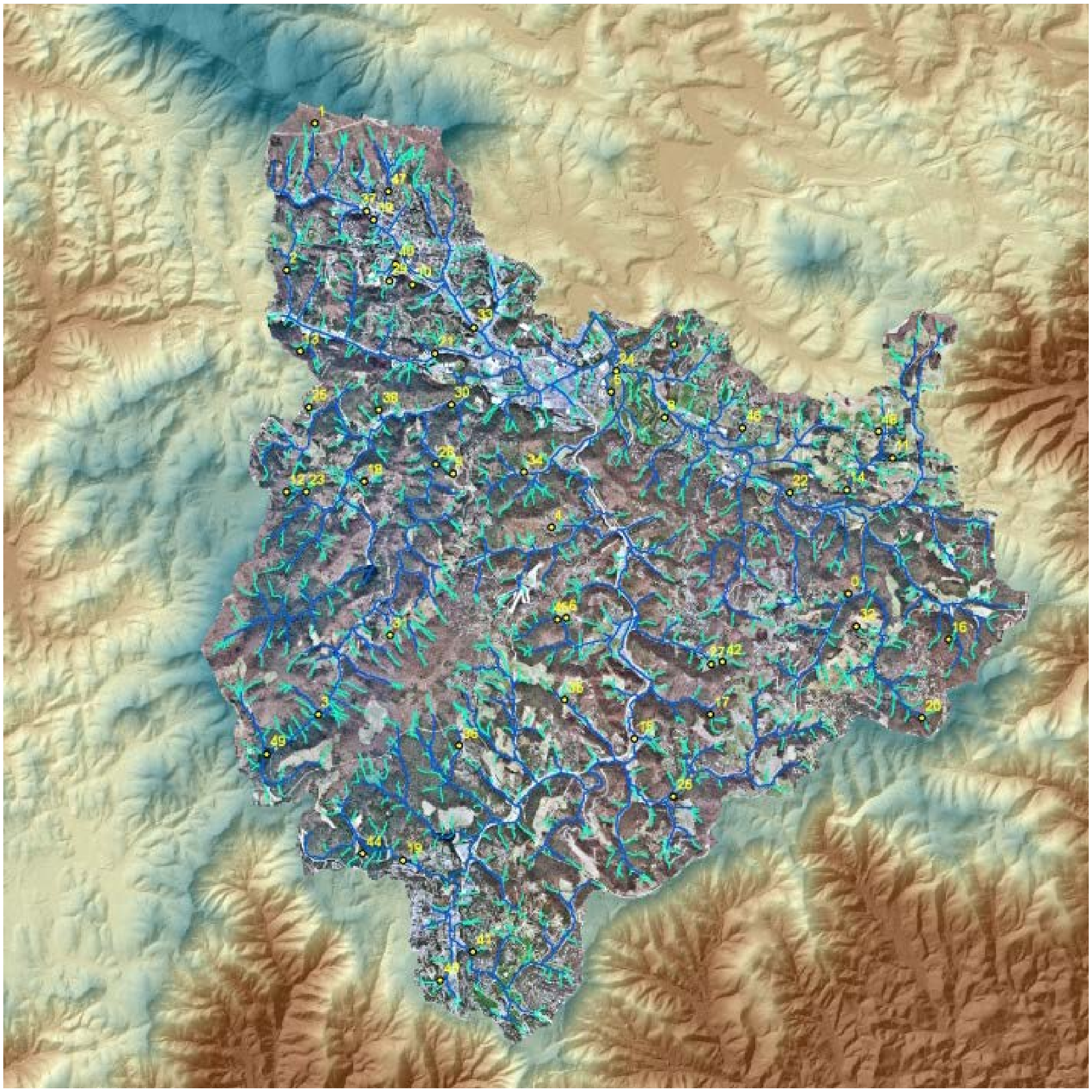


Figure 19. Imagery used for evaluation and accuracy assessment of derived drainage lines from 1 m DEM and 0.072 km^2 stream threshold. 6 inch aerial photograph of the Upper South Fork is draped over the 5 m DEM. Random points have been generated along the drainage lines.

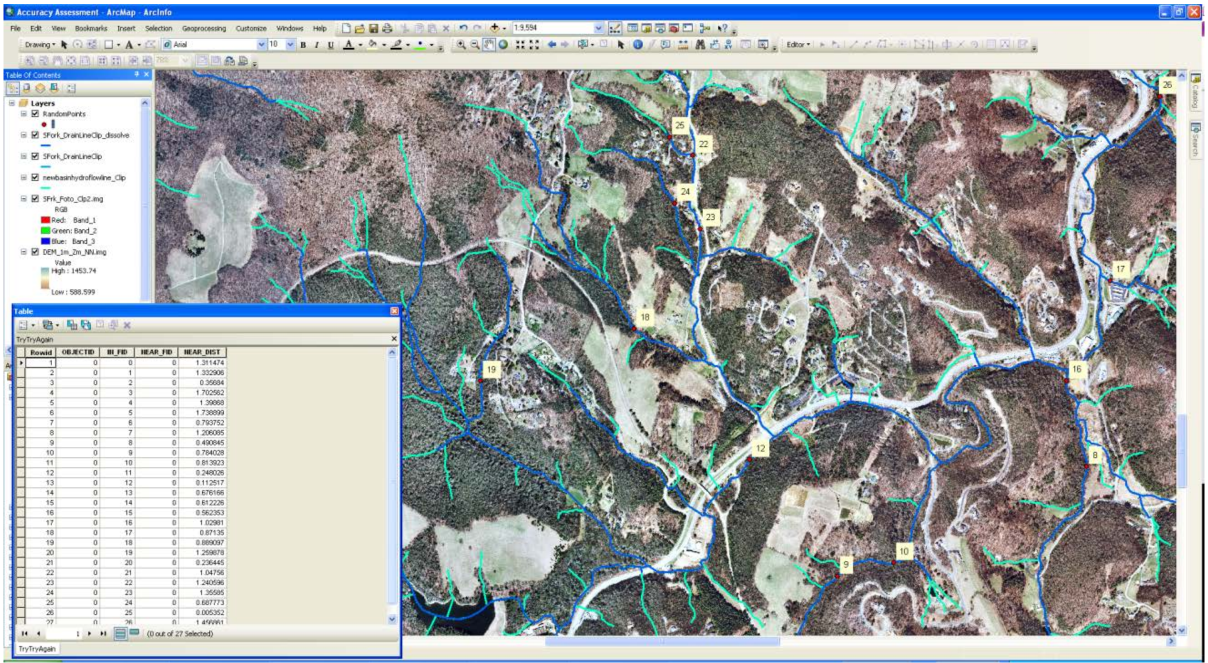


Figure 20. ArcGIS *NEAR* operation results with screenshot of hydrographic modeling document.

The statistical results and accuracy assessments demonstrated that the goal of the hydrographic modeling procedures, the creation of an optimal drainage network and watershed delineation, were achieved. The results of the first of the four evaluation procedures listed on page 51 demonstrated that 0% of the first Strahler order stream segments from the NC Streamlines dataset actually exist, as can be seen in Table 3. The results of the second evaluation operation indicated that significant errors regarding stream existence still existed in a modified NC Streamlines dataset with first order streams removed. Twenty-eight percent of the sampled point locations of this modified NC Streamlines dataset were found to have no stream present in the aerial photograph of ground conditions. The third evaluation operation examined the derived drainage lines from this research, which were generated using a much larger flow accumulation threshold (18 acres) than the commonly used low flow accumulation utilized by the NCSMP (6 acres) in order to reduce the presence of erroneous headwater segments. These derived drainage lines demonstrated a 95% accuracy regarding their actual existence via ground truth (Table 5). This represented a dramatic increase in hydrographic representational accuracy. Additionally, the derived drainage lines from this research appear to be very accurate regarding their alignment with reference image stream centerlines. The derived drainage lines from this research have a median distance of only 0.898 meters, as presented in Table 6, from the reference imagery stream centerlines. With this type of sub-meter accuracy it can be maintained that the results of the hydrographic modeling operations represent a robust digital representation of the study area's actual hydrography.

3.3. Land Cover Classification

Land cover classifications were undertaken using digital image processing techniques in order to provide very high resolution (1 meter) land cover classification datasets of the Upper South Fork utilizing the most current remotely sensed imagery available. Impervious surfaces (such as roads, roofs, parking areas, sidewalks, and buildings) and forest land covers were chosen as the land cover categories of interest, largely due to their identification by the existing scientific literature as key environmental factors which exert significant influence on the water quality of surrounding stream systems (Dow and Zampella 2000; Conway 2007; Lenat and Crawford 1994; Alberti et al. 2007; Burns et al. 2005; Beach 2002; Bolstad and Swank 1997; Chang 2003; Gilvear et al. 2002; Lenat and Crawford 1993; Northington and Hershey 2006; Reynard et al. 2001; Stohlgren et al. 1998; Sudduth et al. 2007; Todd et al. 2007; Li et al. 2009; Gergel et al. 2002; Allan and Johnson 1997; Tran et al. 2010; Sliva and Williams 2001; Bolstad and Swank 1997).

Satellite imagery is often used for land cover classifications in traditional remote sensing applications. One limitation of non-commercial satellite imagery, particularly with modern developments in digital aerial photography, is that it generally has a coarser resolution than aerial photography. For example, imagery from the ASTER instrument is available at 15 meters for certain spectral bands which are very useful for vegetation and land cover classifications. Although 15 meters is an excellent spatial resolution for research covering large areas, research undertaken in small areas of spatial extent such as the Upper South Fork require higher resolution imagery for greater accuracy and enhanced confidence levels in the derived products. Aerial photography for the United States is available at 1 meter resolution from the National Agricultural Inventory Program (NAIP), and local imagery is often available from individual communities, counties, and states at even finer spatial resolutions. For example, one of the image datasets used for this research was available at a 6 inch spatial resolution for Watauga County.

This land cover classification procedures were carried out with the following primary goals:

1. Development a semi-automated, repeatable methodology for the generation of highly accurate, high resolution land cover classifications from publicly available aerial photography.

2. Extraction of impervious surface and forest LULC categories for the Upper South Fork using the above referenced methodology with the most current imagery available.

3. Initial development of a database of current land cover information of the Upper South Fork regarding impervious surfaces and forests for future research regarding land cover changes over time and their effects on water quality.

Feature Analyst (VLS 2008) was selected as the image classification software application for this procedure. Feature Analyst is an extension of ArcGIS that is capable of performing automated feature extractions from aerial photography. Feature Analyst classifies imagery utilizing several classification methodologies, including spectral characteristics, for class separation in a similar fashion to most image classification applications. Feature Analyst has the additional capability to classify imagery by information classes, which consist of similar items such as buildings, forests, roadways, and houses, based on texture, shape, and other unique identifying characteristics. Feature Analyst's use of fuzzy logic, the ability of the user to specify and modify input representation moving windows, and the utilization of hierarchical learning procedures provides an extremely robust and capable application for the classification of high resolution imagery. Research by Miller (2009), Vanderzanden (2002), and Mauger (2006) indicated high levels of success when using Feature Analyst to classify impervious surfaces and forest land covers.

Separate land cover classification operations were undertaken for impervious surfaces and forest land covers. Prior research by the author indicated that extracting multi-class land cover classifications could be problematic when using Feature Analyst for land cover extractions with image files of this size. Multi-class land cover classifications produced substantially inferior results compared to single class extractions. The highly dispersed and heterogeneous spatial distribution of human impacted land covers also made visual examination and implementation of hierarchical learning procedures extremely difficult when attempting multi-class classifications with aerial photography of the study area.

3.3.1. Methods

Impervious surfaces extraction

For the impervious surfaces extraction 2009 aerial photography of Watauga County was acquired from the ArcSDE server of the Department of Geography and Planning at Appalachian State University (ASU). This mosaicked image dataset had been captured during "leaf-off" season, which was theorized to be the optimal time for extracting impervious surfaces due to the decreased presence of obscuring forest canopy coverage. An area of interest comprised of the Upper South Fork watershed was extracted from this image with ArcGIS' *EXPORT DATA* tool at a spatial resolution of one meter. The original aerial photograph had a spatial resolution of 6 inches. Numerous attempts at classifying this original image were unsuccessful due to its large size (over 30 gigabyets). Correspondence from Visual Learning Systems indicated that the Feature Analyst software was incapable of processing such a large image. Attempts were also made to classify the image resampled to 1 foot, with similarly unsuccessful results. The author considered 1 meter to be of sufficiently high resolution for this research. Additionally, the aerial photograph from the NAIP used for the forest classification had a native resolution of 1 m, and the terrain and hydrographic modeling operations were all undertaken using 1 m resolution data, thus providing a uniform spatial resolution of 1 m for all analyses and geospatial database archiving.

Numerous iterations of the impervious classification procedure were undertaken in order to produce the most accurate classification. Different training sites were selected for each classification iteration, with the goal of selecting a wide variety of representative impervious surfaces in order to produce an optimal output. Feature Analyst provides the user with a wide range of options during the

LEARNING SET-UP operation, which allows the user to maintain significant control and customization capabilities regarding the classification routine parameters. The three bands from the visible portion of the electromagnetic spectrum were used as inputs for spectral reflectance classification as well as texture classification. The author was careful to ensure that buildings of various shapes, linear features such as roadways and sidewalks, and oddly shaped impervious surfaces such as driveways and patios were included in each training set. A broad range of colors, hues, and levels of shadow for each impervious object type were also selected to increase classification accuracy and thoroughness.

The *INPUT REPRESENTATION* pattern is one of the most influential factors in the accuracy of land cover classifications with Feature Analyst. This pattern describes the moving analysis window that is utilized by the software during each classification iteration. There are a variety of preset patterns, and the user has the added ability to create custom input representations in order to improve classification results. Research by Miller et al. (2009) concluded that a preset input representation defined as *BULLS EYE 2-7* (Figure 21) consistently produced the best results for impervious surface classifications. As a result the *BULLS EYE 2-7* was tested for this research. Results indicated that this input representation was found to produce the best results when compared to results from using other patterns. Numerous hierarchical learning procedure iterations were subsequently undertaken on the classification results to remove areas of misclassification and to add impervious areas that had been missed.

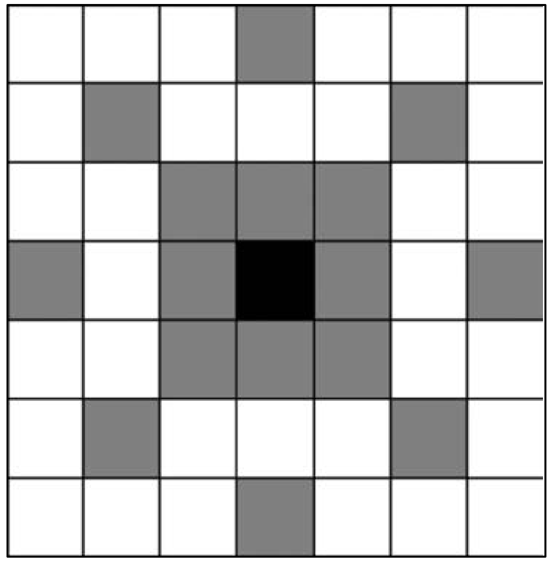


Figure 21. Input representation for impervious extraction from Miller et al. (2009).

A visual inspection of the optimal impervious classification result indicated that there were still areas of missed impervious features, particularly in areas of heavy forest canopy overhang and heavily shadowed areas such as forest roads, ravines, and areas adjacent to ridges. Ancillary layers were added to the Feature Analyst classification results in order to help resolve these missed features. A 2007 road network layer of primary and secondary roads was acquired from the North Carolina Department of Transportation (NCDOT). This roads layer was clipped to the study area boundaries and buffered to a total width of 10 meters to represent the average width of area roadways. A layer of Boone area building footprints was then acquired from the ArcSDE server at ASU. Both of these layers were converted to raster at 1 meter spatial resolution cell size, then combined with the Feature Analyst impervious classification results to produce a final impervious surfaces layer.

Forest extraction

For the forest land cover extraction, a 2010 “leaf-on” digital aerial photograph (NAIP 2010) at 1 meter spatial resolution was acquired for Watauga County. Similar to the reasoning behind the “leaf-off” image choice for impervious surfaces, it was theorized that this “leaf-on” photograph would produce optimal results for forest extraction. The Upper South Fork watershed was extracted from the full extent of the original image to facilitate processing. Training site selection was undertaken with an emphasis on inclusion of both deciduous and evergreen forest samples, small tree clusters as well as large forest stands, and a wide range of colors, hues, and shade levels. The input representation pattern also plays a crucial role in forest extraction, and numerous iterations were undertaken using different input representation patterns. After a series of visual inspections to choose the best forest classification output from the numerous iterations, the optimal classification result was selected. Optimal results were achieved using a custom input representation provided by Vanderzanden and Morrison (2002), which had been developed for forest classification from high resolution remotely sensed imagery by the U.S. Forest Service (Figure 22).

The impervious surfaces layer from the previous land cover classification operation was then subtracted from the forest layer to remove the obscuring effects of forest canopy overhang which had resulted in misclassification of some impervious surfaces, especially roads, as forest. The resultant output from the incorporation of these ancillary data layers represented the final forest land cover classification to be used for the remaining analyses of this research and archiving in the geospatial database.

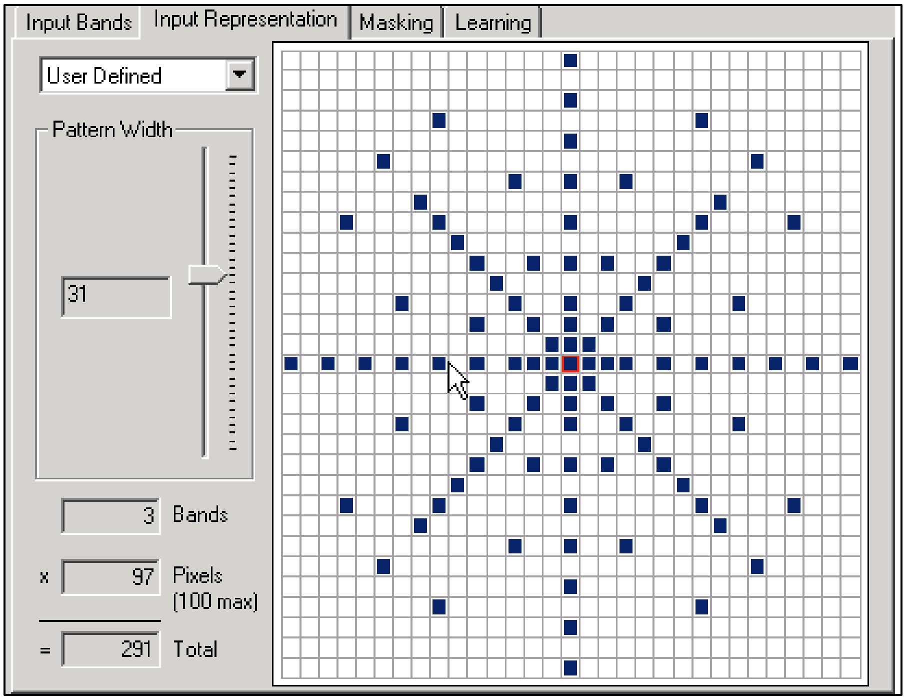


Figure 22. Input representation for forest extraction from Vanderzanden and Morrison (2002).

Spatial scales: watersheds and riparian buffers

The influence of land cover composition at various spatial scales represented an additional area of investigation for this thesis research. A review of the existing scientific literature had produced previous water quality research projects which had investigated the role of land cover composition at different scales such as watershed scale and riparian buffer zones of various widths (Tran et al. 2010; Sponseller et al. 2001; Sliva and Williams 2001; Maillard and Santos 2008; Sparovek et al. 2002; Lee et al. 2009; Xiao and Ji 2007; Alberti et al. 2007; Smart et al. 2001; King et al. 2005; Jones et al. 2001; Griffith 2002; Strayer et al. 2003; Hunsaker and Levine 1995; Allan and Johnson 1997). Contradictory results had been obtained in several of these studies. Therefore, in order to contribute to the literature regarding the effects of scale on land cover and water quality relationships, an examination of land cover composition at select scales in the Upper South Fork was undertaken. In order to quantify land cover composition, the measures of *total percentage impervious area* (TPIA) and *total percentage forest area* (TPFA) were used.

The following spatial scales were selected for analysis: individual watershed (or sub-watershed) scale, 25 meter riparian buffer zone, 50 m buffer, 100 m buffer, and 150 m buffer. Buffers were measured from stream centerline to the outer edge of the buffer, therefore a 50 m buffer has a total edge-to-edge width of 100 m and a 150 m buffer has a total width of 300 m. The 25 m, 50 m, and 100 m buffers were chosen based on a review of the existing scientific literature, with the initial goal of selecting buffers that had either been found to have significance regarding water quality impacts or that seemed logical values for buffers based on trends in results from the literature. The 150 meter buffer was added to the analysis after exploratory environmental modeling regarding land cover and water quality. This initial modeling indicated that a trend could be observed at the increasing riparian buffer zone scales, so 150 meters was selected to test whether this trend would continue or change above the 100 meter buffer distance. Throughout this thesis, the term *watershed* is used to refer to an individual watershed or sub-watershed, meaning that the term can apply to the main Upper South Fork watershed as well as the smaller, nested watersheds within the Upper South Fork (Boone Creek, East Fork, Flannery Fork, Goshen Creek, Middle Fork, and Winkler Creek).

In order to investigate the central hypothesis, land cover composition and total percentages of coverage were calculated for entire Upper South Fork watershed, for each of the six sub-watersheds, and for each buffer distance for the Upper South Fork and each sub-watershed so that more detailed and comprehensive statistical analyses could be undertaken. The riparian buffers were created using the final derived drainage lines from this research from the hydrographic modeling procedure as buffer centerlines. Using this optimal drainage network for buffer creation ensured that the calculations of land cover types and coverage extent percentages would be as accurate as possible, with the goal of properly representing land cover composition. Several buffer images are displayed in Figures 23 and 24.

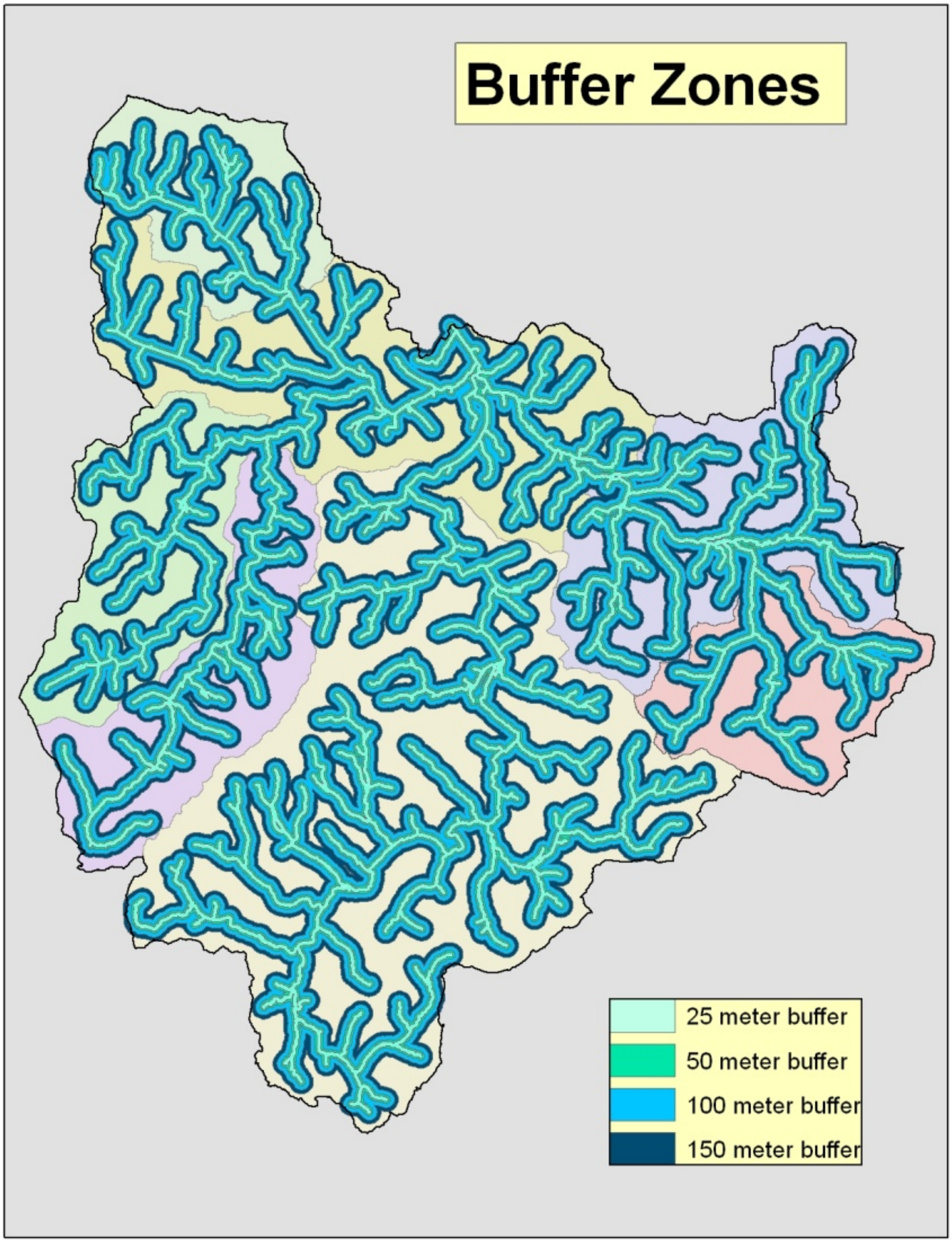
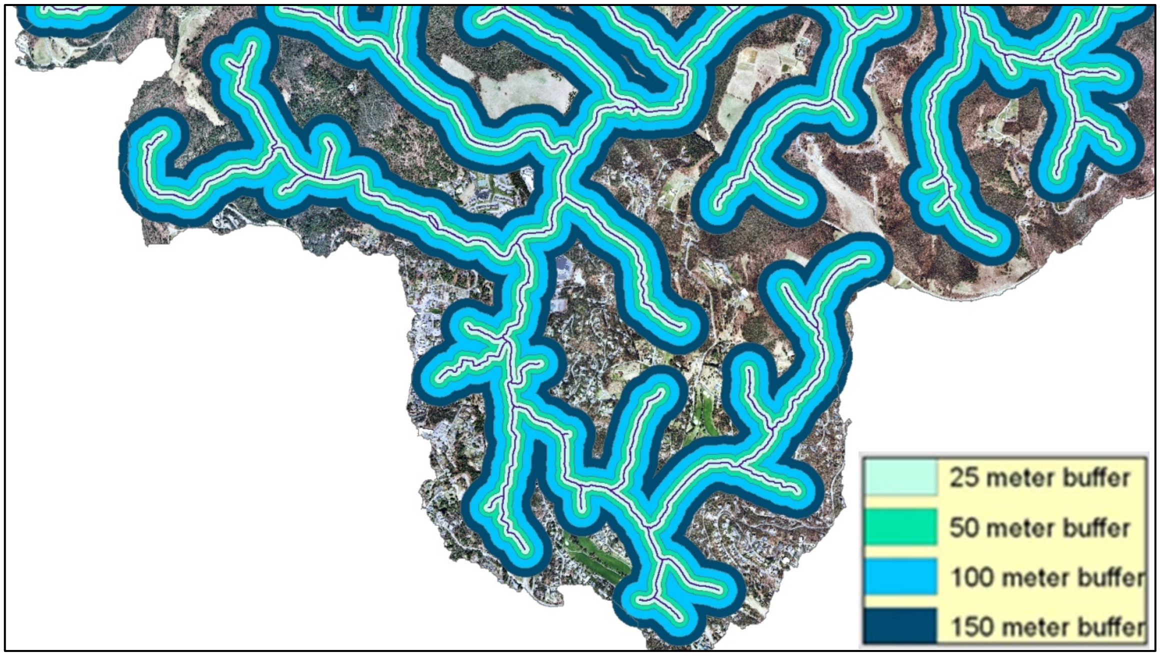


Figure 23. Riparian buffer zones with distances of 25 m, 50 m, 100 m, and 150 m from centerline of derived drainage lines.

(a)


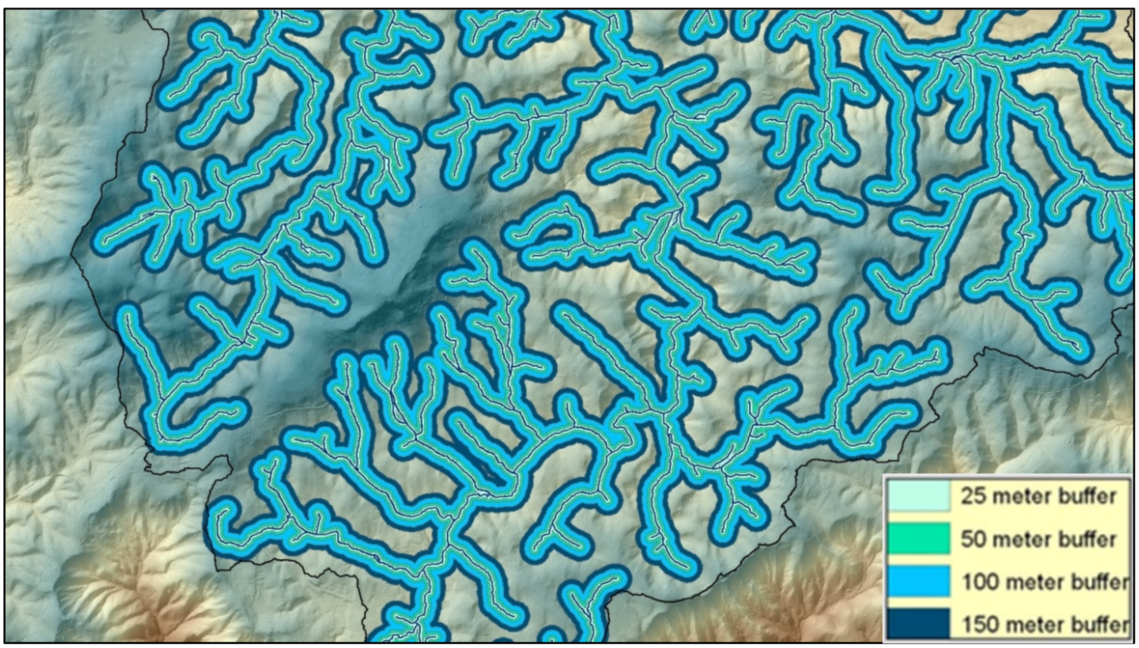
(b)


Figure 24. Details of riparian buffer zones near Blowing Rock. Top image (a) illustrates buffers draped over 6 inch aerial photograph. Bottom image (b) illustrates buffers draped over 5 m DEM.

3.3.2. Results

Qualitative visual assessments of the results of the impervious surface and forest land cover classifications indicated that very high accuracy levels had been achieved. The high resolution (1 meter) of the source imagery had enhanced the level of detail in classification results for both the impervious and forest classification procedures, particularly in edge-zones and transition areas of human development and forests. Particularly impressive was the detail observable in small forest clearings and residential developments, where even relatively small features such as outbuildings and impervious pathways were properly classified as impervious surfaces and properly delineated. Forest border areas were likewise clearly evident in the forest classifications. Feature Analyst produced excellent results regarding differentiation of forest from grass and pasture areas. Results from the impervious surfaces classification are presented in Figures 25 through 29, and forests are presented in Figures 30 through 33.

Standard accuracy assessments were undertaken for both the impervious surface and forest classifications, after Jensen (2007). The results of each of the accuracy assessments, presented as error matrices in Tables 7 and 8, were very robust, indicating success in generating highly accurate, high resolution land cover classifications. For the accuracy assessment of the impervious classification, it was hypothesized that the generation of random points throughout the entire study area would produce a less than acceptable level of confidence in the results since a large majority of the land cover throughout the study area consists of forest. It was believed that a random placement of points throughout the study area would likely place many of the points far away from areas with significant amounts of impervious surfaces, and thus would dilute the significance of the accuracy assessment. To improve the accuracy assessment for impervious surfaces, a 150 meter buffer was created around the NCDOT Roads layer and one hundred random points were generated within this buffer. It was theorized that placing the random points inside this buffer would increase the likelihood that the sampling points would lie near areas of impervious/non-impervious transitions, thereby improving the significance of the accuracy assessment. For the forest land cover accuracy assessment, 105 points were generated throughout the study area, since forest land cover appeared to be well distributed throughout the entire study area. The overall accuracy for each land cover classification was approximately 96%, indicating that each classification procedure had been highly successful. Kappa statistics were also calculated for each classification. The Kappa statistic for the impervious classification was 0.84, a robust figure. The forest classification had an even higher Kappa statistic of 0.91, indicating excellent results from the classification procedure.

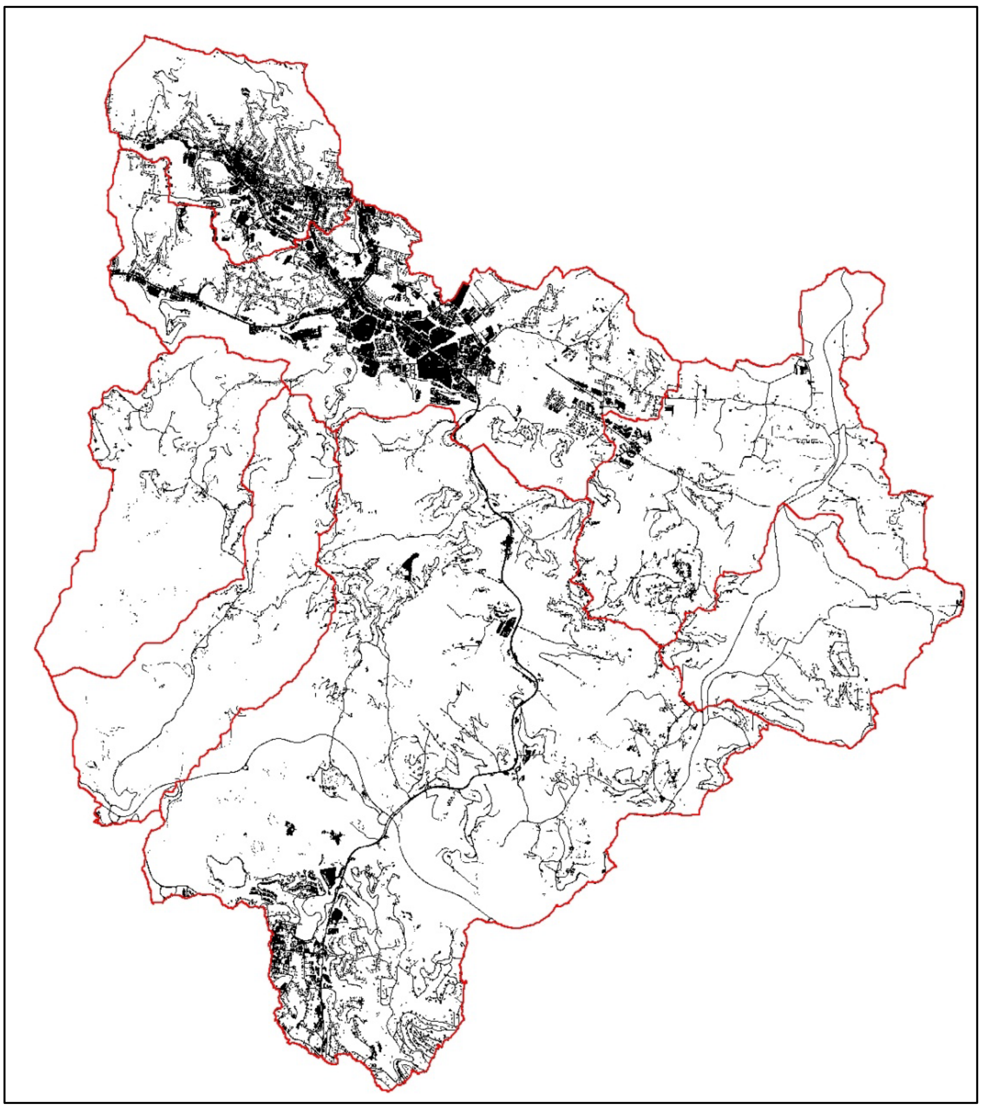


Figure 25. Impervious surfaces shown in black with watershed boundaries in red.

Figure 26. Aerial photograph of example area of interest (AOI) for impervious classification.

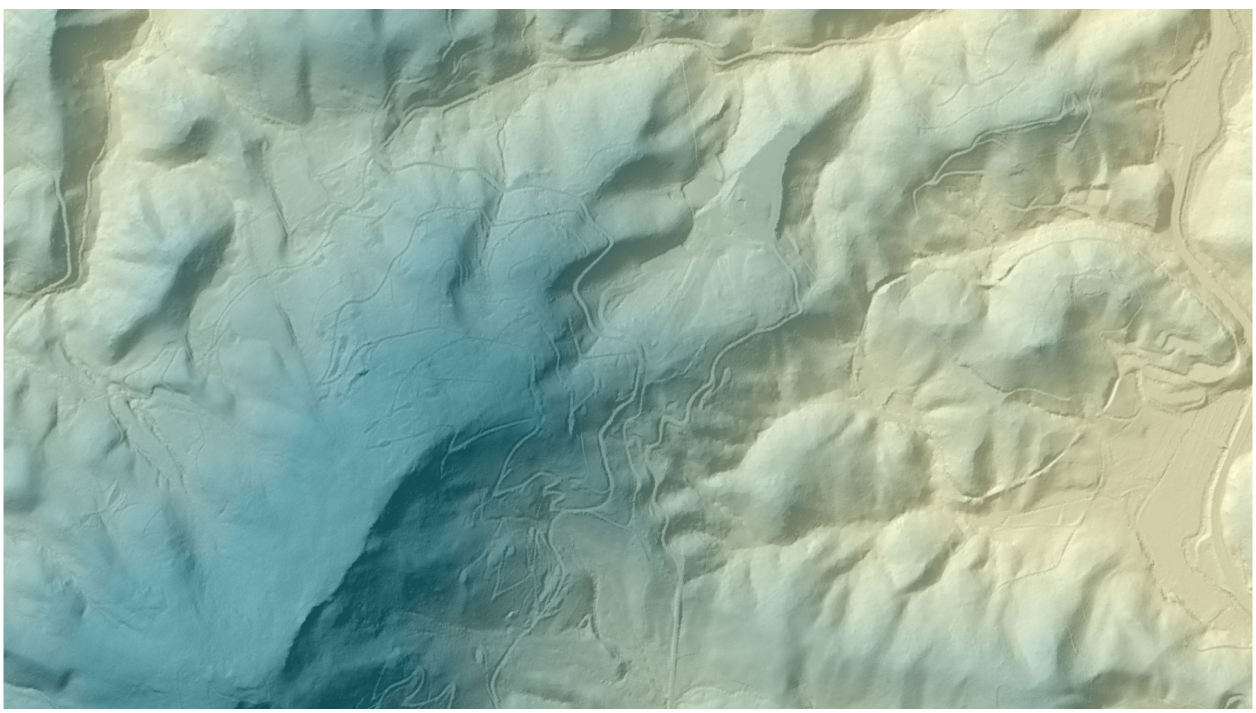


Figure 27. Five meter DEM for AOI.

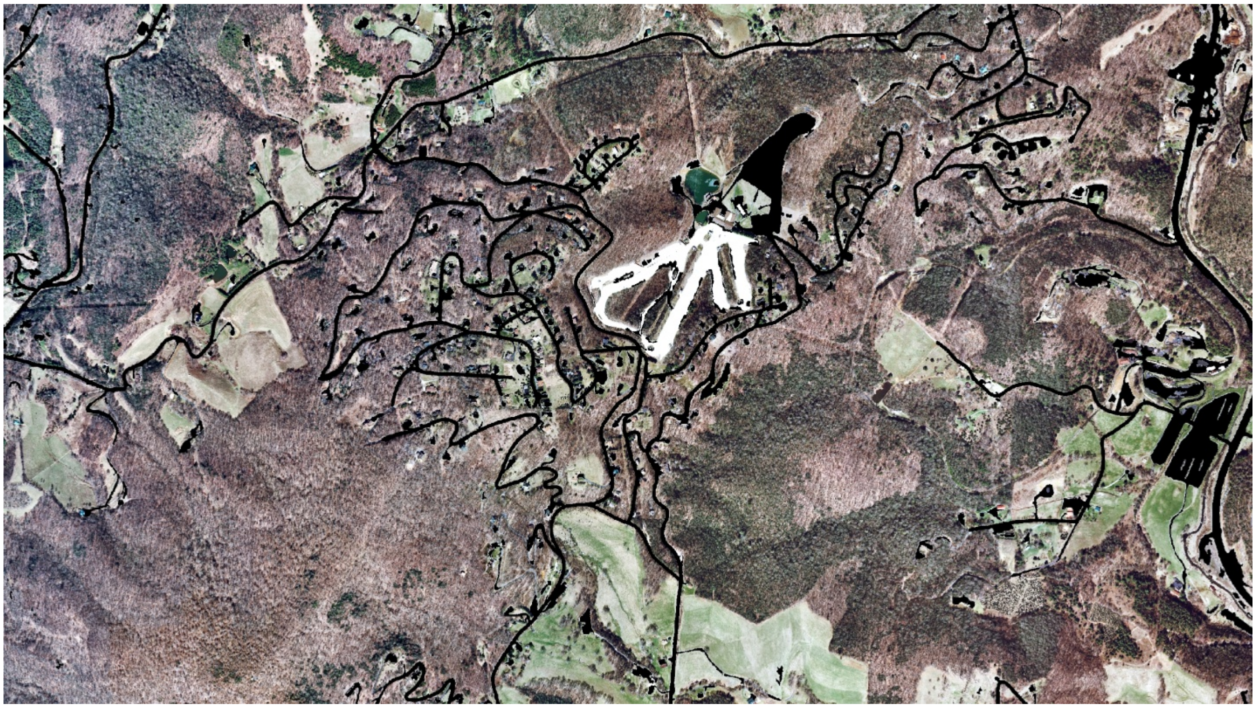


Figure 28. Impervious surfaces (black) draped over aerial photograph of AOI.

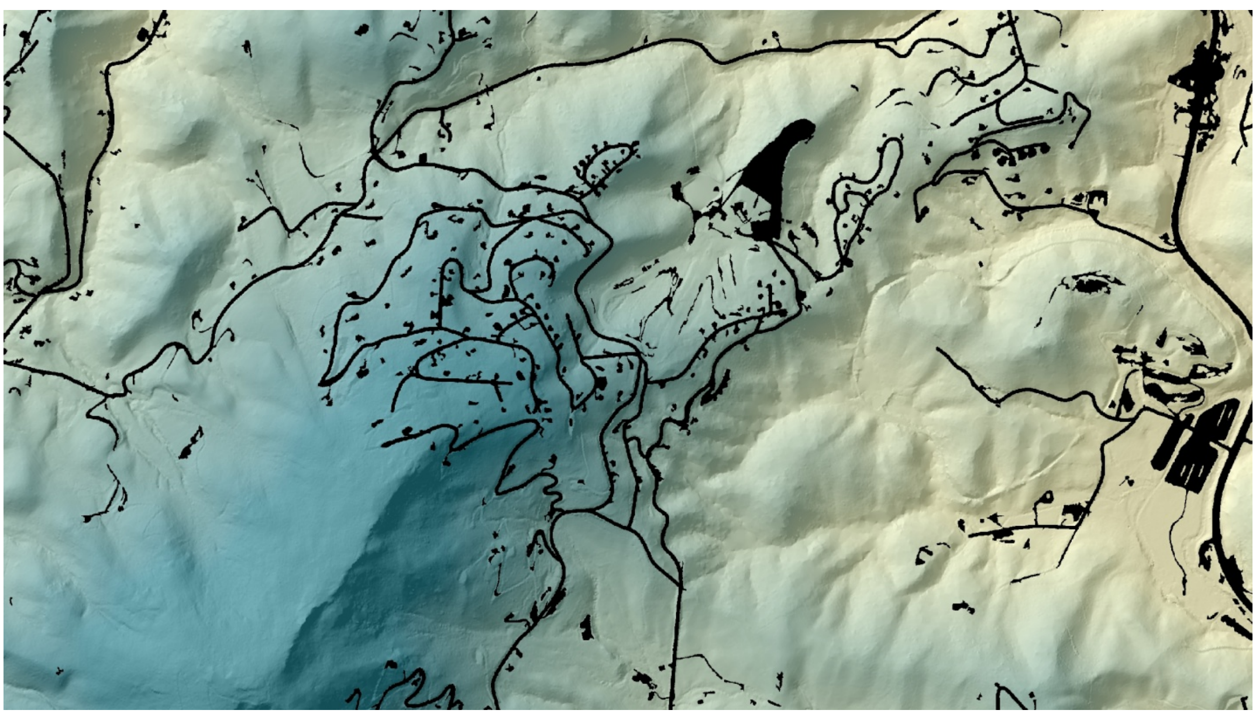


Figure 29. Impervious surfaces (black) draped over 5 m DEM of AOI.

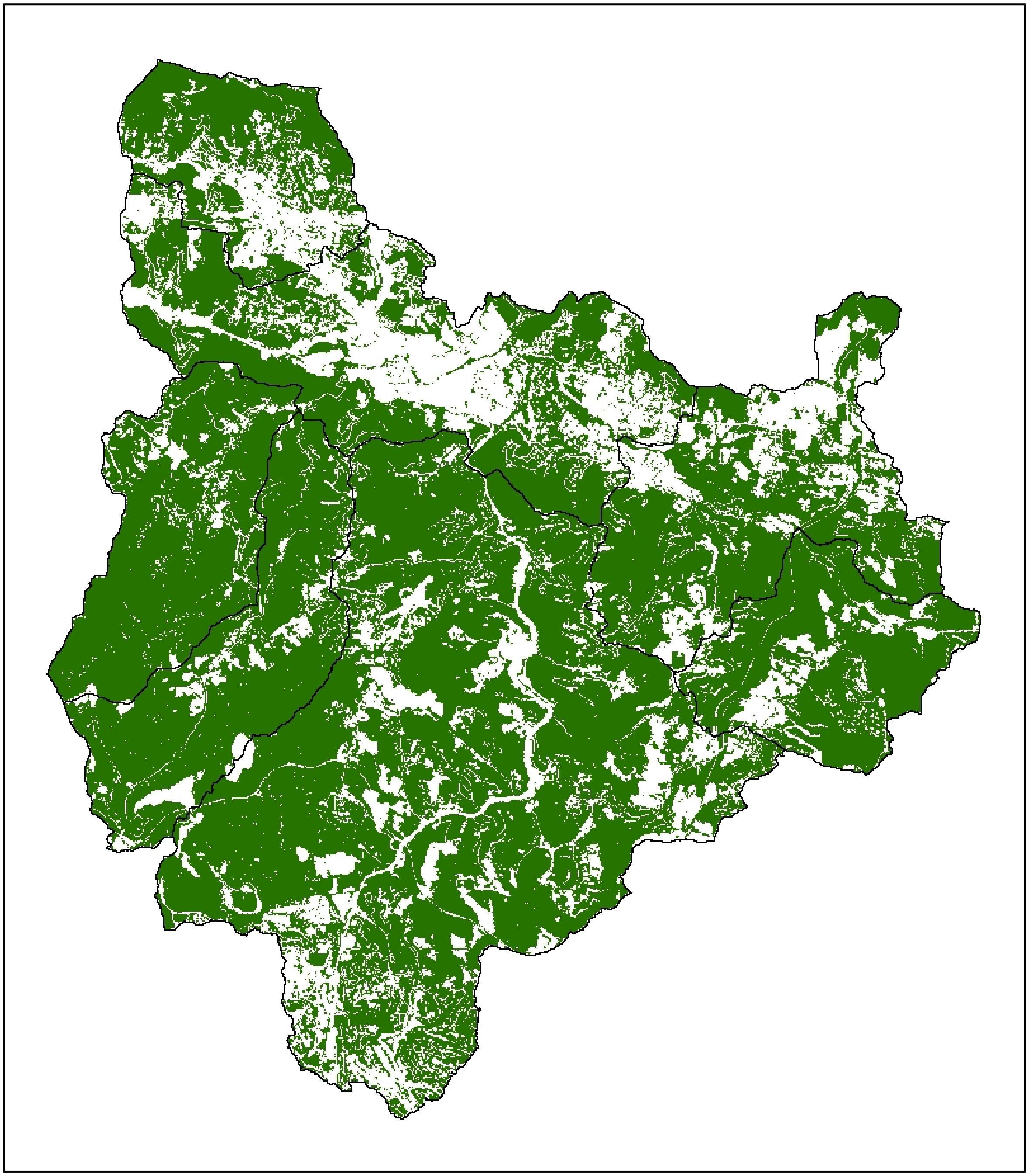


Figure 30. Forest shown in green with watershed boundaries in black.

Figure 31. Aerial photograph of example AOI for forest cover classification.

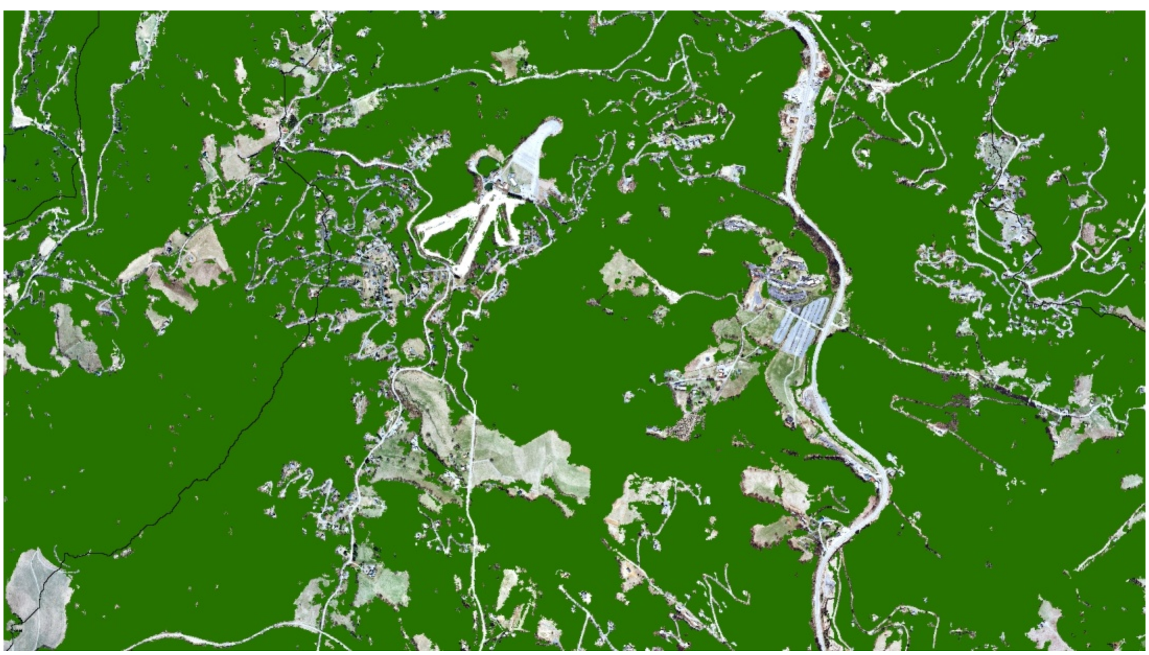


Figure 32. Forest cover classification (green) draped over 6 inch aerial photograph.

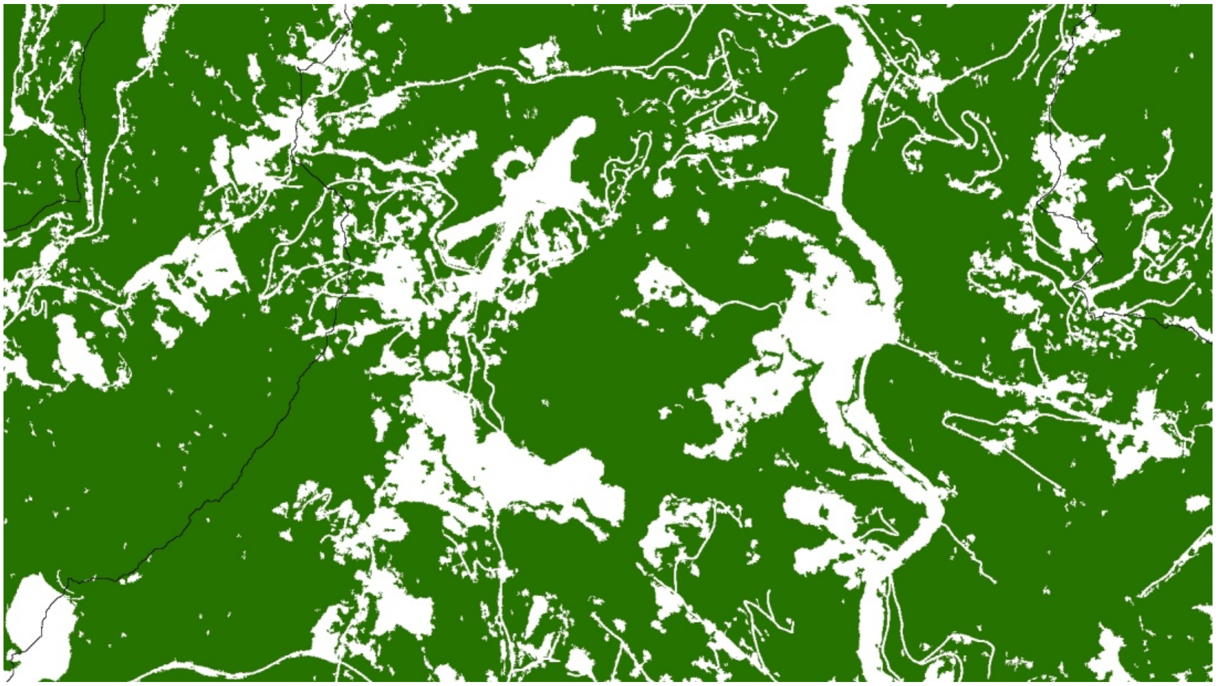


Figure 33. Forest cover classification (green).

Table 7. Impervious surfaces classification error matrix from accuracy assessment.

Error Matrix: Impervious surfaces classification			
	Reference		
	Impervious	**Non-Impervious**	**Column Total**
Impervious	**75**	4	79
Non Impervious	3	**15**	18
Row Total	78	19	94
Overall Accuracy =		**95.74%**	
Producer's Accuracy			**Omission Error**
Impervious	**96.15%**		3.85%
Non-Impervious	**78.95%**		21.05%
User's Accuracy			**Commission Error**
Impervious	**94.94%**		5.06%
Non-Impervious	**83.33%**		16.67%
Kappa =	**83.88%**	**=**	**0.84**

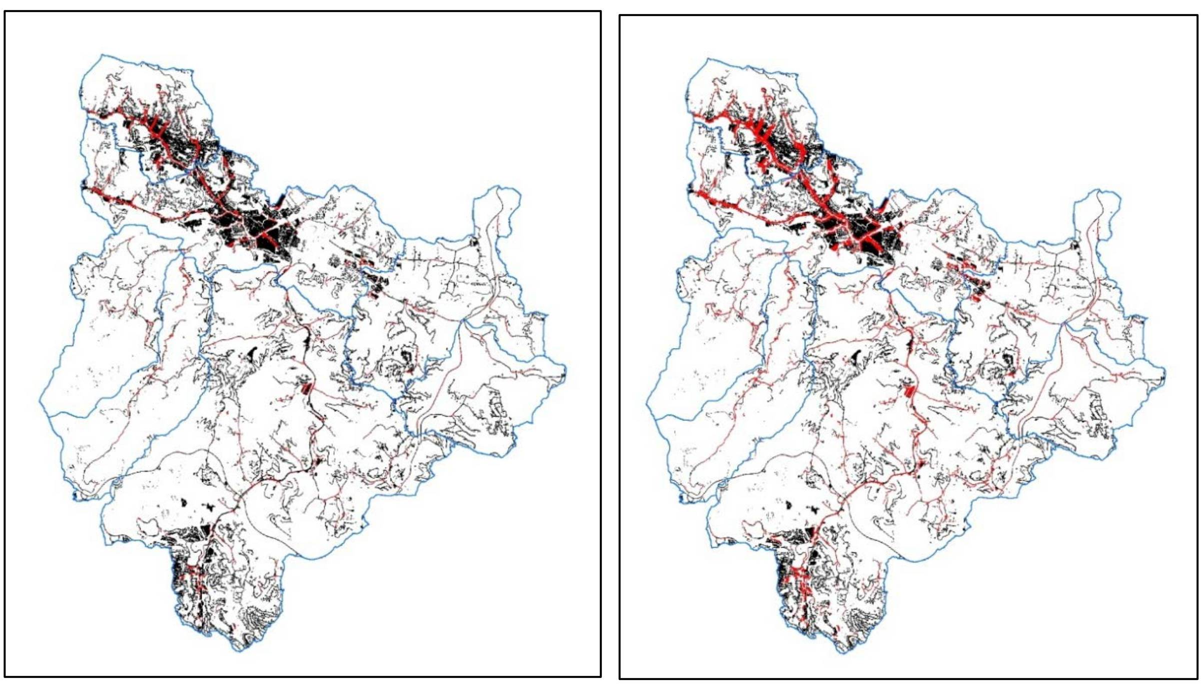
Table 8. Forest cover classification error matrix from accuracy assessment.

Error Matrix: Forest classification			
	Reference		
	Forest	**Non-Forest**	**Column Total**
Forest	**71**	1	72
Non-Forest	3	**30**	33
Row Total	74	31	105
Overall Accuracy =		**96.19%**	
Producer's Accuracy			**Omission Error**
Forest	**95.95%**		4.05%
Non-Forest	**96.77%**		3.23%
User's Accuracy			**Commission Error**
Forest	**98.61%**		1.39%
Non-Forest	**90.91%**		9.09%
Kappa =	**91.01%**	**=**	**0.91**

The final procedure undertaken for the land cover classification research component involved the calculation of land cover totals and percentages at the various spatial scales for TPIA and TPFA. The Python scripting language and ModelBuilder proved to be indispensable tools in the creation of the many buffer products that had to be generated for this procedure as well as the ensuing calculations. Not only did the buffers themselves need to be created, but each land cover type then had to be extracted by each of these buffers and by each of the watersheds, its area value exported, and the percent coverage calculated. With five different spatial scales and seven individual watersheds (the Upper South Fork and the six nested sub-watersheds), this required many different iterations of land cover classifications, followed by area calculations. A matrix of the results of these calculations is presented in Table 9.

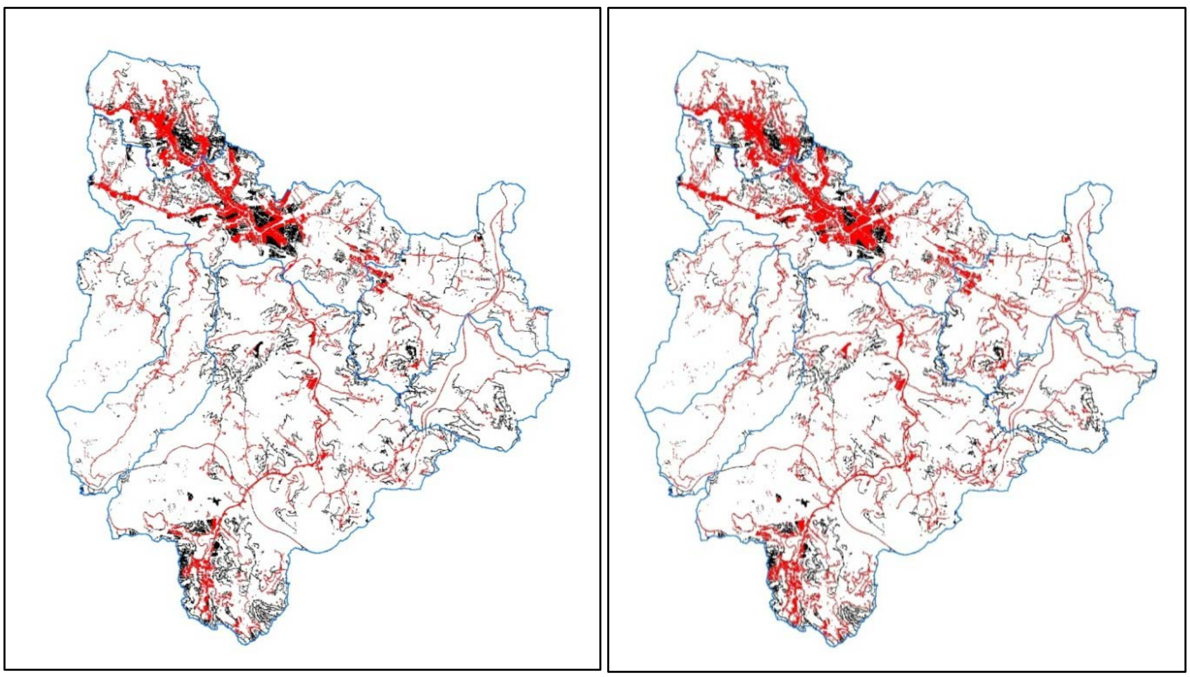
As can be seen in the results, at the individual watershed scale the Boone Creek sub-watershed has the most impervious and least forest at 23.5% and 60.17% respectively. Winkler Creek has the least impervious and most forest at 3.76% and 86.57% respectively. The Boone Creek sub-watershed has the most impervious and least forest of all the sub-watersheds at all of the buffer distances, emphasizing the highly urbanized nature of this watershed. The sub-watershed with the least impervious and most forest varies at each of the buffer scales, with Winkler, Flannery, and Goshen representing the most pristine sub-watersheds in general. Figure 34 demonstrates the spatial distribution of impervious surfaces at the various scales, with watershed scale impervious surfaces depicted in black and impervious surfaces within the riparian buffer zone depicted in red.

Figure 34. Impervious areas depicted with black, and impervious areas within riparian buffer zones depicted in red.



(a) 25 m riparian buffer (b) 50 m riparian buffer

Figure 34 (cont.). . Impervious areas depicted with black, and impervious areas within riparian buffer zones depicted in red.



(c) 100 m riparian buffer (d) 150 m riparian buffer

Table 9. Area calculations matrices for land cover composition (TPIA and TPFA) for individual watersheds and riparian buffer zones of 25 m, 50 m, 100 m, and 150 m.

Watershed Scale

	Total Area m^2	Total Area km^2	Forest total area m^2	TPFA	Impervious total area m^2	TPIA
Boone Creek	5,297,159	5.30	3,187,386	60.17%	1,244,738	23.50%
East Fork	15,942,323	15.94	10,674,472	66.96%	1,169,053	7.33%
Flannery Fork	7,377,134	7.38	6,043,086	81.92%	327,740	4.44%
Goshen Creek	6,014,764	6.01	4,513,664	75.04%	379,414	6.31%
Middle Fork	30,677,282	30.68	21,872,099	71.30%	3,135,410	10.22%
Upper South Fork	79,549,505	79.55	55,163,112	69.34%	9,190,650	11.55%
Winkler Creek	6,993,984	6.99	6,054,451	86.57%	262,947	3.76%

25 meter riparian buffer zone scale

	25 m buffer total area m^2	25 m buffer total area km^2	25 m buffer Forest Area m^2	25 m buffer TPFA	25 m buffer impervious area m^2	25 m buffer TPIA
Boone Creek	659,748	0.66	301,382	45.68%	226,876	34.39%
East Fork	1,978,401	1.98	1,440,847	72.83%	122,669	6.20%
Flannery Fork	850,976	0.85	674,355	79.24%	61,488	7.23%
Goshen Creek	640,572	0.64	524,389	81.86%	40,451	6.31%
Middle Fork	3,526,241	3.53	2,397,041	67.98%	406,166	11.52%
Upper South Fork	9,438,160	9.44	6,203,935	65.73%	1,298,932	13.76%
Winkler Creek	772,990	0.77	610,850	79.02%	49,354	6.38%

50 meter riparian buffer zone scale

	50 m buffer total area m^2	50 m buffer total area km^2	50 m buffer Forest Area m^2	50 m buffer TPFA	50 m buffer impervious area m^2	50 m buffer TPIA
Boone Creek	1,267,107	1.27	584,988	46.17%	433,547	34.22%
East Fork	3,828,350	3.83	2,678,841	69.97%	270,970	7.08%
Flannery Fork	1,650,943	1.65	1,299,676	78.72%	108,164	6.55%
Goshen Creek	1,251,068	1.25	1,017,616	81.34%	73,999	5.91%
Middle Fork	6,839,705	6.84	4,575,724	66.90%	857,604	12.54%
Upper South Fork	18,296,357	18.30	11,768,209	64.32%	2,680,774	14.65%
Winkler Creek	1,500,700	1.50	1,194,954	79.63%	96,177	6.41%

Table 9 (cont.). Area calculations matrices for land cover composition (TPIA and TPFA) for individual watersheds and riparian buffer zones of 25 m, 50 m, 100 m, and 150 m.

100 meter riparian buffer zone scale						
	100 m buffer total area m^2	100 m buffer total area km^2	100 m buffer Forest Area m^2	100 m buffer TPFA	100 m buffer impervious area m^2	100 m buffer TPIA
Boone Creek	2,394,064	2.39	1,213,051	50.67%	732,406	30.59%
East Fork	7,202,596	7.20	4,952,735	68.76%	506,284	7.03%
Flannery Fork	3,102,767	3.10	2,498,327	80.52%	164,928	5.32%
Goshen Creek	2,399,927	2.40	1,939,980	80.83%	121,913	5.08%
Middle Fork	12,996,847	13.00	9,047,566	69.61%	1,462,888	11.26%
Upper South Fork	34,630,241	34.63	22,903,208	66.14%	4,708,999	13.60%
Winkler Creek	2,897,956	2.90	2,391,119	82.51%	155,517	5.37%

150 meter riparian buffer zone scale						
	150 m buffer total area m^2	150 m buffer total area km^2	150 m buffer Forest Area m^2	150 m buffer TPFA	150 m buffer impervious area m^2	150 m buffer TPIA
Boone Creek	3,355,799	3.36	1,831,782	54.59%	923,993	27.53%
East Fork	10,081,925	10.08	6,914,615	68.58%	718,260	7.12%
Flannery Fork	4,386,069	4.39	3,564,282	81.26%	206,602	4.71%
Goshen Creek	3,429,637	3.43	2,753,243	80.28%	172,817	5.04%
Middle Fork	18,581,815	18.58	13,240,943	71.26%	1,946,193	10.47%
Upper South Fork	49,107,251	49.11	33,295,969	67.80%	6,252,814	12.73%
Winkler Creek	4,194,960	4.19	3,569,366	85.09%	188,121	4.48%

3.3.3. Discussion

The suggestions from Miller et al. (2009) proved to be of great value when conducting the Feature Analyst classification operations. One of the chief obstacles to the accuracy of the classification involved the repeated confusion of brown rooftops with brown tree canopy areas of similarly small spatial footprints, despite the inclusion or exclusion of these areas from the respective classification's training classes. In most cases, these areas were included or excluded during processing via hierarchical learning operations of the Feature Analyst software or through manual editing of the inappropriately included or excluded areas. Manual digitizing in particular proved to be an extremely laborious procedure, and its use was excluded from final datasets in order to maintain a repeatable, semi-automated procedure for future image classifications of this nature. Another difficulty of impervious classification regarded the repeated software classification confusion regarding white and very light surfaces. White roofs, mostly found on large commercial structures were often confused with white sandy areas such as golf courses or quarries, and proved difficult for Feature Analyst to distinguish due to their similar brightness, color, spectral, and textural values in the source imagery. Images from the impervious classification from a small area south of Boone are illustrated in Figures 26 through 29, with impervious surfaces represented by black pixels. The impervious classification for the entire study area is presented in Figure 25. The population centers of Boone to the north and Blowing Rock to the south can be clearly seen.

The description by Vanderzanden and Morrison (2002) regarding the results of their testing of Feature Analyst for classification of forest land covers proved to be an extremely useful resource. Their input representation, which they had created specifically created for their software analysis, was particularly useful during the many forest cover classification iterations undertaken during this thesis research. Dark green roof areas, especially those on the campus of Appalachian State University, and grassy areas with similar color and spectral characteristics as the forest training classes were particularly troublesome during training runs with the software. Numerous training set selection procedures, training set calibrations and reparameterizations, and hierarchical learning procedure iterations were required for the final classifications.

3.4. Water Quality Monitoring

In order to monitor water quality and evaluate the health of the headwater streams in the Upper South Fork New River watershed of Watauga County, NC, an ambient water quality monitoring program was instituted in the summer of 2010. Data collected during the first eight months of the program, July 2010 to January 2011, were used for the water quality analyses, environmental modeling, and hypothesis testing phases of this thesis research. Water quality instruments were located at each of the seven watershed outlet points identified during the hydrographic modeling phase, and water quality readings were collected by these instruments, or sondes. Grab samples were also collected on a monthly basis to provide additional water quality parameters not measured by the sondes.

One of the unique contributions of this research project to the scientific literature is the project's collection of primary water quality data via the data collection instruments and regularly scheduled grab samples. A review of the existing literature regarding water quality/ land cover studies indicated the predominant use of secondarily sourced water quality in the majority of these studies. As a result, the research designs of these projects were required to utilize existing water quality data collection points, and therefore predefined watershed and catchment units, for their analyses. By selecting water quality data collection sample locations, the design for this thesis research project was able to accommodate the creation of sub-watershed units for data collection purposes based on the logical spatial arrangements and environmental compositions of the local headwater stream systems of the Upper South Fork. The outlet points for the sub-watersheds were initially selected based on several criteria: similarities in size among one or more sub-watersheds (i.e., Goshen Creek and Boone Creek); to ensure contrasting land cover compositions (Winkler Creek and Boone Creek); to allow for geographically and anecdotally local logical watershed compositions; and to provide nested watershed hierarchical arrangements.

The design of the sondes and their software granted the researchers precise control over the instruments' data collection schedules. The 15 minute data collection intervals selected for the monitoring program was designed to sync with the hydrologic and water quality data collection intervals utilized by the USGS and to allow for fine temporal resolution data collection. This should be of great utility for future research, particularly with regards to issues such as TPIA impacts on hydrologic response to precipitation events, water quality response to precipitation events based on land cover compositions and coverage percentages, temperature responses to hydrologic and precipitation events, and many other potential research issues.

3.4.1. Fieldwork

The Water Resources Preservation Committee (WRPC) of Appalachian State University had previously planned on establishing a water quality monitoring program in the Upper South Fork watershed. Goshen Creek had been identified by the WRPC as a likely starting point for monitoring, so in October 2009 an instrument installation housing was constructed at the Goshen Creek outlet point by Dr. Jeff Colby, Dr. Chris Thaxton, Dr. Shea Tuberty, and Chris Coffey. The housing consisted of a section of standard 4 inch PVC DWV pipe attached to a section of slotted 4 inch PVC pipe at the base, with a removable, lockable cap at the top to facilitate researchers' access while eliminating unwanted intrusions. The entire assembly was attached to a bridge at the outlet location, then affixed to the stream bed with steel stakes. The condition of the instrument housing was observed throughout the winter and following spring to gauge its suitability for instrument protection and water quality monitoring purposes. The success of this first housing installation in withstanding flood events, winter storm events, and tampering by bridge maintenance crews without damage or excessive repair requirements led the researchers to adopt this housing design as the standard model for the other installation housings.

During the summer of 2010 the remaining six instrument housing installations were constructed at the drainage outlet points by Dr. Jeff Colby, Dr. Chuanhui Gu, and Chris Coffey. Assistance was provided on two of these installations by Dr. Shea Tuberty and Ashleigh Turner. Once the installations were secure, an In-Situ Troll 9500 ™ water quality sonde was deployed in each housing. Six of these sondes had been provided by the WRPC and the seventh was provided by Dr. Gu. The instruments collect data for the following variables: temperature, depth, turbidity, pH, dissolved oxygen, and specific conductivity. Grab samples were taken at monthly intervals to provide additional parameters not recorded by the sondes: Cl- (Chloride), NO43- (Nitrate), and SO42- (Sulfate). These grab samples were analyzed by Dr. Gu in his laboratory facilities in the Department of Geology at Appalachian State University.

3.4.2. ***Data management***

Data management was of primary importance for the long term maintenance of the ambient water quality monitoring program. Water quality data collection by the seven sondes at 15 minute intervals generates a massive amount of data, with approximately 96 readings per day taken at each station. This results in nearly 3,000 data recording events per month per station, with multiple water quality parameters measured at each recording event. To facilitate long-term management of this enormous data archive, a database was created for this purpose by the author. This database, *StreamLine: Upper South Fork New River Water Quality Monitoring Database* (Figure 35), was created using Microsoft Access, and will eventually allow researchers to not only view, store, retrieve, append, and query the data for each of the watersheds, but to also maintain a log of all activities associated with the water quality monitoring program. This is of particular importance since the project is quite labor intensive, involving a significant time and resource requirement for such activities as instrument cleaning and maintenance, instrument calibration, water quality monitoring station cleaning and debris removal, recording of data retrieval activities, and the data retrieval and management activities themselves. An Excel workbook, also titled *Streamline*, was created as a companion application to the database, and serves as an additional data management, organization, archiving, and backup tool.

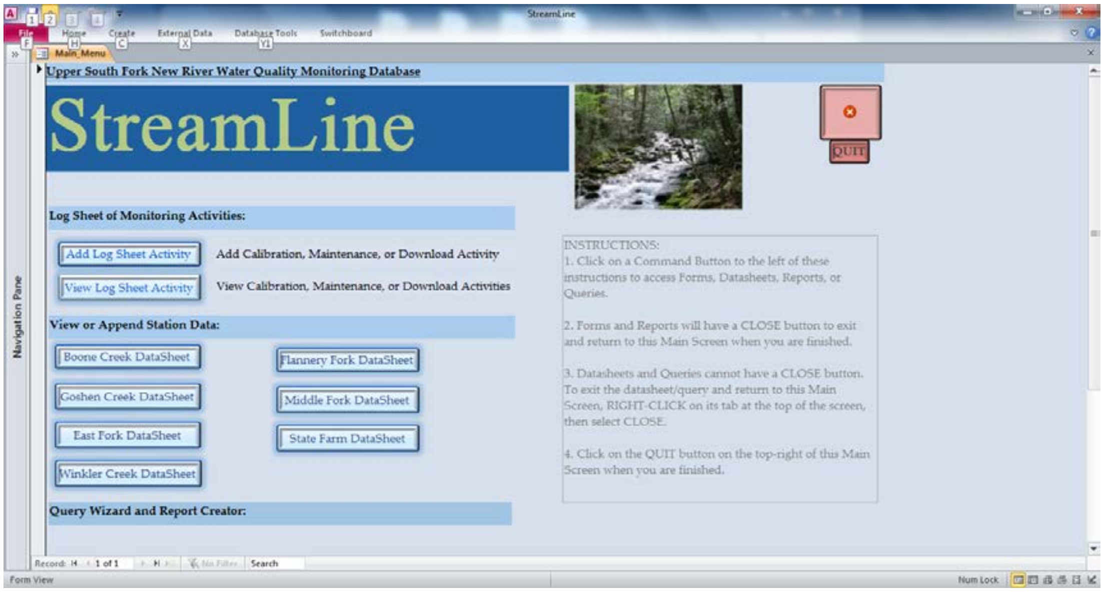


Figure 35. *Streamline* database for Upper South Fork ambient water quality monitoring program.

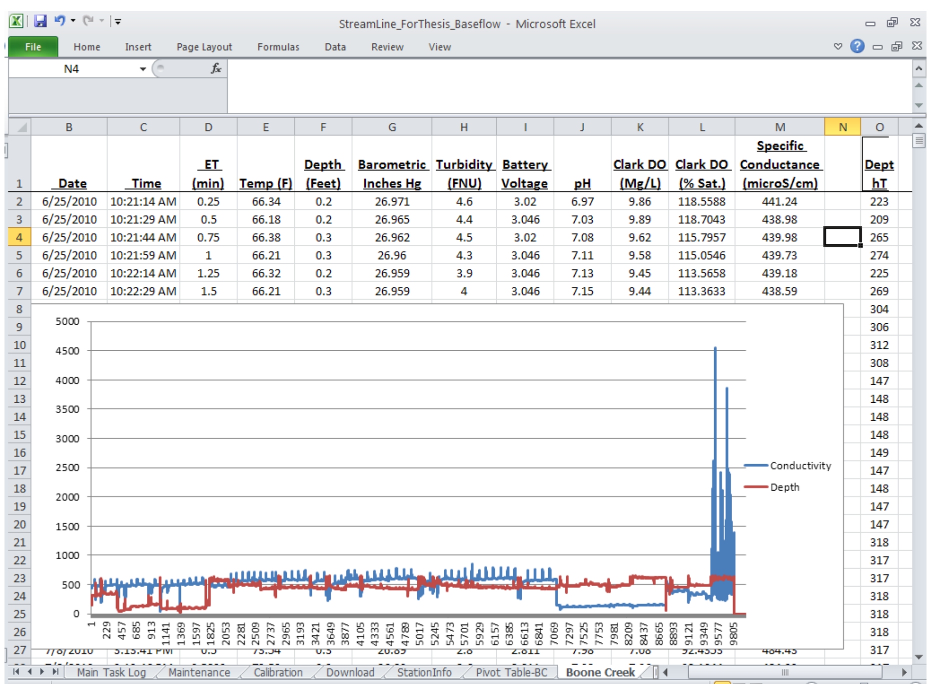


Figure 36. *Streamline* Excel workbook for Upper South Fork ambient water quality monitoring program.

CHAPTER FOUR

Environmental Modeling: Land Cover and Water Quality

4.1. Introduction

Completion of the four principal research components of this thesis research, terrain modeling, hydrographic modeling, water quality monitoring, and land cover classification provided the modeling inputs required for testing of the central hypothesis of the thesis:

> *There is a statistically significant relationship between land cover and water quality in the headwater stream systems of the Upper South Fork watershed of the New River, with impervious surfaces exerting a negative influence and forest land covers exerting a positive influence on water quality.*

Descriptive statistics were generated in order to explore this relationship, and inferential statistical analysis techniques were undertaken to determine the strength of various components of this relationship in addition to the explanatory values of individual variables.

Correlation analysis and linear regression were used to determine the presence and strength of possible correlations between water quality and land cover variables as well as the explanatory value of land cover type and composition for water quality indicator variable indices within these relationships. In order to examine the effects of temporal scale on the relationships between land cover and water quality, median water quality variables for the entire eight month study period were examined in one series of statistical procedures, and monthly median water quality variables were examined in a separate series. Land cover variables were considered to be consistent and without variation during the study period.

4.2. Methods

4.2.1. Data preparation

Water quality data for this thesis research had been collected from June 2010 through January 2011. Data for temperature, depth, turbidity, pH, dissolved oxygen, and specific conductivity were collected by the ambient monitoring sondes, while data for chloride, nitrate, and sulfate were collected once a month by grab samples. Grab sample data collection had begun in July 2010, therefore this dataset spanned the 7 month time period of July 2010 through January 2011. Due to delays in instrument deployment, specific conductivity was unavailable for Middle Fork and Upper South Fork for the months of July and August. Site access issues due to inclement winter weather also resulted in a loss of specific conductivity data for Middle Fork for January 2011. This resulted in a specific conductivity dataset of monthly median values for each watershed with a sample size (n) of 51, and sample sizes of 49 for chloride, nitrate, and sulfate.

Specific conductivity, chloride, nitrate, and sulfate were chosen as the best indicator variables for water quality assessment in this research. Specific conductivity (SC) is an excellent index variable for rapid stream health assessment (Conway 2007; Dow and Zampella 2000; Tran 2010; Sponseller et al. 2001; EPA 1997; Li et al. 2009; Hunsaker and Levine 1995) and is particularly useful in examinations such as this one of the effects of non-point source pollution on water quality. Conductivity is a measure of the amount of dissolved ions a liquid contains along with its ability to conduct electricity, and provides a good indication of contamination events which can cause an increase in the concentration of salts and minerals in a stream or dilution events (In Situ 2009). Conductivity increases with increased levels of inorganic dissolved solids such as chloride, phosphates, sulfate, nitrate, sodium, magnesium, calcium, iron, and aluminum (EPA 1997). Throughout this paper, conductivity is referred to and described quantitatively as *specific conductivity*, which is the measure of conductivity at a temperature of 25° C. SC is measured in micro-mhos per centimeter, equivalent to microsiemens/cm. All water quality instruments for this research have been programmed and calibrated to record conductivity in this manner to ensure a consistent reporting and analytical framework across all monitoring stations and watersheds. Clean freshwater has a low conductivity, with impaired or saline waters producing high conductivities. In order to support healthy fish populations conductivity should not exceed 500 μhos/cm (EPA 1997). North Carolina freshwater streams in their natural state should have a baseline specific conductivity of 17- 65 μhos/cm (NCDWQ 2010).

Nitrates are excellent indicators of non-point source pollution such as runoff from residential and agricultural areas, and also indicate the presence of point source pollutants such as septic field leaching, industrial discharge, wastewater discharge, and livestock waste product storage contamination (EPA 1997). Chlorides are generally found in extremely low levels in natural stream systems, and can result in elevated levels due to contamination from road salting, agricultural runoff, and wastewater discharge (Iowa 2009). Of particular concern in the Upper South Fork is the impact of large amounts of winter road salting activities on the region's surface and ground water resources, which were anticipated to produce higher specific conductivity and chloride levels in the time periods following these events. Sulfates naturally occur in water systems, but the level of sulfate can become artificially elevated due to point source inputs such as sewage treatment plants and industrial discharges, as well as non-point source inputs such as agricultural and urban runoff (EPA 1997). Heightened levels of these chemicals in conjunction with higher TPIA levels within a watershed or riparian buffer zone could be used as evidence supporting the assertion that contamination of precipitation runoff events from activities and effects associated with impervious surfaces leads to degradation of water quality.

Several of the other water quality variables measured by the sondes were reviewed and deemed unsuitable for inclusion in this thesis research. Temperature can be a very useful variable for assessing stream system health. It is particularly useful for examining the effects of deforestation on altering stream temperature due to canopy removal and the effects of impervious surfaces on altering stream temperature due to heated runoff from solar-heated impervious surfaces during precipitation events. In trout supporting stream systems such as the headwaters of the New River, temperature is of particular importance for these and other temperature-sensitive species. Temperature was excluded from this research, however, due to the requirement for fine temporal analysis of temperature fluctuations and precipitation events that were outside the scope of this research. Depth was also excluded, since it is only one component of the more useful measure of stream discharge. Calculations of the required stream discharge rating curves were also outside the scope of this research, and deemed unnecessary for the testing of the central hypothesis regarding the relationship between land cover and water quality.

Turbidity provides a measure of the clarity of water, and can be used for calculation of total suspended solids, a very important component for determining the status of impaired stream systems and potential inclusion or delisting from the federal 303d list (EPA 1997). Unfortunately the water quality instruments used in this research consistently failed to produce reliable turbidity readings for any consistent period of time. This problem is not isolated to the instruments used in this thesis research according to anecdotal and regulatory evidence, however, and is likely the reason that State and Federal agencies will not accept turbidity readings from ambient monitoring equipment, only from grab samples. As a result turbidity was not included as a water quality indicator variable in this thesis research. pH is also regarded as a reliable indicator variable for water quality, and has even been used as one of the prime indicator values in studies involving the relationship between land cover and water quality (Conway 2007; Dow and Zampella 200). pH exhibited little variation between monitoring stations throughout the data collection period of this research, however, and was consequently not included in statistical analysis.

Once the final water quality parameters had been selected, the data was carefully reviewed to determine the presence of outliers and erroneous readings. On several instances instruments had undergone periods of non-immersion due to drought periods, instrument housing movement from flood events, and, in the Boone Creek instrument's case, from stream rerouting and pumping activities due to construction on the Appalachian State University campus. All data observations recorded by the sondes during these periods of non-immersion were removed from the datasets. Several of the instruments displayed brief periods of instrument error during which the value of a parameter would become "stuck," such as a specific conductivity of -1.27 (SC values should always be positive) being reported for approximately two weeks at one of the instrument stations. All data observations during these periods of instrument error were also removed from the final datasets. These error periods often appeared to be synchronous with precipitation and flooding events, and were corrected through calibration or cleaning procedures.

An additional step in data preparation came as a result of the decision that stormflow events did not represent the normal baseflow conditions of the headwater streams, and would likely produce specific conductivity values outside the normal baseline range that would be expected at baseflow and streamflow conditions. Additionally, water grab samples for chloride, nitrate, and sulfate were taken monthly in immediate proximity to the sondes during baseflow or streamflow conditions. Hydrographs of depth readings were examined for each of the watersheds' water quality datasets (Figure 37), along with the mode of the monthly median depth values, in order to determine the baseflow levels for each stream at the monitoring station locations. Once the baseflow value had been established, all the water quality observations with a depth greater than this baseflow value were removed from the final dataset. The monthly median value for specific conductivity was then calculated for each monitoring station using the specific conductivity values at baseflow.

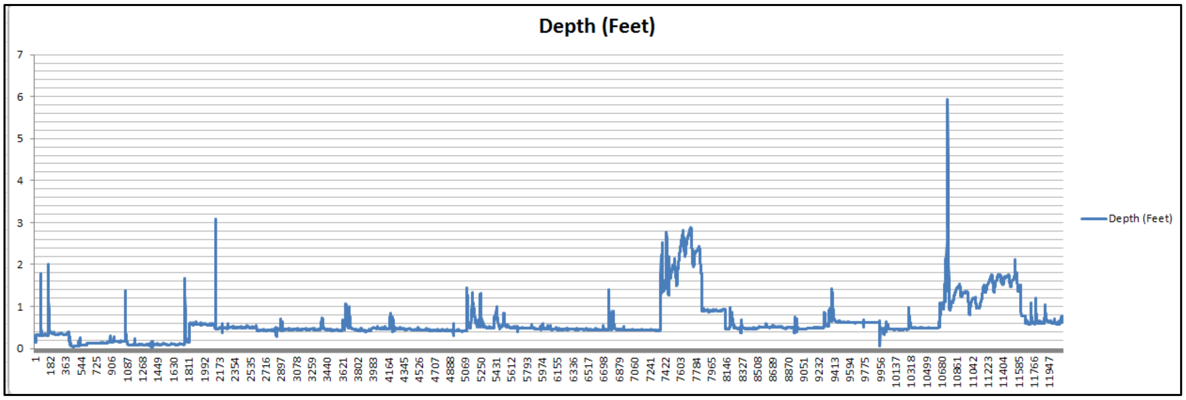


Figure 37. Hydrograph of depth readings in the Boone Creek watershed, June 2010- January 2011.

4.2.2. Data Analysis

SPSS 19.0 ™statistical software by IBM was used for exploratory data analysis, descriptive statistics generation, correlation analysis, and ordinary least-squares linear regression analysis utilizng the water quality and land cover datasets. Monthly median specific conductivity values were entered into an SPSS document and an Excel workbook along with monthly grab sample data (chloride, nitrate, sulfate), and land cover percentage data (TPIA and TPFA) for each watershed at each spatial scale (watershed and riparian buffers). Descriptive statistics, histograms, Q-Q plots, and Kolmogorov-Smirnov tests for normality were undertaken on each of the water quality variables and each of the land cover at scale variables. In order to carry out more robust analyses, logarithmic transformations using the base-10 logarithm were undertaken on each of the variables for all water quality variables and land cover at scale variables. Due to the improved normality of the log-transformed datasets, these datasets were used for correlation and regression analyses.

Data analysis procedures were implemented in two distinct phases in order to assess the influences of temporal resolution on the environmental modeling results of the effects of impervious surfaces and forests on water quality. In the first analysis phase, monthly median values for each water quality variable (specific conductivity, chloride, nitrate, sulfate) were aggregated into a single median value for the entire study period. This resulted in a sample size (*n*) of 7 for each of the 4 water quality variables, for a total *n* of 28. The seven watersheds were each represented by 10 distinct combinations of land cover composition at scale values for a total *n* of 70: TPIA at the watershed scale, TPIA at the 25 meter buffer scale, TPIA at the 50 m buffer, TPIA at the 100 m buffer, TPIA at the 150 m buffer, TPFA at the watershed scale, TPFA at the 25 m buffer, TPFA at the 50 m buffer, TPFA at the 100 m buffer, and TPFA at the 150 m buffer. Correlation analyses and linear regression analyses were undertaken on the $\log_{10}(x)$ transformed values for these variables in order to determine correlation coefficients, *p*-values, and *R squared* values for each pair of log-transformed variables.

The second phase involved statistical analyses of individual monthly median values for each water quality variable and land cover composition variables. This phase was undertaken with the intention of providing a more temporally detailed and comprehensive examination of the relationship between water quality and land cover. The results of this analytical phase were anticipated to provide insight into monthly and seasonal fluctuations within the water quality data as well as variances in the relationship strength and explanatory values of individual land cover compositions for water quality indices. Monthly median values for each water quality variable for the Upper South Fork watershed each sub-watershed had sample sizes of 49- 56, with a total *n* of 202 for the 4 water quality variables. The watershed and sub-watersheds were again represented by the 10 distinct land cover and spatial scale values for a total *n* of 70. As in the previous analysis phase utilizing the single study period median, correlation analyses and linear regression analyses were undertaken on the $\log_{10}(x)$ transformed values for these variables in order to determine correlation coefficients, p-values, and *R squared* values for each pair of log-transformed variables.

4.3. Results

4.3.1. Analysis of median water quality data from entire study period

For the first environmental modeling analysis phase, the median water quality value for each water quality variable over the entire study period was calculated for each watershed. The median specific conductivity value for each watershed was calculated from the baseflow specific conductivity measurements from the entire dataset for the June 2010 through January 2011 study period. The number of samples for specific conductivity for each watershed ranged from 6,069 for the Middle Fork to 16,951 for Winkler Creek. The median study period values for chloride, nitrate, and sulfate were calculated from the values obtained by once monthly grab samples taken during baseflow conditions. These values were organized within an Excel spreadsheet and an SPSS data document along with land cover composition at scale, and are presented in Table 10.

Descriptive statistics

Descriptive statistics were generated for each of the water quality and land cover variables. These statistics are presented in Table 11. Histograms were generated for the arithmetic datasets and log-transformed datasets to examine the normality of the data distribution for each of the water quality and land cover variables and to compare the normality of the arithmetic data with that of the log-transformed data. These histograms are presented in Figure 38.

Table 10. Median water quality values from entire study period with land cover compositions.

					Total Percentage Impervious Area					Total Percentage Forest Area				
Watershed	Conductivity	Chloride	Nitrate	Sulfate	watershed	25m buffer	50m buffer	100m buffer	150m buffer	watershed	25m buffer	50m buffer	100m buffer	150m buffer
Boone Creek	518.31	203.88	7.01	5.77	23.5	34.39	34.22	30.59	27.53	60.17	45.68	46.17	50.67	54.59
East Fork	55.53	7.21	1.85	1.22	7.33	6.2	7.08	7.03	7.12	66.96	72.83	69.97	68.76	68.58
Flannery Fork	35.86	1.37	0.79	1.33	4.44	7.23	6.55	5.32	4.71	81.92	79.24	78.72	80.52	81.26
Goshen Creek	32.19	3.47	1.32	0.94	6.31	6.31	5.91	5.08	5.04	75.04	81.86	81.34	80.83	80.28
Middle Fork	227.37	23.93	2.86	2.28	10.22	11.52	12.54	11.26	10.47	71.3	67.98	66.9	69.61	71.26
Upper South Fork	154.18	41.02	2.71	2.88	11.55	13.76	14.65	13.6	12.73	69.34	65.73	64.32	66.14	67.8
Winkler Creek	39.12	4.5	0.87	1.15	3.76	6.38	6.41	5.37	4.48	86.57	79.02	79.63	82.51	85.09

Table 11. Descriptive statistics of study period median water quality variables and land cover composition.

	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Specific Conductivity	486.12	32.19	518.31	151.79	177.84	31,626.57	1.83	3.33
Chloride	202.51	1.37	203.88	40.77	73.34	5,378.99	2.45	6.14
Nitrate	6.22	0.79	7.01	2.49	2.16	4.65	1.90	4.00
Sulfate	4.83	0.94	5.77	2.22	1.71	2.94	1.85	3.48
TPIA, watershed scale	19.74	3.76	23.50	9.59	6.76	45.68	1.75	3.43
TPIA, 25 m buffer	28.19	6.20	34.39	12.26	10.20	104.09	2.22	5.13
TPIA, 50 m buffer	28.31	5.91	34.22	12.48	10.18	103.61	2.08	4.54
TPIA, 100 m buffer	25.51	5.08	30.59	11.18	9.18	84.19	2.00	4.21
TPIA, 150 m buffer	23.05	4.48	27.53	10.30	8.22	67.62	1.92	3.91
TPFA, watershed scale	26.40	60.17	86.57	73.04	8.99	80.87	0.25	-0.50
TPFA, 25 m buffer	36.18	45.68	81.86	70.33	12.44	154.73	-1.48	2.39
TPFA, 50 m buffer	35.17	46.17	81.34	69.58	12.29	150.98	-1.21	1.51
TPFA, 100 m buffer	31.84	50.67	82.51	71.29	11.28	127.17	-0.95	0.75
TPFA, 150 m buffer	30.50	54.59	85.09	72.69	10.45	109.21	-0.65	0.10

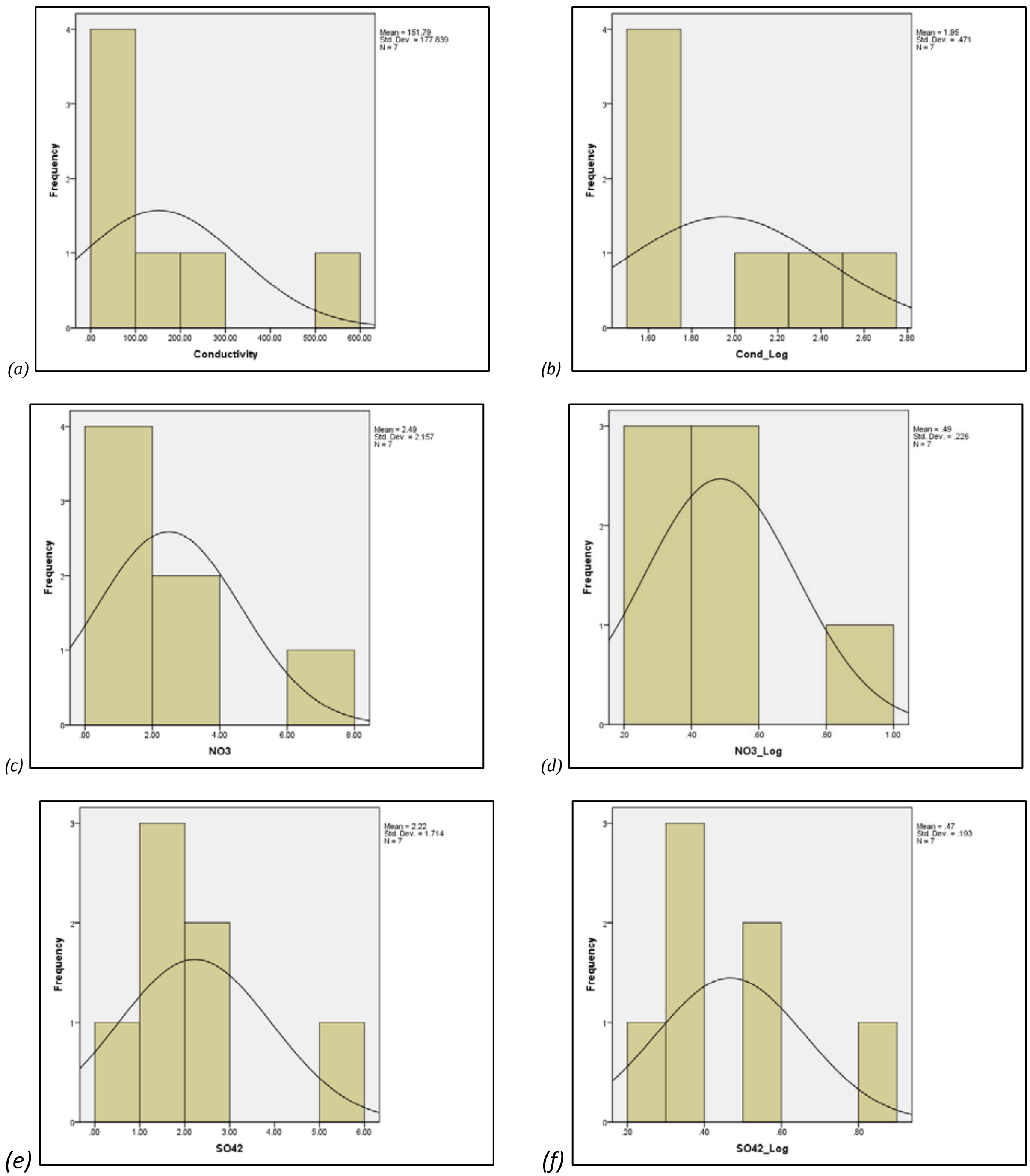
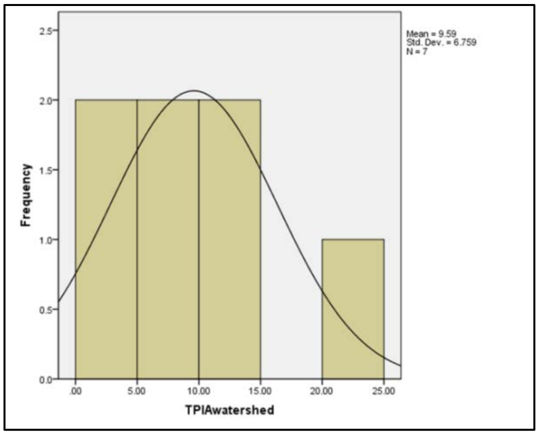
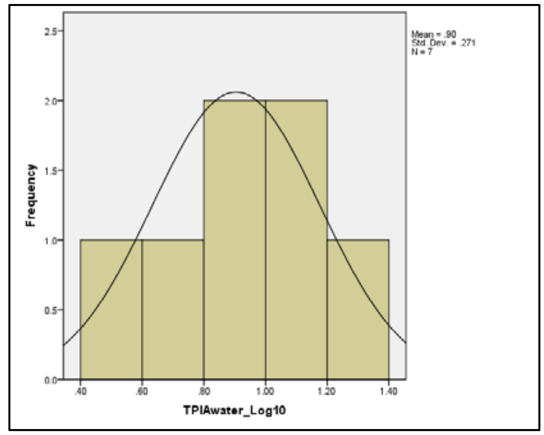


Figure 38. Histograms of arithmetic and log-transformed water quality data of study period median values and land cover data. Arithmetic data is arranged on left side of page and log-transformed on right. Water quality variables: (a) specific conductivity (b) log-transformed specific conductivity (c) nitrate (d) log-transformed nitrate (e) sulfate (f) log-transformed sulfate.



(g)



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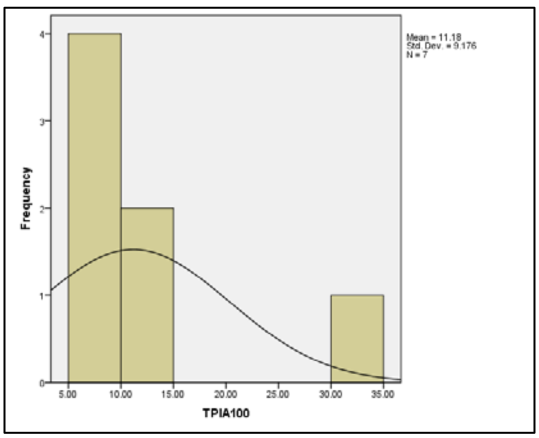
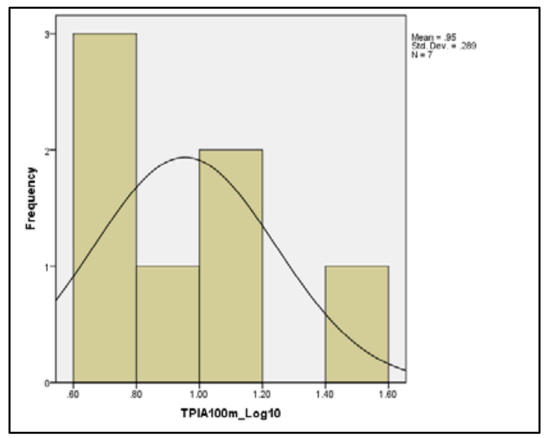


(i)



(j)

Figure 38 (cont.). Histograms of arithmetic and log-transformed water quality data of study period median values and land cover data. Arithmetic data is arranged on left side of page and log-transformed on right. Water quality variables: (g) TPIA at the watershed scale (h) log-transformed TPIA at the watershed scale (i) TPIA at the 100 m riparian buffer distance (j) log-transformed TPIA at the 100 m riparian buffer distance.

Correlation and regression analysis

Pearson's product –moment correlation analysis was undertaken to determine the existence, strength, and significance of correlations between land cover variables and water quality variables. The results of correlation analysis are presented in Table 13. TPIA within the 100 meter buffer exhibited the strongest correlations with increasing water quality contaminant indicator variables. TPIA at the 100 m buffer had correlation coefficient values, *r*, of 0.971 for specific conductivity, 0.984 for chloride, 0.973 for nitrate, and 0.987 for sulfate, with a *p* value of 0.000 for each. These figures are indicative of an extremely strong correlation between water quality indicator levels and TPIA at the 100 m buffer. Strong correlations between TPIA and water quality contaminant levels were likewise observed at all the other spatial scales: individual watershed scale, 25 m riparian buffer, 50 m buffer, and 150 m buffer. The lowest correlation coefficient among any of the variable pairs is observed with TPIA at the individual watershed scale and sulfate. A strong relationship can still be discerned, however, with an *r* value of 0.915 and a *p* value of 0.004.

Forests also demonstrated some very strong correlations with water quality. As hypothesized, increasing percentages of forest at the various spatial scales demonstrated increasingly enhanced levels of water quality and decreasing levels of contaminant presence. The negative correlation coefficient (*r*) values are indicative of this negative relationship between forest presence and water quality contamination. TPFA at the 50 meter riparian buffer zone was found to have the strongest negative relationship with water quality contaminant levels, indicated by an *r* value of 0.928 with a *p* value of 0.003 for specific conductivity, an *r* value of 0.951 with a *p* value of 0.001 for chloride, an *r* value of 0.968 with a *p* value of 0.000 for nitrate, and an *r* value of 0.963 with a *p* value of 0.000 for sulfate. High correlation values are also observable at the 25 m and 100 m buffer zones, with less significant results seen at the watershed scale and the 150 m buffer scale. These results demonstrate the highly significant role that forest riparian buffer zones can play, with the 50 meter riparian buffer being the most statistically significant.

Table 12. Correlations and regression analysis results of median water quality values from entire study period with land cover composition at watershed and riparian buffer distances.

Spatial scale	Value	Specific conductivity	Chloride	Nitrate	Sulfate
TPIA, watershed scale	Pearsons *r*	.929	.951	**.986**	.915
	p value (significance)	.002	.001	**.000**	.004
	R square	.863	.903	**.973**	.836
TPIA, 25 m buffer	Pearsons *r*	.935	.942	.931	.993
	p value (significance)	.002	.002	.002	.000
	R square	.875	.887	.868	.987
TPIA, 50 m buffer	Pearsons *r*	.966	.972	.958	**.996**
	p value (significance)	.000	.000	.001	**.000**
	R square	.932	.945	.918	**.992**
TPIA, 100 m buffer	Pearsons *r*	**.971**	**.984**	.973	.987
	p value (significance)	**.000**	**.000**	.000	.000
	R square	**.942**	**.968**	.947	.974
TPIA, 150 m buffer	Pearsons *r*	.965	.982	.985	.969
	p value (significance)	.000	.000	.000	.000
	R square	.931	.964	.971	.940
TPFA, watershed scale	Pearsons *r*	-.779	-.821	-.906	-.747
	p value (significance)	.039	.023	.005	.054
	R square	.606	.675	.821	.558
TPFA, 25 m buffer	Pearsons *r*	-.922	-.946	-.958	**-.969**
	p value (significance)	.003	.001	.001	**.000**
	R square	.849	.896	.918	**.939**
TPFA, 50 m buffer	Pearsons *r*	**-.928**	**-.951**	-.968	-.963
	p value (significance)	**.003**	**.001**	.000	.000
	R square	**.861**	**.905**	.936	.928
TPFA, 100 m buffer	Pearsons *r*	-.906	-.940	**-.970**	-.931
	p value (significance)	.005	.002	**.000**	.002
	R square	.821	.883	**.941**	.867
TPFA, 150 m buffer	Pearsons *r*	-.881	-.915	-.961	-.894
	p value (significance)	.009	.004	.001	.007
	R square	.776	.838	.924	.798

Linear regression was then undertaken using ordinary least-squares, with individual water quality variable datasets input as the dependent variables and land cover composition at the various spatial scales input as dependent variables for each test. The coefficient of determination, or *R squared* (R^2), regression values produced by these tests are presented in Table 12 along with the correlation testing results. Similar patterns to those obtained from correlation analysis can be observed in the regression analysis results regarding the influence of TPA and TPFA on water quality. Scatterplots of a selection of these regression results are presented in Figure 39 which clearly demonstrate the nearly linear positive relationship between TPIA and water quality contaminant levels and the nearly linear negative relationship between TPFA and water quality contaminants.

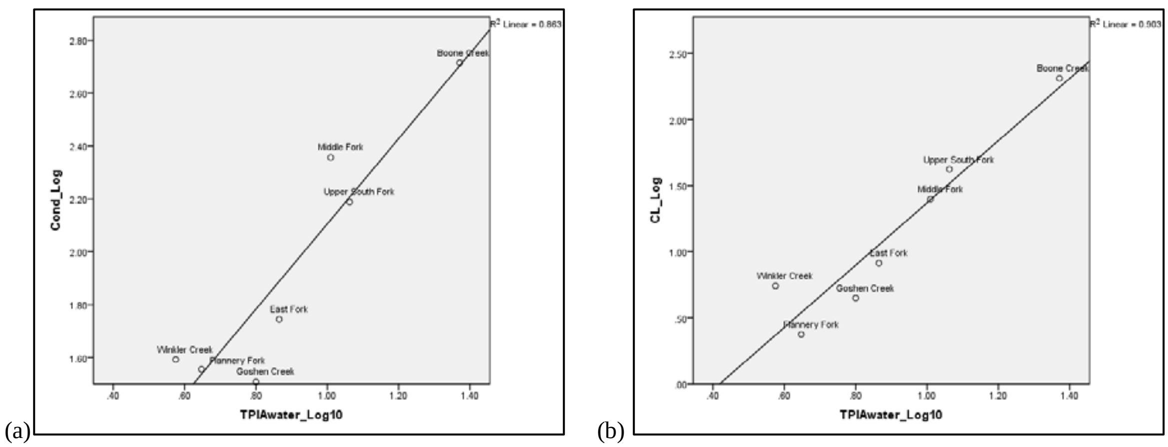


Figure 39. Scatterplots of log-transformed data showing regression lines from regression results for select pairs of study period median water quality and land cover at scale variables. (a) Specific conductivity and TPIA at the watershed scale (b) chloride and TPIA at the watershed scale.

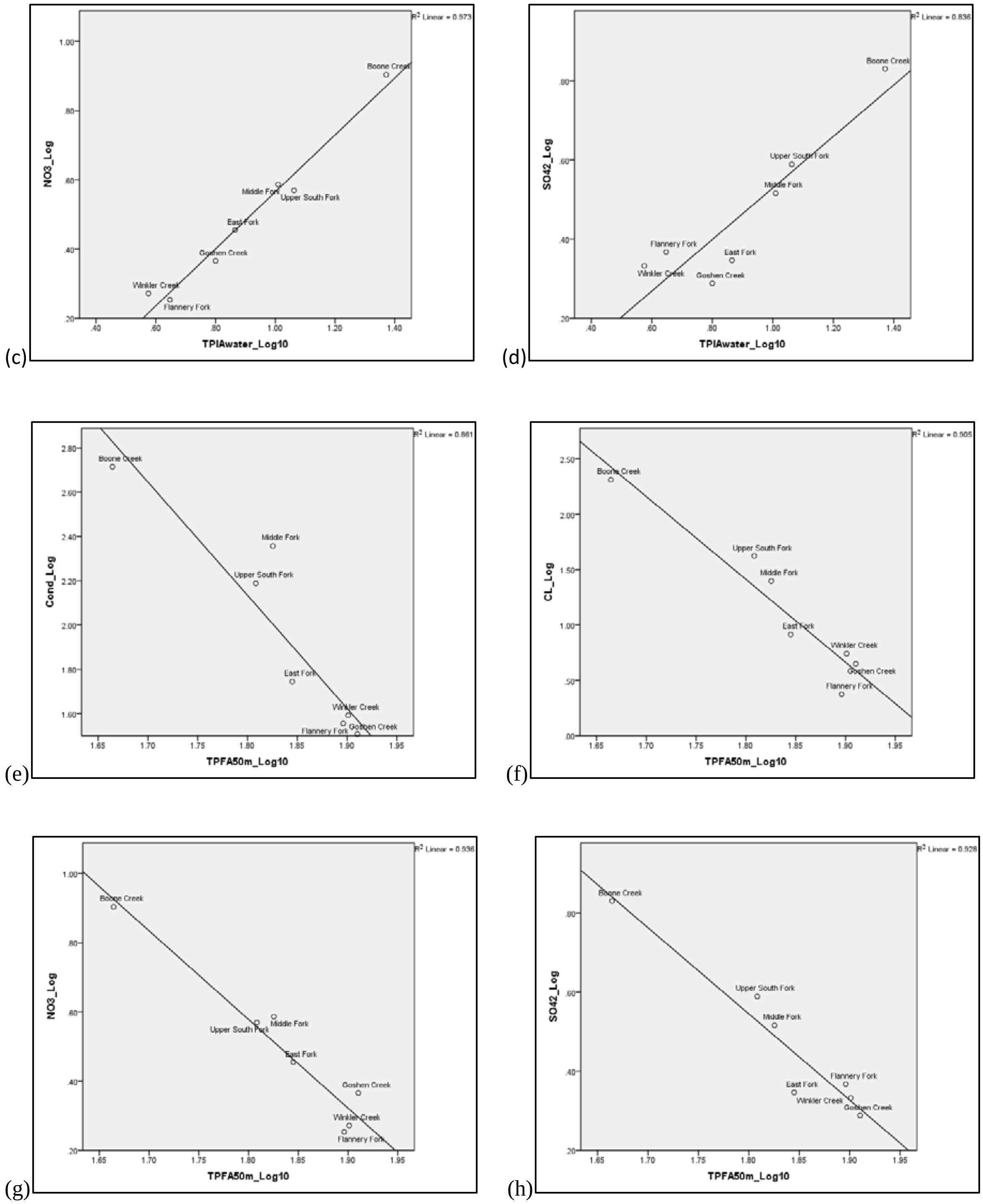


Figure 40. Scatterplots of log-transformed data showing regression lines from regression results for select pairs of study period median water quality and land cover at scale variables. (c) Nitrate and TPIA at the watershed scale (d) sulfate and TPIA at the watershed scale (e) conductivity and TPFA at the 50 m buffer (f) chloride and TPFA at the 50 m buffer (g) nitrate and TPFA at the 50 m buffer (h) sulfate and TPFA at the 50 m buffer.

4.3.2. Analysis of monthly median water quality data

For the second environmental modeling analysis phase, the monthly median water quality value for each water quality variable was calculated for each watershed. Monthly median specific conductivity values were calculated for each watershed from the baseflow data from June 2010 through January 2011. The monthly values for chloride, nitrate, and sulfate had been obtained by monthly grab samples taken during baseflow conditions. These values were organized within an Excel spreadsheet and an SPSS data document along with the land cover composition variables for each watershed unit and each buffer distance by watershed. The monthly median water quality data is presented in Table 13.

Descriptive statistics

Descriptive statistics were then generated for each of the water quality variables by watershed. These statistics are presented in Table 14. Histograms and Q-Q plots were generated for the arithmetic monthly median datasets to examine the normality of the data distribution for each of the water quality and land cover variables, some of which are presented in Figure 41. Histograms of the log-transformed datasets were also generated in order to examine the effects of the data transformation on the normality of the data distributions. Several of these histograms are presented in Figure 42 which demonstrates the improvement in normality of the data distribution as a result of log-transformation of the water quality data.

Table 13. Monthly median water quality data.

Monitoring Station	Parameter	June	July	August	September	October	November	December	January
Boone Creek	Conductivity (μhos/cm)	439.36	490.95	559.49	578.62	589.27	147.92	418.65	591.12
East Fork	Conductivity (μhos/cm)	55.75	61.17	56.38	54.58	58.55	58.30	31.50	30.43
Flannery Fork	Conductivity (μhos/cm)	31.62	36.39	37.42	36.19	36.83	32.32	17.01	16.72
Goshen Creek	Conductivity (μhos/cm)	32.12	32.10	34.55	31.81	34.85	32.32	15.84	21.37
Middle Fork	Conductivity (μhos/cm)	102.78	NoData	NoData	227.63	243.45	71.81	67.65	NoData
Upper South Fork	Conductivity (μhos/cm)	134.23	NoData	NoData	149.85	197.86	84.03	122.79	176.35
Winkler Creek	Conductivity (μhos/cm)	36.13	40.23	42.87	40.67	41.13	36.93	25.77	27.26
Boone Creek	Cl-(mg/L)	NoData	150.88	209.64	203.88	144.96	166.03	369.90	288.97
East Fork	Cl-(mg/L)	NoData	7.21	9.75	8.51	4.51	5.19	4.88	9.83
Flannery Fork	Cl-(mg/L)	NoData	2.59	4.04	3.31	0.70	1.37	1.01	0.59
Goshen Creek	Cl-(mg/L)	NoData	3.47	4.29	3.85	3.58	1.58	1.64	2.78
Middle Fork	Cl-(mg/L)	NoData	31.85	26.76	23.93	18.15	17.70	23.06	42.69
Upper South Fork	Cl-(mg/L)	NoData	22.50	43.26	41.02	26.30	26.01	189.68	144.70
Winkler Creek	Cl-(mg/L)	NoData	3.08	5.29	4.50	1.51	5.50	2.40	8.14
Boone Creek	NO3-(mg/L)	NoData	6.79	8.15	7.88	4.98	7.01	7.73	6.48
East Fork	NO3-(mg/L)	NoData	1.76	2.12	1.85	0.70	1.73	3.07	2.54
Flannery Fork	NO3-(mg/L)	NoData	0.67	1.03	0.79	0.20	0.27	1.47	1.02
Goshen Creek	NO3-(mg/L)	NoData	0.95	1.47	1.32	0.00	1.00	1.84	1.65
Middle Fork	NO3-(mg/L)	NoData	2.14	5.92	2.64	1.37	4.27	3.23	2.86
Upper South Fork	NO3-(mg/L)	NoData	1.99	4.46	2.71	0.87	2.68	3.24	2.93
Winkler Creek	NO3-(mg/L)	NoData	0.84	1.16	0.87	0.03	0.62	1.45	1.38
Boone Creek	SO42- (mg/L)	NoData	5.09	6.21	5.77	5.12	4.50	6.51	6.24
East Fork	SO42- (mg/L)	NoData	1.22	1.59	1.43	0.67	1.00	1.34	1.14
Flannery Fork	SO42- (mg/L)	NoData	1.31	1.54	1.48	0.95	1.20	1.46	1.33
Goshen Creek	SO42- (mg/L)	NoData	1.25	1.21	1.10	0.43	0.79	0.88	0.94
Middle Fork	SO42- (mg/L)	NoData	2.28	3.17	2.87	2.05	2.36	1.99	2.09
Upper South Fork	SO42- (mg/L)	NoData	2.25	3.17	2.88	1.79	1.88	4.00	4.36
Winkler Creek	SO42- (mg/L)	NoData	1.09	1.25	1.15	0.32	0.80	1.68	1.51

Table 14. Descriptive statistics of monthly median water quality variables.

Monitoring Station	Parameter	Range	Minimum	Maximum	Median	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Boone Creek	Conductivity (µhos/cm)	443.20	147.92	591.12	525.22	476.92	149.32	22,295.55	-1.79	3.52
East Fork	Conductivity (µhos/cm)	30.74	30.43	61.17	56.07	50.83	12.43	154.46	-1.33	-0.12
Flannery Fork	Conductivity (µhos/cm)	20.70	16.72	37.42	34.26	30.56	8.71	75.92	-1.21	-0.36
Goshen Creek	Conductivity (µhos/cm)	19.01	15.84	34.85	32.11	29.37	6.90	47.66	-1.51	1.06
Middle Fork	Conductivity (µhos/cm)	175.80	67.65	243.45	102.78	142.66	86.05	7,403.79	0.52	-3.10
Upper South Fork	Conductivity (µhos/cm)	113.83	84.03	197.86	142.04	144.19	40.31	1,624.63	-0.18	-0.23
Winkler Creek	Conductivity (µhos/cm)	17.10	25.77	42.87	38.58	36.37	6.48	42.00	-1.00	-0.55
Boone Creek	Cl-(mg/L)	224.94	144.96	369.90	203.88	219.18	82.58	6,818.71	1.19	0.62
East Fork	Cl-(mg/L)	5.32	4.51	9.83	7.21	7.12	2.30	5.29	0.08	-2.22
Flannery Fork	Cl-(mg/L)	3.46	0.59	4.04	1.37	1.94	1.37	1.88	0.60	-1.48
Goshen Creek	Cl-(mg/L)	2.71	1.58	4.29	3.47	3.03	1.07	1.14	-0.55	-1.38
Middle Fork	Cl-(mg/L)	24.99	17.70	42.69	23.93	26.31	8.72	76.01	1.18	1.31
Upper South Fork	Cl-(mg/L)	167.18	22.50	189.68	41.02	70.49	67.77	4,592.87	1.33	0.05
Winkler Creek	Cl-(mg/L)	6.63	1.51	8.14	4.50	4.34	2.24	5.01	0.51	0.01
Boone Creek	NO3-(mg/L)	3.17	4.98	8.15	7.01	7.00	1.08	1.17	-1.08	1.20
East Fork	NO3-(mg/L)	2.37	0.70	3.07	1.85	1.97	0.74	0.55	-0.29	1.08
Flannery Fork	NO3-(mg/L)	1.27	0.20	1.47	0.79	0.78	0.45	0.20	0.11	-0.56
Goshen Creek	NO3-(mg/L)	1.84	0.00	1.84	1.32	1.18	0.61	0.37	-1.23	1.86
Middle Fork	NO3-(mg/L)	4.55	1.37	5.92	2.86	3.20	1.50	2.24	0.95	0.96
Upper South Fork	NO3-(mg/L)	3.58	0.87	4.46	2.71	2.70	1.10	1.21	-0.14	1.27
Winkler Creek	NO3-(mg/L)	1.42	0.03	1.45	0.87	0.91	0.49	0.24	-0.82	0.58
Boone Creek	SO42- (mg/L)	2.01	4.50	6.51	5.77	5.63	0.75	0.56	-0.37	-1.41
East Fork	SO42- (mg/L)	0.92	0.67	1.59	1.22	1.20	0.30	0.09	-0.67	0.50
Flannery Fork	SO42- (mg/L)	0.59	0.95	1.54	1.33	1.32	0.20	0.04	-1.07	0.97
Goshen Creek	SO42- (mg/L)	0.82	0.43	1.25	0.94	0.94	0.28	0.08	-0.92	0.84
Middle Fork	SO42- (mg/L)	1.18	1.99	3.17	2.28	2.40	0.45	0.20	1.05	-0.28
Upper South Fork	SO42- (mg/L)	2.57	1.79	4.36	2.88	2.90	1.01	1.02	0.38	-1.45
Winkler Creek	SO42- (mg/L)	1.36	0.32	1.68	1.15	1.11	0.45	0.20	-0.71	0.53

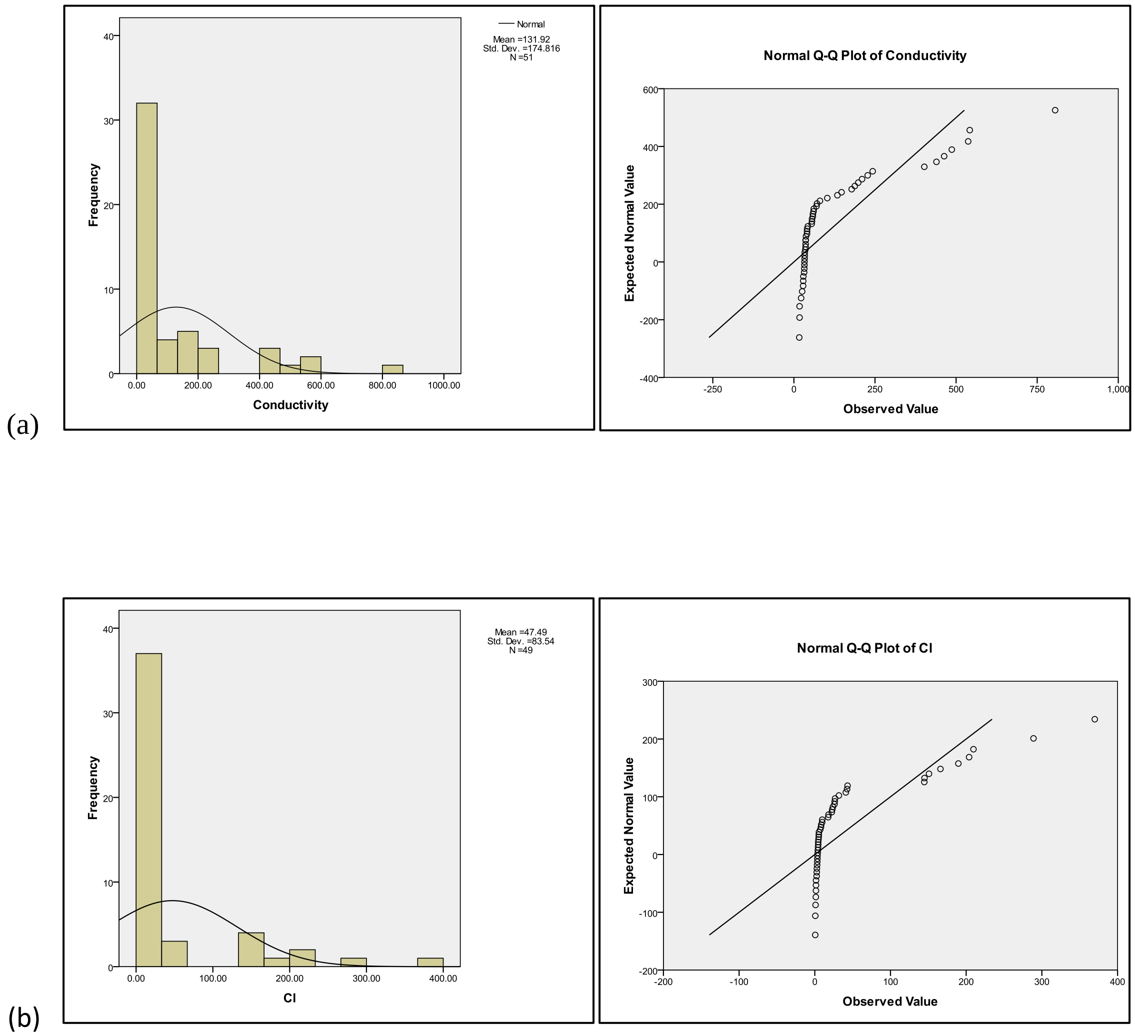
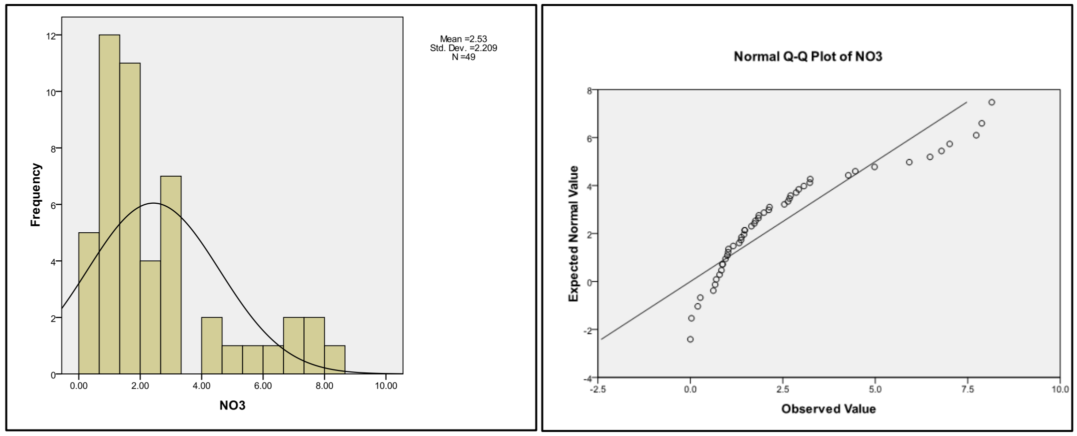


Figure 41. Histograms and Q-Q plots for monthly median water quality values. (a) Specific conductivity (b) chloride.

(c)



(d)

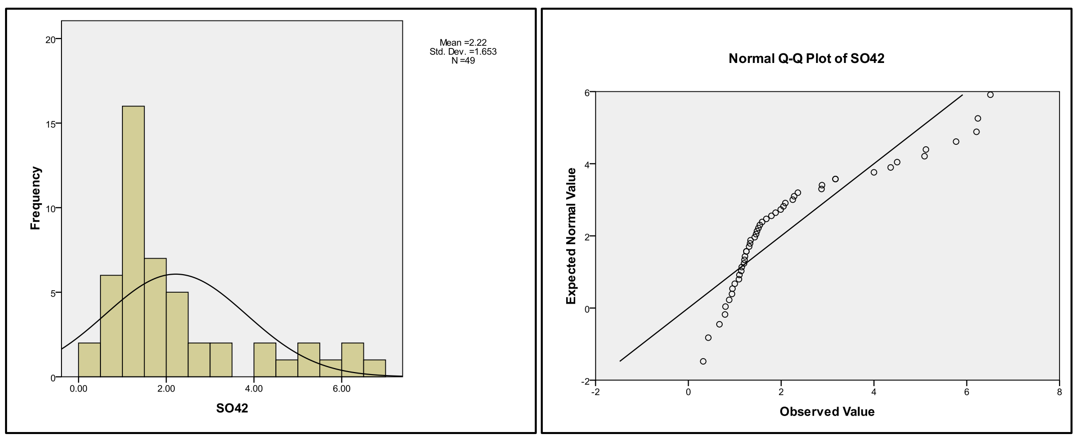
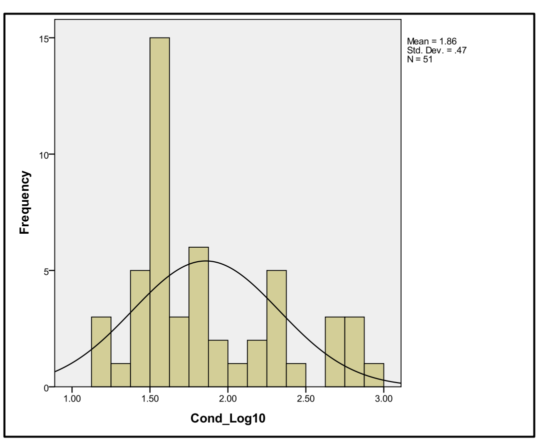


Figure 41 (cont.). Histograms and Q-Q plots for monthly median water quality values. (c) nitrate (d) sulfate.

(a)



(b)

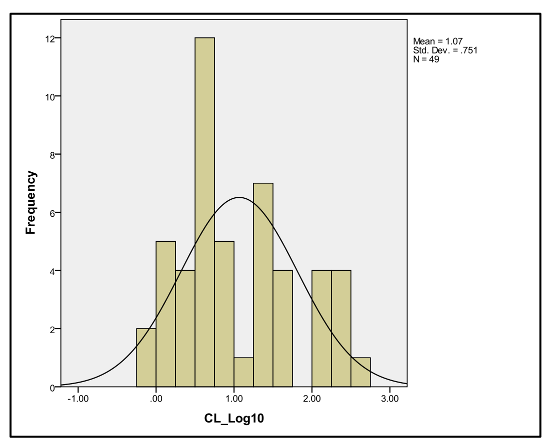


Figure 42. Histograms for log-transformed monthly median water quality values. (a) Specific conductivity (b) chloride.

Correlation and regression analysis

To examine any potential temporal variations in the effects impervious surfaces and forests exert on water quality, monthly median values of specific conductivity were examined along with land cover through correlation analysis. Pearson's product moment correlation analysis was used (as had also been used in the study period median analysis phase) as the correlation test, with the monthly median specific conductivity value for each watershed input as the water quality dataset and the TPIA and TPFA values for each watershed at each scale input as the land cover composition dataset. The correlation coefficients and significance values for each month are presented in Table 15. Correlation analyses of each of the other three water quality variables was outside the scope of this research, so specific conductivity was chosen for its usefulness as an excellent indicator variable for rapid stream system health assessment.

Similar results regarding the relative influence of certain land cover compositions were observed in the results from the correlation analysis of monthly median specific conductivity values as had been observed in correlation results from tests involving the study period median water quality values. TPIA within the 100 meter riparian buffer zone again exhibited the strongest explanatory value for water quality values. Forests also demonstrated strong correlations with water quality variables when analyzed at the monthly temporal scale. TPFA at the 50 meter riparian buffer zone was found to have the strongest negative relationship with water quality contaminant levels, demonstrating the ameliorating effect of forest land covers on water quality impairment. As with TPIA, TPFA had differing r values and p values for different months. These trends were primarily characterized by higher correlations during Summer and Winter months, and lower levels of correlation during the dry Fall period of September through November.

Table 15. Correlations and linear regression results of monthly median water quality values with TPIA and TPFA at the watershed and riparian buffer spatial scales.

		Specific Conductivity Median Value							
Spatial scale	**Value**	**June**	**July**	**August**	**September**	**October**	**November**	**December**	**January**
TPIA, watershed scale	Pearsons *r*	0.959	0.943	0.939	0.926	0.935	0.948	0.927	0.937
	p value (significance)	0.001	0.016	0.018	0.003	0.002	0.001	0.003	0.006
	R square	0.919	0.888	0.882	0.858	0.874	0.898	0.859	0.879
TPIA, 25 m buffer	Pearsons *r*	0.966	0.967	0.978	0.943	0.938	0.910	0.962	0.964
	p value (significance)	0.000	0.007	0.004	0.001	0.002	0.004	0.001	0.002
	R square	0.934	0.934	0.957	0.889	0.880	0.828	0.925	0.929
TPIA, 50 m buffer	Pearsons *r*	0.990	0.990	0.996	0.970	0.969	0.954	0.986	0.984
	p value (significance)	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000
	R square	0.981	0.980	0.992	0.942	0.938	0.911	0.972	0.968
TPIA, 100 m buffer	Pearsons *r*	0.999	0.998	0.999	0.973	0.975	0.978	0.992	0.988
	p value (significance)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	R square	0.997	0.997	0.998	0.948	0.951	0.956	0.983	0.976
TPIA, 150 m buffer	Pearsons *r*	0.996	0.992	0.989	0.965	0.970	0.983	0.981	0.980
	p value (significance)	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.001
	R square	0.991	0.983	0.978	0.932	0.941	0.966	0.962	0.960
TPFA, watershed scale	Pearsons *r*	-0.839	-0.826	-0.804	-0.774	-0.782	-0.872	-0.786	-0.783
	p value (significance)	0.018	0.085	0.101	0.041	0.038	0.011	0.036	0.066
	R square	0.704	0.682	0.647	0.598	0.611	0.760	0.618	0.613
TPFA, 25 m buffer	Pearsons *r*	-0.976	-0.999	-0.999	-0.931	-0.919	-0.945	-0.962	-0.951
	p value (significance)	0.000	0.000	0.000	0.002	0.003	0.001	0.001	0.004
	R square	0.952	0.998	0.998	0.867	0.844	0.893	0.926	0.905
TPFA, 50 m buffer	Pearsons *r*	-0.981	-0.998	-0.993	-0.935	-0.926	-0.963	-0.965	-0.951
	p value (significance)	0.000	0.000	0.001	0.002	0.003	0.000	0.000	0.004
	R square	0.963	0.996	0.987	0.875	0.858	0.928	0.931	0.904
TPFA, 100 m buffer	Pearsons *r*	-0.969	-0.982	-0.971	-0.911	-0.906	-0.967	-0.945	-0.932
	p value (significance)	0.000	0.003	0.006	0.004	0.005	0.000	0.001	0.007
	R square	0.938	0.964	0.944	0.829	0.821	0.935	0.893	0.869
TPFA, 150 m buffer	Pearsons *r*	-0.945	-0.953	-0.938	-0.882	-0.882	-0.956	-0.914	-0.902
	p value (significance)	0.001	0.012	0.018	0.009	0.009	0.001	0.004	0.014
	R square	0.894	0.908	0.879	0.778	0.777	0.914	0.835	0.813

Linear regression was then undertaken using ordinary least-squares, with median specific conductivity values for each month input as the dependent variables and land cover composition at the various spatial scales input as dependent variables for each test. The coefficient of determination, or *R squared* (R^2), regression values produced by these tests are presented in Table 15 along with the correlation testing results. Similar patterns to those obtained from correlation analysis can be observed in the regression analysis results regarding the influence of TPIA and TPFA on water quality. Monthly variations in the explanatory power of TPIA and TPFA for water quality at each spatial scale can be observed in Figures 43 and 44.

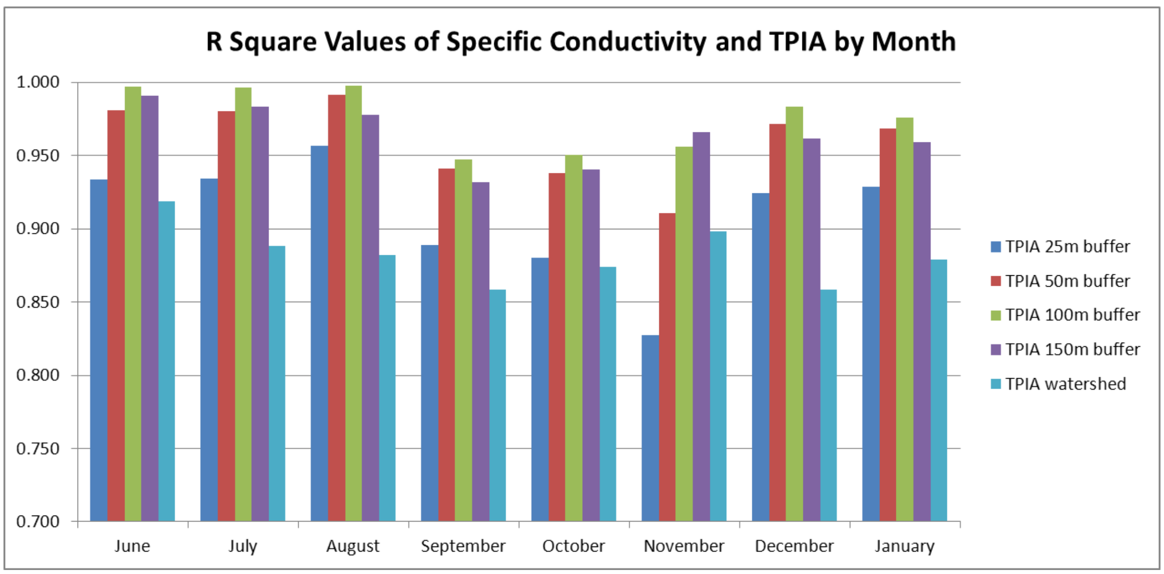


Figure 43. R squared values from linear regression testing of median monthly specific conductivity values and TPIA at watershed and riparian buffer distances.

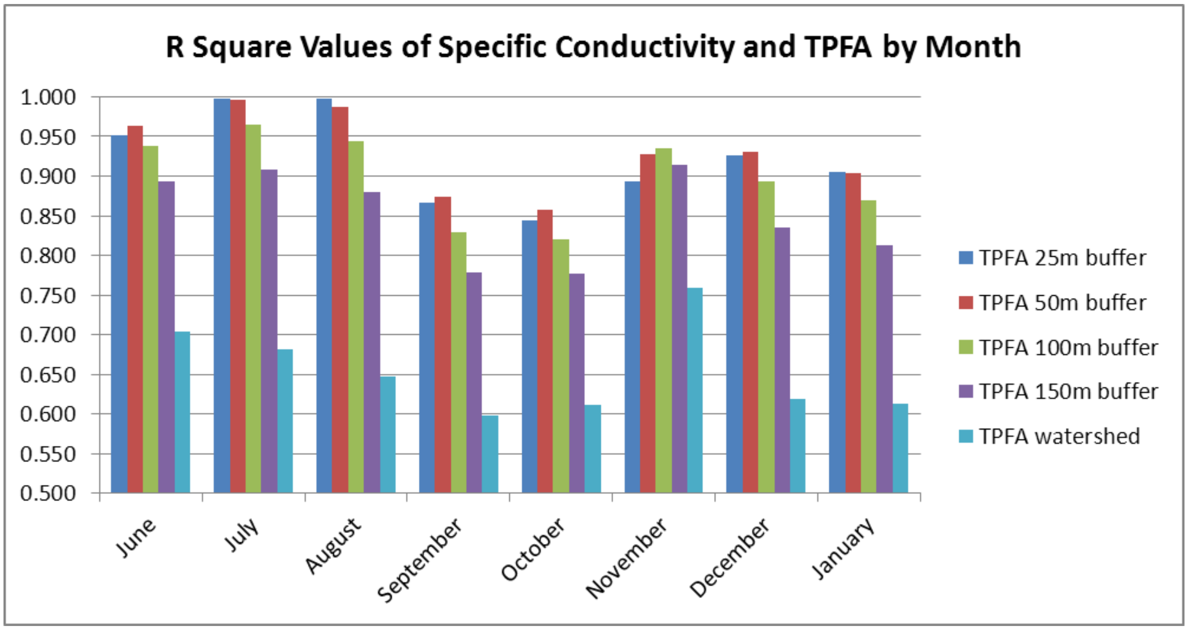


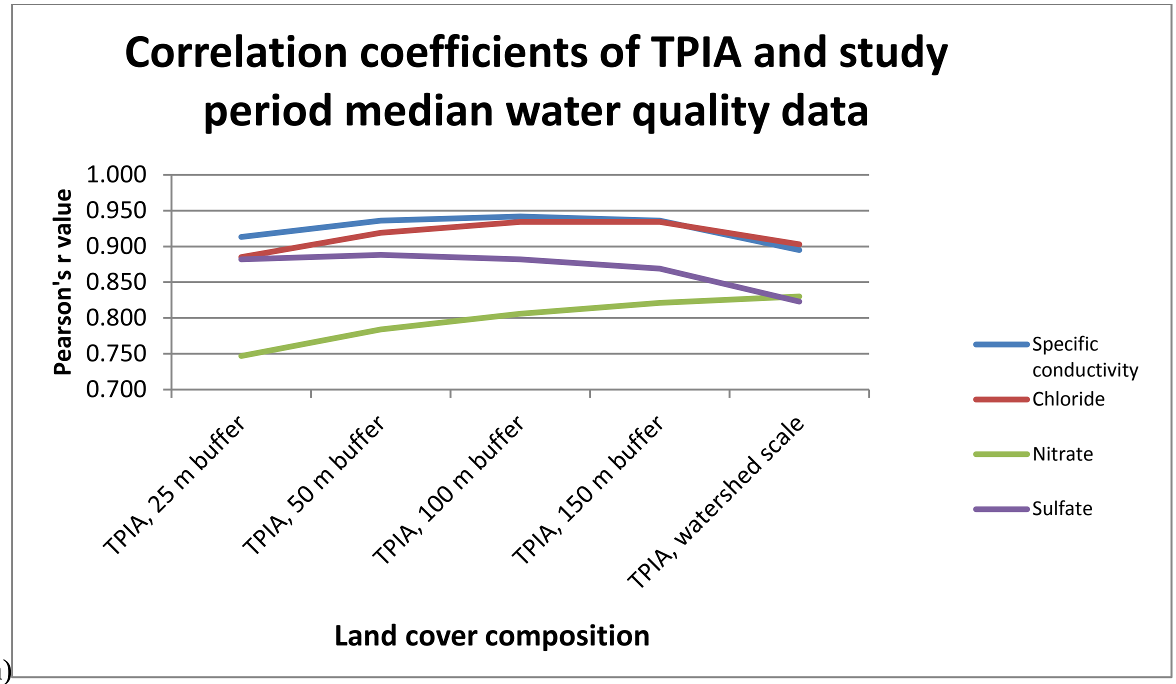
Figure 44. R squared values from linear regression testing of median monthly specific conductivity values and TPFA at watershed and riparian buffer distances.

4.4 Discussion

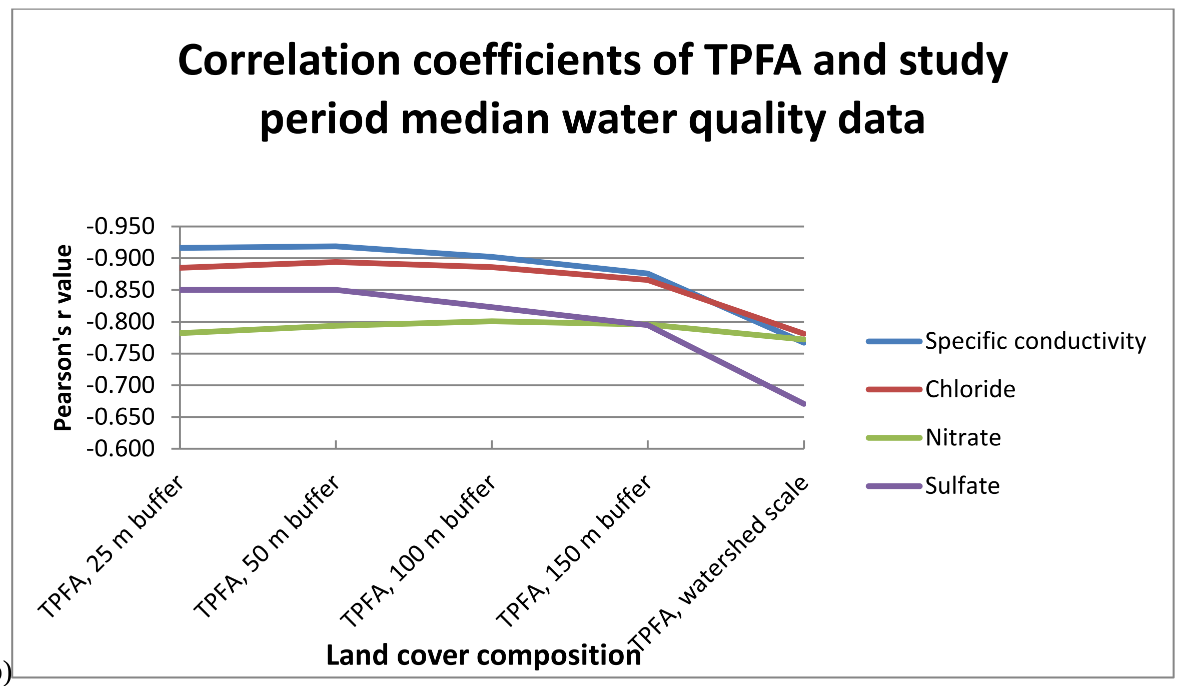
The results of this research affirm the central hypothesis: *There is a statistically significant relationship between land cover and water quality in the headwater stream systems of the Upper South Fork watershed of the New River, with impervious surfaces exerting a negative influence and forest land covers exerting a positive influence on water quality.* The results of the descriptive statistics, correlation analyses, and linear regression analyses generated during the environmental modeling phase of this research demonstrated that this relationship is a strong one, with particularly robust results observable in the *r* values and *p* values obtained from correlation analyses with both the study period median and monthly median water quality datasets, and the *R squared* values obtained from the linear regression analyses of both datasets. Correlation coefficients and regression results are depicted graphically in Figures 45 and 46.

Examination of the study period median water quality variables along with the composition of impervious surfaces and forest land covers at the different spatial scales revealed that, in general, watersheds with higher levels of impervious surfaces possessed higher levels of water quality contaminants. This trend is observable across the riparian buffer distances, and a similar ranking of the watershed and sub-watersheds based on impervious levels at the various buffer distances can be seen as well.

Results of statistical analyses from both the study period median and monthly median modeling procedures indicated that there are quantifiable and statistically significant relationships between impervious surfaces and water quality as well as forest land covers and water quality. Overall results from correlation analysis indicated that impervious surfaces exert a significant effect on water quality, with the different spatial scales (buffer distances and individual watershed scale) showing varying degrees of influence and explanatory value. The total percentage of impervious area at the 100 meter riparian buffer scale generally exhibited the strongest correlations with water quality variables and the greatest explanatory value and statistical significance. Total percentage forested area also demonstrated varying levels of correlation with water quality indicators at the different spatial scales, with very strong overall results for all spatial and temporal scales. The amount of forest present in the 50 meter riparian buffer corridor demonstrated the strongest correlations, explanatory value, and *p*-value significance levels in general.



(a)



(b)

Figure 45. Correlation coefficients for study period median water quality data and land cover composition. (a) TPIA (b) TPFA

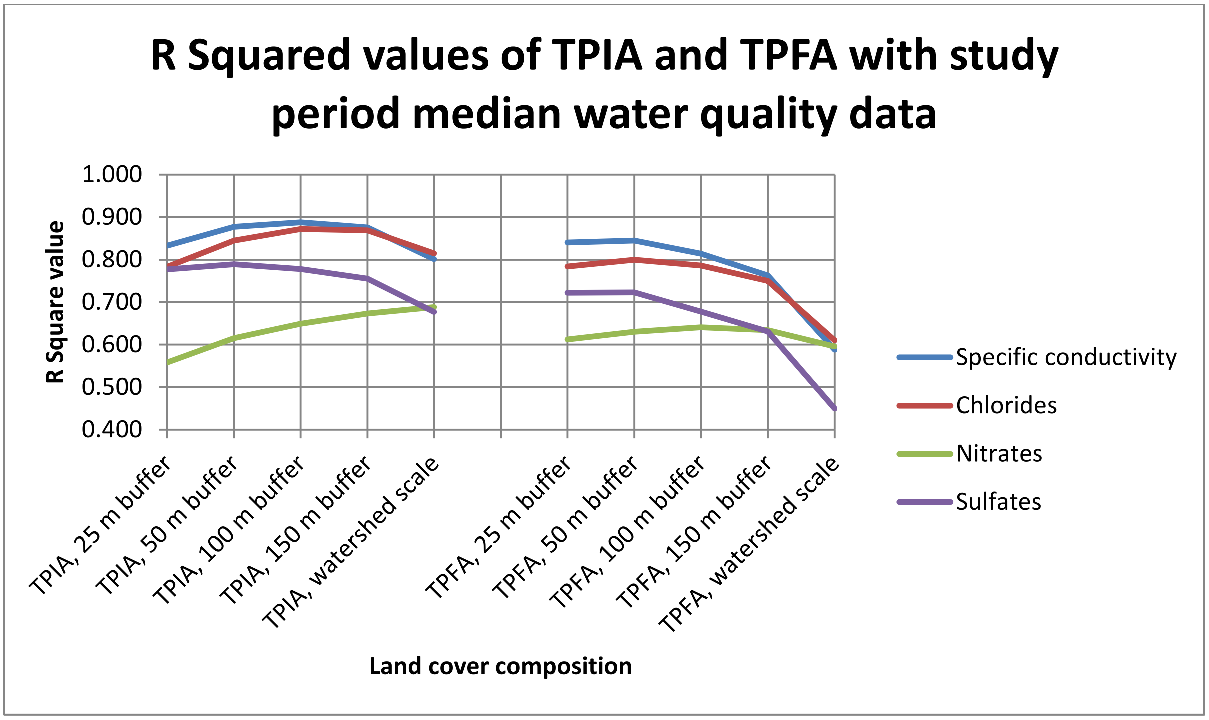


Figure 46. R squared values from regression analysis of study period median water quality data and land cover composition.

Examination of the correlation and regression results for the study period median water quality results indicates that TPIA at the 100 meter buffer scale exerts the strongest effect on water quality, with TPIA at the 50 m and 150 m buffers demonstrating nearly identical results. The *r* value for TPIA at the 100 m buffer and specific conductivity is 0.971 with a *p* value of 0.000. Chloride, nitrate, and sulfate have correlation coefficients of 0.984, 0.973, and 0.987 respectively, with a *p* value of 0.000 for each of the three water quality variables. The same trend is evident in the correlation and regression results for the monthly median water quality data for specific conductivity. The 100 m buffer again demonstrates the greatest correlations with specific conductivity levels for all months, ranging from an r value of 0.973 in September to an *r* value of 0.999 in June and August. All *p* values for monthly specific conductivity and TPIA at the 100 m buffer are 0.000. TPIA at the 50 m and 150 m buffers also show the next highest correlation and regression results with the monthly median specific conductivity data.

TPFA did not demonstrate the same degree of extremely high correlation and regression results at all spatial scales that TPIA demonstrated. Greater variation in correlations and explanatory value of TPFA values for water quality was observable at the various spatial scales. However, strong correlation and regression results indicated that TPFA does exert significant influence on water quality at several spatial scales, with TPFA at the 50 m buffer zone demonstrating the greatest impact on water quality, and TPFA at the 25 m buffer and 100 m buffer zones also demonstrating significant impacts on water quality. These trends were observable in both the study period median water quality data and the monthly median data. TPFA at the 50 m buffer and specific conductivity from the study period median data had an *r* value of -0.928, a *p* value of 0.003, and an *R squared* value of 0.861. Chlorides had an *r* value of -0.951, a *p* value of 0.001, and an *R squared* value of 0.905. Similarly strong results were observable in correlations and regression using the monthly median specific conductivity data and TPFA at the 50 m buffer. July had an *r* value of -0.998, a *p* value of 0.000, and an *R squared* value of 0.996, and the weakest results were seen in October, with an *r* value of -0.926, a *p* value of 0.003, and an *R squared* value of 0.858.

Although the results of these analyses demonstrate an especially strong relationship between water quality variables and land cover composition at 50 meter, 100 meter, and 150 meter riparian buffer distances, the relationship between TPIA and water quality at the watershed scale is also a very strong one. Correlation and regression results of water quality data and TPIA at the watershed scale have high values from both the study period median data analyses and the monthly median data analyses. These results indicate that at the watershed scale, the higher the amount of TPIA in the watershed the more likely it is that water quality contaminant indicators will exhibit a similar increase. In contrast, preservation of the highest possible TPFA, particularly at the 25, 50, and 100 meter riparian buffer zones, can play a significant role in ameliorating the negative effects of contaminated runoff from impervious surfaces.

Thresholds of impervious surfaces

An impervious surfaces threshold pattern similar to the ones discussed by Beach (2002), Schuler (1994), Arnold and Gibbons (1996), and others becomes discernable upon examination of the specific conductivity and land cover at scale results presented in Table 16. These researchers had suggested that beyond a threshold of 10% TPIA within a watershed, water quality becomes impacted by the non-point source pollution generated by the impervious surfaces. They further theorized that water quality becomes much more impacted beyond a threshold of 20% TPIA within a watershed, with severe degradation occurring to water quality and stream system health beyond a TPIA of 30% within a watershed. This threshold pattern can be observed in the results of this thesis research with both the study period median water quality data and with the monthly median water quality data. This data is also presented graphically in Figures 47 and 48 which clearly display the rapid rise in contaminant levels for all water quality variables beyond a TPIA level of approximately 10% at the watershed and 100 meter riparian buffer scales. With data for all variables sorted in ascending value based on monthly average specific conductivity values, several observations can be made:

- Watersheds with TPIA values of less than 10% (Goshen Creek, Flannery Fork, Winkler Creek, and East Fork) possess low conductivity values, indicating excellent stream health.
- Watersheds with TPIA greater than 10% (Boone Fork, Middle Fork and Upper South Fork) exhibited much greater specific conductivity values than the more pristine stream systems.
- Boone Creek, with a TPIA varying between 23.5% and 34.4% when measured at the watershed scale and 25 m riparian buffer respectively, exhibited the greatest specific conductivity levels.

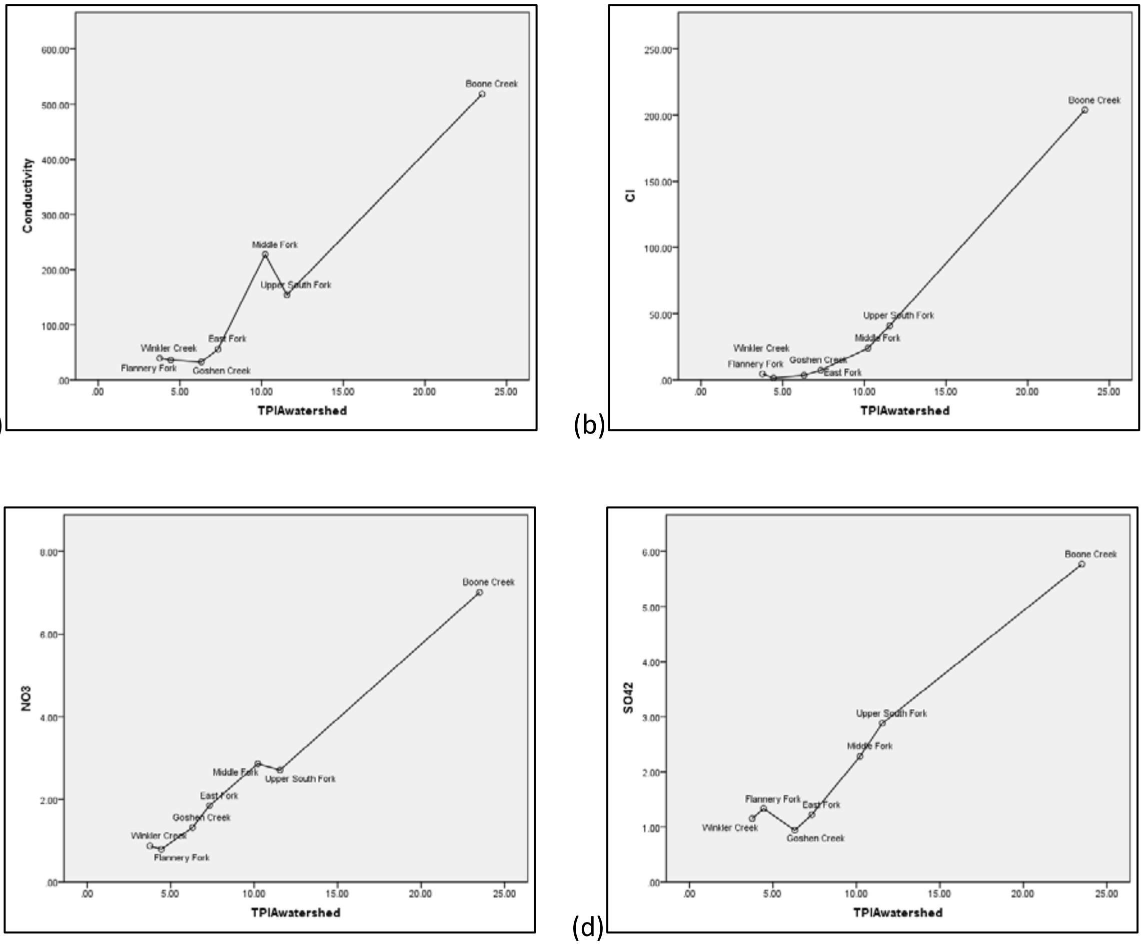


Figure 47. Scatterplots of water quality data and land cover composition. (a) Specific conductivity and TPIA at the watershed scale (b) chloride and TPIA at the watershed scale (c) nitrate and TPIA at the watershed scale (d) sulfate and TPIA at the watershed scale.

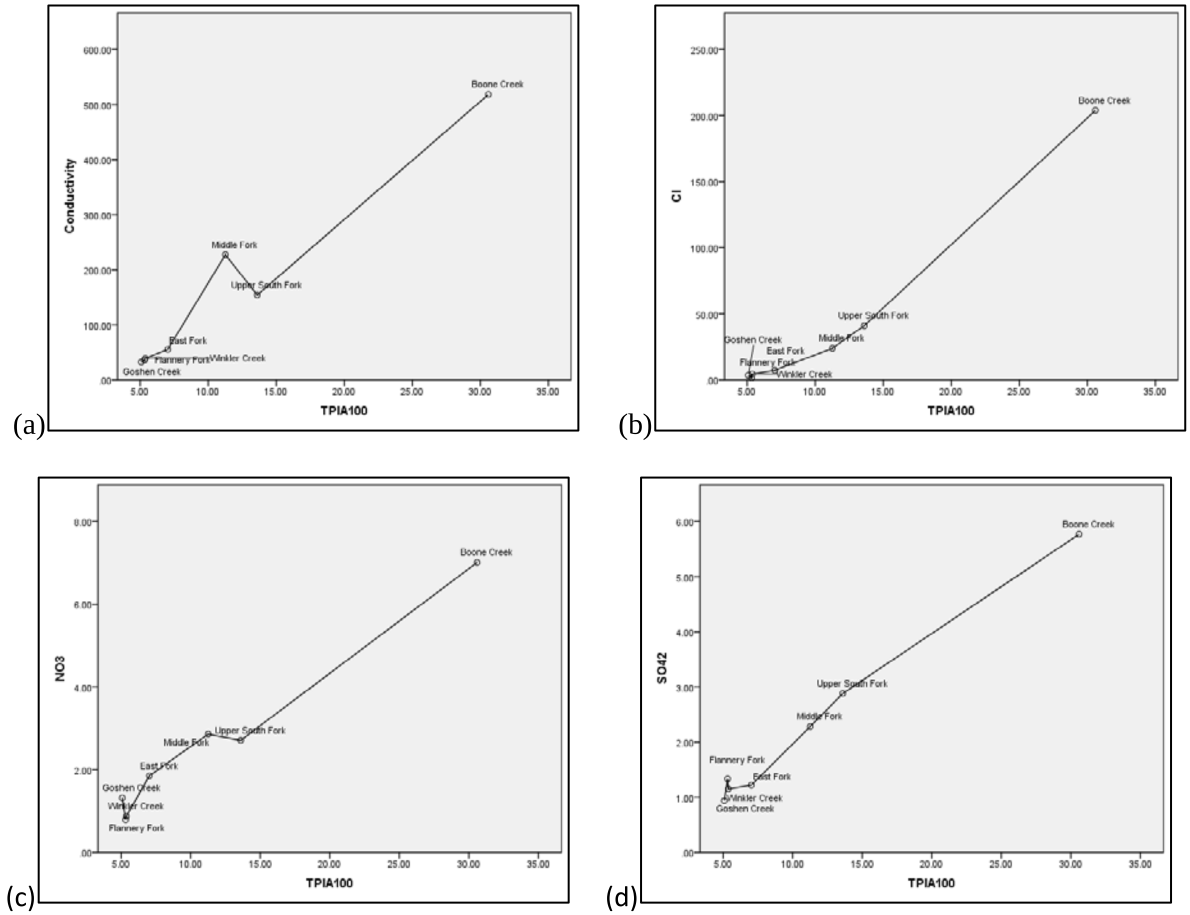


Figure 48. Scatterplots of water quality data and land cover composition. (a) specific conductivity and TPIA at the 100 m riparian buffer distance (b) chloride and TPIA at the 100 m riparian buffer distance (c) nitrate and TPIA at the 100 m riparian buffer distance (d) sulfate and TPIA at the 100 m riparian buffer distance.

In a similar fashion, the range of specific conductivity values appears to rise significantly with increased TPIA, indicating the possible inability of the potentially impaired stream systems to maintain a consistent specific conductivity value due to events such as rapid influx of contaminated runoff from impervious surfaces during precipitation events and snowmelt events. It can also be observed from Table 16 that TPFA at the 25 m and 50 m buffer scales occur in descending order when the data is sorted in ascending order by specific conductivity, exhibiting an inversely proportional relationship. This further supports the strong negative relationship indicated by correlation and regression analyses between TPFA and water pollution indicator values.

The same pattern emerges from the data presented in Tables 17 through 19. Each of the tables represents a single water quality parameter taken from grab samples, sorted in ascending order according to the median value of that parameter. Watersheds with less than 10% TPIA at the watershed scale and all buffer distances (Goshen Creek, Flannery Fork, Winkler Creek, and East Fork) possessed the lowest levels of these potential contaminants; those with TPIA between 10% and 20% (Middle Fork and Upper South Fork) at the watershed scale and all buffer distances exhibited the central set of values of the chemicals; and Boone Creek, with a TPIA greater than 20% at the watershed scale and all buffer distances, possessing chloride, nitrate, and sulfate levels nearly an order of magnitude greater than the more heavily forested watersheds. The following pattern of increased levels of water quality contaminants can be observed:

- Lowest contaminant levels: Flannery Fork, Goshen Creek, Winkler Creek, and East Fork
  TPIA<10%
- Median contaminant levels: Middle Fork and Upper South Fork
  TPIA>10% and TPIA<20%
- Highest contaminant levels: Boone Creek
  TPIA>20%

Table 16. Specific conductivity median value of monthly medians sorted in ascending order along with land cover compositions at scale.

Station	Parameter	Mean	Median	Range	TPIA-watershed	TPIA - 25m buffer	TPIA-50m	TPIA - 100m	TPIA - 150m	TPFA-watershed	TPFA - 25m buffer	TPFA-50m	TPFA - 100m	TPFA - 150m
Goshen Creek	Conductivity (µhos/cm)	29.37	32.11	19.01	6.31%	6.31%	5.91%	5.08%	5.04%	75.04%	81.86%	81.34%	80.83%	80.28%
Flannery Fork	Conductivity (µhos/cm)	30.56	34.26	20.70	4.44%	7.23%	6.55%	5.32%	4.71%	81.92%	79.24%	78.72%	80.52%	81.26%
Winkler Creek	Conductivity (µhos/cm)	36.37	38.58	17.10	3.76%	6.38%	6.41%	5.37%	4.48%	86.57%	79.02%	79.63%	82.51%	85.09%
East Fork	Conductivity (µhos/cm)	50.83	56.07	30.74	7.33%	6.20%	7.08%	7.03%	7.12%	66.96%	72.83%	69.97%	68.76%	68.58%
Middle Fork	Conductivity (µhos/cm)	142.66	102.78	175.80	10.22%	11.52%	12.54%	11.26%	10.47%	71.30%	67.98%	66.90%	69.61%	71.26%
Upper South Fork	Conductivity (µhos/cm)	144.19	142.04	113.83	11.55%	13.76%	14.65%	13.60%	12.73%	69.34%	65.73%	64.32%	66.14%	67.80%
Boone Creek	Conductivity (µhos/cm)	476.92	525.22	443.20	23.50%	34.39%	34.22%	30.59%	27.53%	60.17%	45.68%	46.17%	50.67%	54.59%

Table 17: Chloride and land cover composition at scale by watershed.

Station	Parameter	Mean	Median	Range	TPIA-watershed	TPIA - 25m buffer	TPIA-50m	TPIA - 100m	TPIA - 150m	TPFA-watershed	TPFA - 25m buffer	TPFA-50m	TPFA - 100m	TPFA - 150m
Flannery Fork	Cl-(mg/L)	1.94	1.37	3.46	4.44%	7.23%	6.55%	5.32%	4.71%	81.92%	79.24%	78.72%	80.52%	81.26%
Goshen Creek	Cl-(mg/L)	3.03	3.47	2.71	6.31%	6.31%	5.91%	5.08%	5.04%	75.04%	81.86%	81.34%	80.83%	80.28%
Winkler Creek	Cl-(mg/L)	4.34	4.50	6.63	3.76%	6.38%	6.41%	5.37%	4.48%	86.57%	79.02%	79.63%	82.51%	85.09%
East Fork	Cl-(mg/L)	7.12	7.21	5.32	7.33%	6.20%	7.08%	7.03%	7.12%	66.96%	72.83%	69.97%	68.76%	68.58%
Middle Fork	Cl-(mg/L)	26.31	23.93	24.99	10.22%	11.52%	12.54%	11.26%	10.47%	71.30%	67.98%	66.90%	69.61%	71.26%
State Farm	Cl-(mg/L)	70.49	41.02	167.18	11.55%	13.76%	14.65%	13.60%	12.73%	69.34%	65.73%	64.32%	66.14%	67.80%
Boone Creek	Cl-(mg/L)	219.18	203.88	224.94	23.50%	34.39%	34.22%	30.59%	27.53%	60.17%	45.68%	46.17%	50.67%	54.59%

Table 18. Nitrate and land cover composition at scale by watershed.

Station	Parameter	Mean	Median	Range	TPIA-watershed	TPIA - 25m buffer	TPIA-50m	TPIA - 100m	TPIA - 150m	TPFA-watershed	TPFA - 25m buffer	TPFA-50m	TPFA - 100m	TPFA - 150m
Flannery Fork	NO3-(mg/L)	0.78	0.79	1.27	4.44%	7.23%	6.55%	5.32%	4.71%	81.92%	79.24%	78.72%	80.52%	81.26%
Winkler Creek	NO3-(mg/L)	0.91	0.87	1.42	3.76%	6.38%	6.41%	5.37%	4.48%	86.57%	79.02%	79.63%	82.51%	85.09%
Goshen Creek	NO3-(mg/L)	1.18	1.32	1.84	6.31%	6.31%	5.91%	5.08%	5.04%	75.04%	81.86%	81.34%	80.83%	80.28%
East Fork	NO3-(mg/L)	1.97	1.85	2.37	7.33%	6.20%	7.08%	7.03%	7.12%	66.96%	72.83%	69.97%	68.76%	68.58%
Upper South Fo	NO3-(mg/L)	2.70	2.71	3.58	11.55%	13.76%	14.65%	13.60%	12.73%	69.34%	65.73%	64.32%	66.14%	67.80%
Middle Fork	NO3-(mg/L)	3.20	2.86	4.55	10.22%	11.52%	12.54%	11.26%	10.47%	71.30%	67.98%	66.90%	69.61%	71.26%
Boone Creek	NO3-(mg/L)	7.00	7.01	3.17	23.50%	34.39%	34.22%	30.59%	27.53%	60.17%	45.68%	46.17%	50.67%	54.59%

Table 19. Sulfate and land cover composition at scale by watershed.

Station	Parameter	Mean	Median	Range	TPIA-watershed	TPIA - 25m buffer	TPIA-50m	TPIA - 100m	TPIA - 150m	TPFA-watershed	TPFA - 25m buffer	TPFA-50m	TPFA - 100m	TPFA - 150m
Goshen Creek	SO42- (mg/L	0.94	0.94	0.82	6.31%	6.31%	5.91%	5.08%	5.04%	75.04%	81.86%	81.34%	80.83%	80.28%
Winkler Creek	SO42- (mg/L	1.11	1.15	1.36	3.76%	6.38%	6.41%	5.37%	4.48%	86.57%	79.02%	79.63%	82.51%	85.09%
East Fork	SO42- (mg/L	1.20	1.22	0.92	7.33%	6.20%	7.08%	7.03%	7.12%	66.96%	72.83%	69.97%	68.76%	68.58%
Flannery Fork	SO42- (mg/L	1.32	1.33	0.59	4.44%	7.23%	6.55%	5.32%	4.71%	81.92%	79.24%	78.72%	80.52%	81.26%
Middle Fork	SO42- (mg/L	2.40	2.28	1.18	10.22%	11.52%	12.54%	11.26%	10.47%	71.30%	67.98%	66.90%	69.61%	71.26%
Upper South Fo	SO42- (mg/L	2.90	2.88	2.57	11.55%	13.76%	14.65%	13.60%	12.73%	69.34%	65.73%	64.32%	66.14%	67.80%
Boone Creek	SO42- (mg/L	5.63	5.77	2.01	23.50%	34.39%	34.22%	30.59%	27.53%	60.17%	45.68%	46.17%	50.67%	54.59%

Forests and water quality

Forest land cover does not seem to follow quite as distinct or linear a pattern with regards to the predictive power of TPFA values at the different spatial scales for water quality variable values as do impervious surfaces. Examination of the correlation and regression results for both the study period median and monthly median water quality datasets revealed significant results at the 25 m, 50 m, and 100 m riparian buffers. Both study period median and monthly median water quality datasets demonstrated weak correlations between water quality and TPFA at the watershed scale, with similarly weak explanatory values from regression analysis. For TPFA at the 150 m riparian buffer, however, contrasting results were obtained. Correlation and regression analyses of the study period median water quality data revealed weak correlation and regression results at this scale, whereas much stronger results were obtained from the monthly median water quality data.

Further examination of the correlation coefficient and linear regression results in Tables 13 and 16 reinforce the important role forested riparian buffer zones appear to play in mitigating the levels of water quality contaminants. Possible explanations for this include nutrient uptake by the forest vegetation root systems as well as the filtering effects of these forested riparian buffer strips on run-off from impervious surfaces and other human altered land covers. Interestingly, comparison of water quality data from the East Fork watershed in comparison with data from the other three "Least contaminated" watersheds indicates that in the cases of specific conductivity, chloride, and nitrate, East Fork, which has only 67% TPFA at the watershed scale, possesses significantly higher levels of these water quality variables than the other three watersheds. The Flannery Fork, Winkler Creek, and Goshen Creek watersheds each contain between 75% and 87% forest land cover dependent on spatial scale, and contain significantly lower levels of water quality contaminant levels than the other four watersheds in the study. This may indicate that forests do play a very important role in the removal of non-point source contaminants from runoff.

Monthly and seasonal variations in water quality

Monthly water quality data values organized by watershed demonstrated seasonal and monthly variations over the eight month study period, with greater magnitudes of variation observable in watersheds with the highest TPIA levels. Specific conductivity, shown in Figure 49, exhibited a slight rise during the summer months for watersheds with higher TPIA, then a rapid decline in the Fall, followed by a rise during the winter months. The watersheds with the lowest TPIA and highest TPFA show little variation over the study period, with specific conductivity levels actually declining during the winter months of December and January. Chloride, nitrate, and sulfate levels generally exhibited their lowest levels during the Fall, with higher levels observed in the Summer and Winter months. Figures 50, 51, and 52 present graphs for chloride, nitrate, and sulfate.

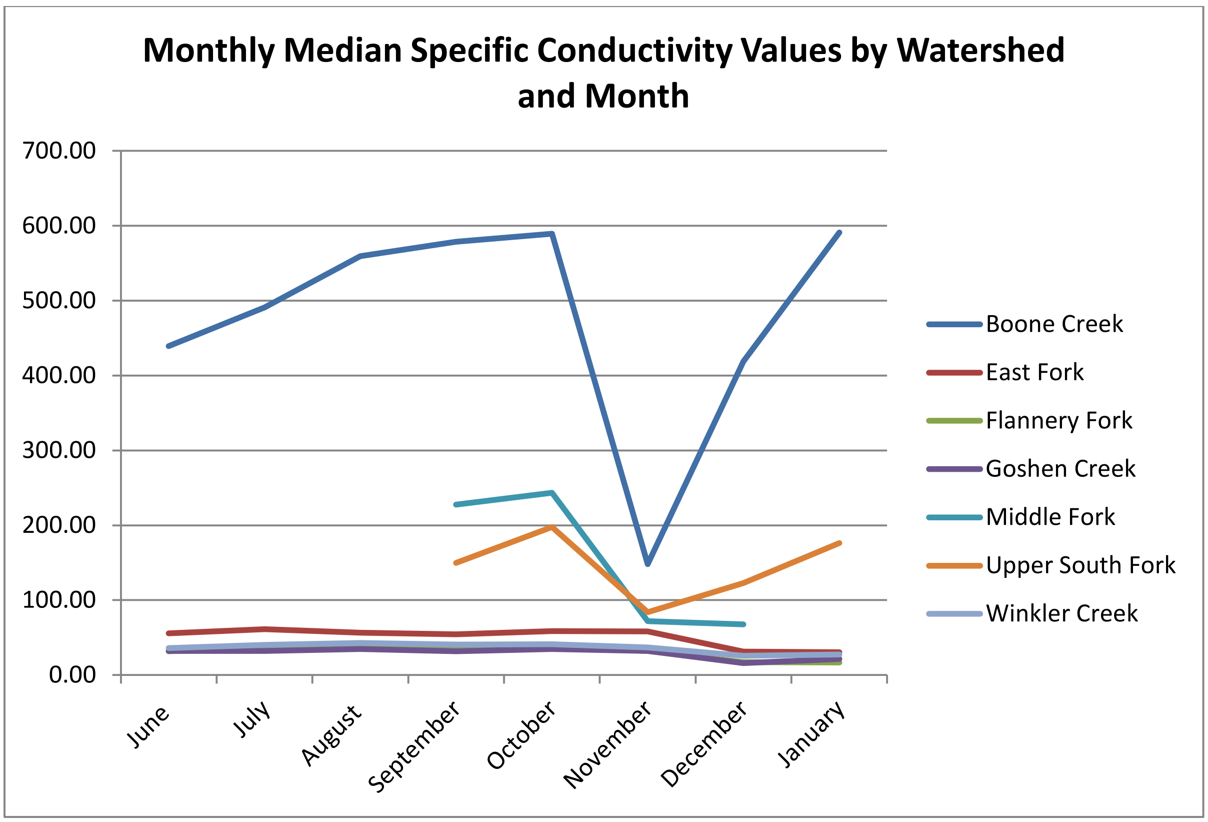


Figure 49. Monthly median specific conductivity values by watershed.

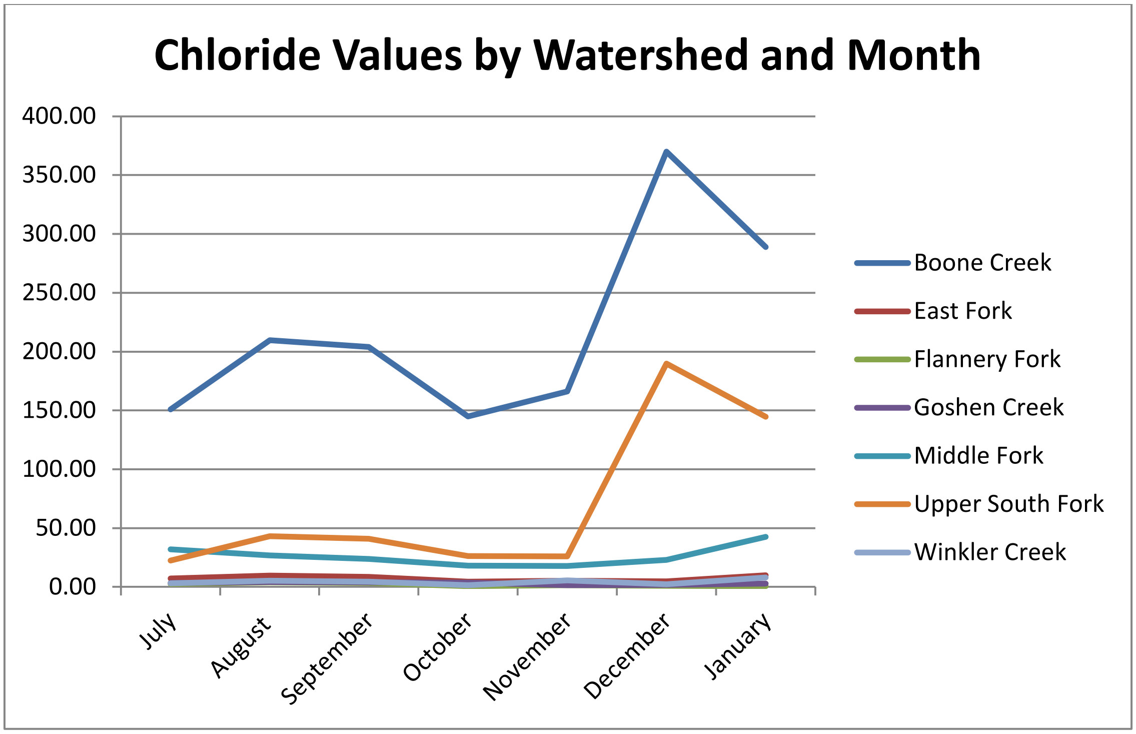


Figure 50. Monthly chloride values by watershed.

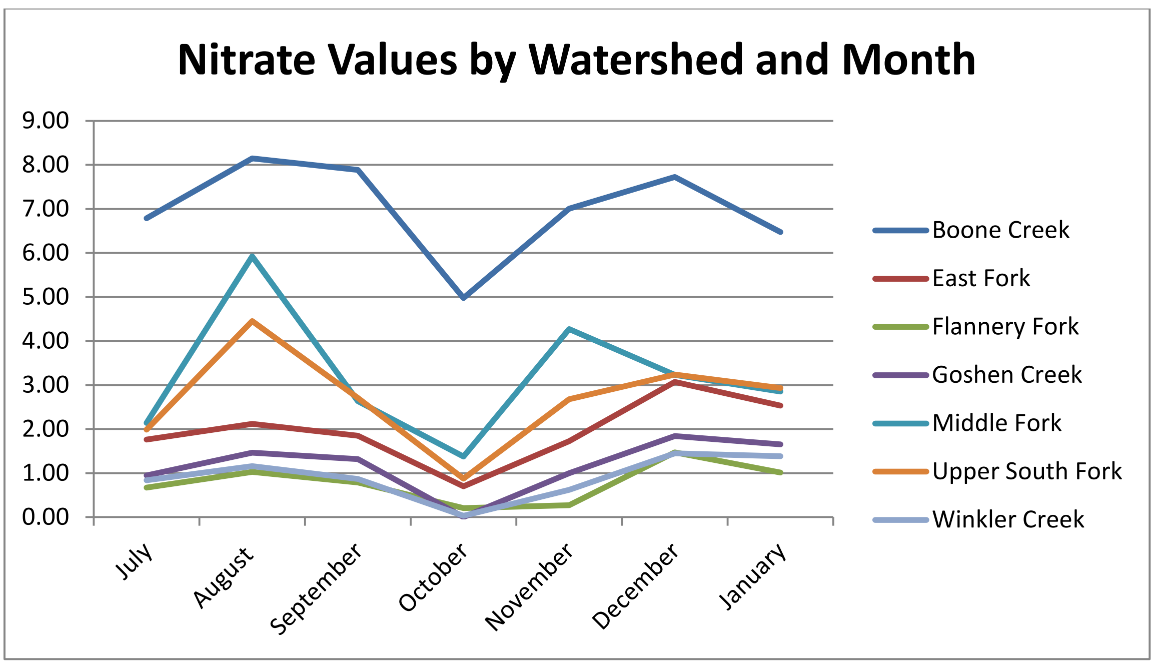


Figure 51. Monthly nitrate values by watershed.

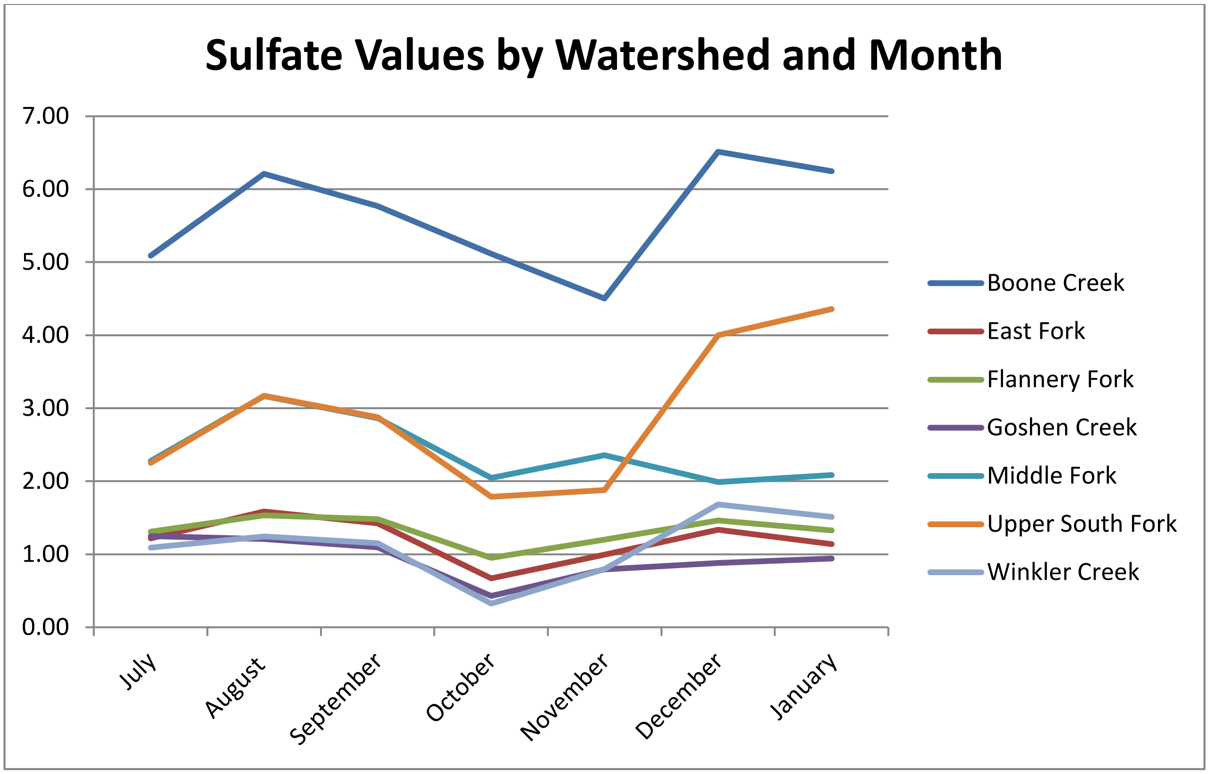


Figure 52. Monthly sulfate values by watershed.

Winter precipitation events in the form of snowfall, freezing rain, and ice build-up produced some interesting trends. The Boone Creek sub-watershed and Upper South Fork watershed exhibited marked increases in specific conductivity and chloride levels during the months of December 2010 and January 2011, which can most likely be attributed to road-salting operations surrounding winter precipitation events. Specific conductivity data from the Middle Fork instrument was unavailable for the month of January due to equipment malfunctions during a lengthy period of winter storm activity, but chloride levels were obtained via grab sample. The chloride levels for the Middle Fork obtained from the grab sample indicated a markedly higher level of chloride in comparison with other months. This was similar to the levels of chloride observed at Boone Creek and Upper South Fork. These three watersheds possess the highest impervious surface coverage of the seven, with TPIA levels above 10% at all scales for Middle Fork and Upper South Fork, and TPIA levels greater than 20%

and above 30% at certain buffer distances for Boone Creek. Interestingly, the four other watersheds, all with TPIA values below 10%, exhibited decreased specific conductivity levels in the winter months of December and January in comparison with earlier summer and fall values. Chloride levels increased during the winter months for East Fork and Winkler Creek, while decreasing for Flannery Fork and Goshen Creek. The major stream branches at East Fork and Winkler Creek have roads (Bamboo Road and Winkler Creek Road respectively) which closely follow their courses and are built in very close proximity to the streams themselves. Runoff from road salting activities on these roads is able to easily enter these streams due to this proximity. Flannery Fork Creek and Goshen Creek each have much lower levels of impervious surfaces within their riparian buffer zones than the other stream systems, and as a result have less road salting activities occurring within them.

Future research

Although the water quality data used for this thesis research project consisted of specific conductivity data collected by monitoring equipment at 15 minute intervals at baseflow conditions (with data during stormflow events removed) and grab samples collected monthly at baseflow conditions for chloride, nitrate, and sulfate, some response to precipitation events was observable within the specific conductivity datasets Without accessing outside data sources regarding precipitation events or generating discharge volumes and rating curves for flow and volumetric calculations, the occurrence of precipitation events and consequent stream level rise could be detected via the depth readings provided by the sondes. These depth readings record the depth from the water surface to the water quality instrument with a precision of one one-thousandth of a foot. Sudden depth changes to the order of one tenth of a foot which occur within a range of approximately two to eight of the 15 minute increment readings (30 minutes to 2 hours) can reliably be determined to represent precipitation events based on the author’s experience with the sondes and datasets.

Numerous examinations of the raw data surrounding precipitation events has revealed several interesting trends. After a lengthy dry period following deployment of the instrument at Goshen Creek In June 2010, specific conductivity readings were observed to "spike," suddenly increasing dramatically in value, immediately following the initial rainfall event following the initial dry period. The specific conductivity levels returned to their average baseflow conditions following this initial rainfall event, and subsequent precipitation events in the days or weeks immediately following produced very little change in specific conductivity. A likely explanation for this spike in specific conductivity would be that contaminated runoff from local roadways and other impervious surfaces would build up during the dry period, then wash into local streams during this initial precipitation event. The newly cleaned impervious surfaces consequently produced less contaminated runoff in the ensuing precipitation events. Winkler Creek and Flannery Fork exhibited decreases in specific conductivity immediately following similar initial precipitation episodes, with specific conductivity decreasing in value from baseline levels during subsequent rainfalls. Winkler and Flannery have the lowest levels of TPIA at the watershed scale, with 3.76% and 4.44% TPIA respectively. Boone Creek, which has by far the highest TPIA of all the sub-watersheds at all spatial scales, exhibited a strong, rapid decrease in conductivity for nearly all rainfall events. This is likely due to the dilution effect of cleaner rain water entering this highly urbanized stream, which typically has a very high conductivity level in contrast to the other streams. Contrastingly, some precipitation events following lengthy dry periods did exhibit specific conductivity spikes for Boone Creek, most likely attributable to the generation of contaminated runoff from impervious surfaces such as parking areas and roadways following long periods of contaminant build-up during the dry periods.

Analysis of water response to climatic, hydrologic, and precipitation events represents an exciting avenue of research that could be conducted with data from this water quality monitoring database in future research activities. For instance, specific conductivity was observed to possess outlier "spikes" in values, which often coincided with precipitation events as well as road-salting events (Figure 53). Long term changes in water quality variables or land cover composition over future years and decades also represents a very intriguing research domain for future work with this data. In this thesis research, the development of geospatial and water quality databases, along with analysis and hypothesis testing of the relationship between land cover and water quality served as the research focus. Future studies hold the potential to provide tremendous insight into headwater stream systems, the impacts of their environment on water quality, and temporal analyses into both short and long term responses to precipitation, hydrologic, and other events.

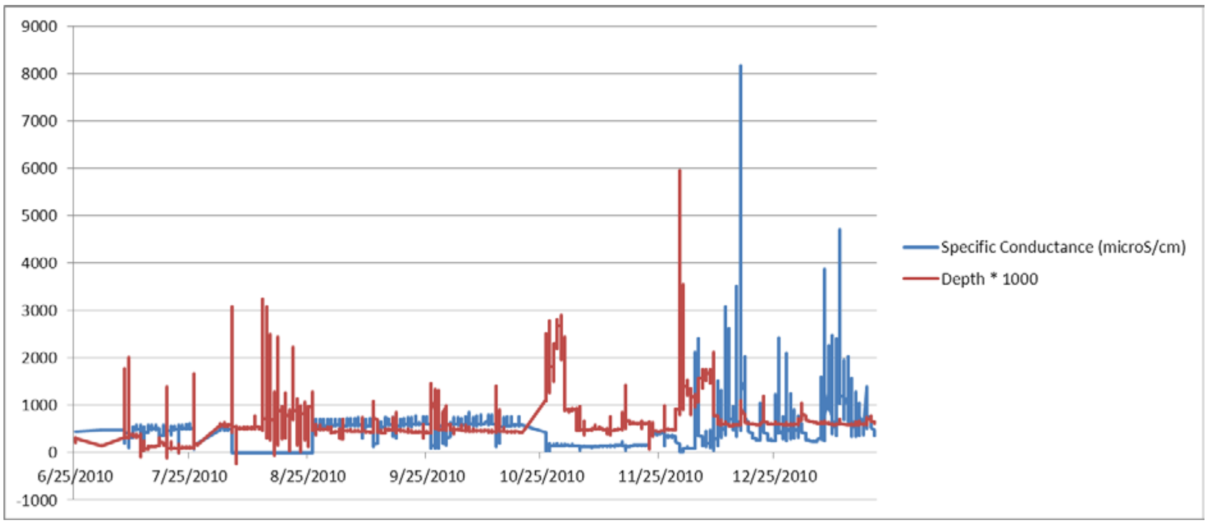


Figure 53. Specific conductivity response to precipitation events in Boone Creek.

CHAPTER FIVE

Conclusion

This thesis research successfully established the existence of a statistically significant relationship between land cover and water quality in the headwater stream systems of the Upper South Fork watershed of the New River, with impervious surfaces exerting a negative influence and forest land covers exerting a positive influence on water quality. An examination of the correlation and regression results reveals that the strength of this relationship varies based on the land cover composition at different riparian buffer distances as well as at the individual watershed and sub-watershed scale, which demonstrates that the effects exerted upon water quality by impervious surfaces and forests varies spatially. Overall, the results of the descriptive statistics, correlation analyses, and linear regression analyses demonstrate that the relationships are very strong, with particularly robust results observable in the correlation coefficients and significance levels obtained from correlation with both the study period median and monthly median water quality datasets, and the *R squared* values obtained from the linear regression analyses of both water quality datasets.

The correlation and regression results indicate that TPIA at the 100 meter buffer distance exerts the strongest effect on water quality, with TPIA at the 50 m and 150 m buffers demonstrating very similar results. Greater variation in correlations and explanatory value of TPFA composition for water quality was observable at the various spatial scales. TPFA at the 50 m buffer distance demonstrated the greatest impact on water quality, with TPFA at the 25 m and 100 m buffer distances also demonstrating significant correlation and regression results.

Additionally, the primary goals of this research as presented in Chapter One have been accomplished:

1. Highly accurate digital terrain models, including a terrain dataset and DEMs of various resolutions, have been generated.

2. Hydrographic modeling and analyses resulted in the creation of an optimal drainage network pattern and delineation of the study area's watersheds, along with development of a repeatable hydrographic modeling methodology.

3. High resolution land cover datasets of impervious surface and forest coverage have been created, along with development of a repeatable land cover extraction methodology.

4. A long-term ambient water quality monitoring program has been established for the Upper South Fork watershed and its sub-watersheds.

5. Environmental modeling of the relationship between land cover and water quality affirmed the primary hypothesis and provided valuable new data regarding the nature of this relationship with regards to the varying effects of spatial scale.

The Upper South Fork watershed of the New River is an excellent example of the potential for damage to water quality as a consequence of unrestricted growth and urban development. The Boone Creek sub-watershed, with a total impervious area of 23.5% at the watershed scale and nearly 35% at the 25 meter riparian buffer scale, provides substantial evidence of the negative effects of urban growth on water quality in headwater streams. The median conductivity in Boone Creek over the study period was 525 µhos/cm, far outside the normal range of natural North Carolina streams of 17- 65 µhos/cm described by the North Carolina Division of Water Quality (2009). The extreme hydrologic response to precipitation events, or "flashiness," exhibited by Boone Creek is further evidence of the negative effects of such a high degree of urban development to the stream system.

Land cover composition within the 50 meter and 100 meter buffer zones appears to be of particular importance for all water quality variables. Consideration of land cover composition at the 50 meter and 100 meter riparian buffer zones would seem to be warranted for any types of development, infrastructure, planning, commercial, or other projects that could impact this composition in order to ensure that water quality is not compromised by depletion of forests within riparian buffer zones and the introduction of impervious surfaces. It would be in the best public interests for environmental protection regulation, zoning and planning measures, and other public-policy administration organizations to use this information to help inform future public-policy decisions. The results of this research demonstrate that the effects of impervious surfaces and forests on stream water quality are clearly identifiable and significant. Limiting the amount of impervious surfaces that occur within 100 meters of streams and establishing a 50 meter forested stream buffer zone would serve to protect stream water quality from the effects of non-point source pollution. Prohibiting impervious surfaces from being introduced within a 100 meter buffer zone surrounding the stream, and encouraging the protection or restoration of forest within these zones would help to protect these valuable headwater streams. Conservation, preservation, and restoration measures are all excellent candidates for headwater stream protection legislation, initiatives, and public policy decisions regarding the conservation of suitable land covers for water quality preservation and natural resource protection.

The importance of continued emphasis on water quality analysis and watershed monitoring programs in North Carolina is of paramount significance, particularly in light of increasing population growth, land cover conversion, and changing climatic conditions in the 21st century. A very positive indicator for future water quality preservation can be seen in the reduction of impaired stream listings in North Carolina from the federal 303d list from 14% in 1998 to 9% in 2006 (NCDENR 2007). It is imperative that future public policy decisions regarding these issues of water quality assessment and watershed monitoring be guided by smart planning and ecologically responsible public policy decisions, as well as the support of a well-informed public.

Preservation of water resources is one of the primary issues facing societies in the twenty-first century. As populations increase and urban development continues to expand, existing water resources face ever greater threats to their quality and quantity. This is an issue that is encountered on scales from the local to the global. Areas such the Upper South Fork watershed, which may appear at first glance to have a nearly pristine mountain environment and untouched natural resources, may become increasingly compromised in the quality of their water resources and preservation of the natural land covers in the surrounding landscapes.

With regards to emergent technologies and future research, most likely we will continue to see an increase in the integration of remote sensing technologies and geographic information systems (including temporally capable applications) with water quality assessment and watershed monitoring programs. Geospatial databases, linked to water quality databases, hold the potential for increasingly important roles in environmental assessments and decision support systems regarding natural resource and water quality issues. As the public becomes more aware of water resource issues, there will hopefully be a corresponding interest seen in the actions of policy makers and regulatory agencies. Increasing awareness of the realities of climate change also seems to be coupled with a renewed public interest in topics such as sustainability. It is the hope of this author that environmentally and socially beneficial scientific research will continue to be conducted in these areas, and that science can work hand in hand with public agencies and information services in order to help assure us all of a future with plentiful, protected, good quality water resources for current and future generations.

The results of this research have provided robust evidence to support the hypothesis that impervious surfaces exert a strong negative effect on headwater streams' water quality, whether examined at the catchment scale or the riparian buffer scale, and that forest land covers serve to protect and enhance the water quality of local streams. The exploratory results and environmental modeling data produced by this thesis research project represents a great beginning for what will, hopefully, remain a long-term ambient water quality monitoring program for the Upper South Fork New River watershed. This type of water quality monitoring provides invaluable data for researchers, local communities, education outreach programs, planning agencies, governmental organizations, and public-policy decision makers. It is exceedingly unlikely that population growth and urban development will cease in the Upper South Fork New River Watershed, but one can hope that this research project will contribute towards a greater understanding of the measures that need to be taken to ensure that such growth is well-planned and monitored, and that the ecosystems and beautiful natural environment of the Upper South Fork watershed and the entire Appalachian mountain range can be preserved through protection of its headwater stream systems.

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VITA

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Following his time at UGA, Chris spent ten years or so working as a water garden builder, cabinetmaker, carpenter, home builder, and musician in Georgia, Mississippi, New Orleans, Seattle, and St. Croix. After his return to western North Carolina in 2000, Chris earned his general contractor's license and became a project manager and vice president of RCB Development Group and Redmon Coffey Builders. His design and construction specialties included historic renovations, sustainable building practices, and conservation subdivisions.

Chris entered the M.A. program in the Department of Geography and Planning at Appalachian State University in the Fall of 2009 and graduated in August 2011. He has been deeply involved in the research work surrounding this thesis along with his faculty mentor and thesis chairperson, Dr. Jeffrey Colby. Chris' chief research interests include hydrology, hydrography, GISystems, GIScience, information systems integration, natural resources preservation, and energy distribution issues.