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The quality of rivers and streams are affected by the land-use-land-cover (LULC) compositions that are present within their watersheds and riparian buffers. Hence, understanding how these LULC compositions, present within watersheds, influences water quality of these water bodies is very important for river management and restoration. This dissertation research was undertaken with the goal of examining the effects changing LULC on stream system. The research was conducted in the Reedy Fork-Buffalo Creek watershed in Guilford County, North Carolina to provide a study area of streams within a nested watershed assemblage with a variety of sub-watersheds and varying LULC proportions for comparison. Toward this end, LULC spatial fragmentation of the Reedy Fork-Buffalo Creek watershed was quantified for the 2002 through 2013 study period based on remote sensing data. This watershed is located at the headwaters of the Cape Fear River basin, the largest river basin in North Carolina. Analysis of how river flow and several water quality variables were related to landscape attributes at three scales: 100 m, 150 m, and watershed was then performed. The Soil and Water Assessment Tool (SWAT) was used to examine the contribution of LULC to water yield and nitrate loadings in the year 2030 relative to future LULC change scenarios.

Results show that the water quality of the Reedy Fork-Buffalo Creek changed significantly during the recent decades. These changes in space and time indicate a trend of accelerating deterioration in water quality. Also, LULC pattern had major impacts on

the flow and water quality of the Reedy Fork Creek at multiple spatial scales. In particular, impervious LULC, although small in percent cover, exerted a disproportionately large influence both locally and over distance. Results also shows that most water quality variables (Conductivity, hardness, nitrate, TKN, and Turbidity) were correlated with landscape pattern on all three spatial scales although the correlation was stronger at the watershed scale than at the buffer scales. Additionally, results from the scenario analysis shows that compared to the current situation (2010), a 13.5% increase in surface runoff, 9.26% increase in water yield, and 31.85% in increase in nitrate yield was recorded for 2030. These increases were due to the conversion of forest and grass into impervious surfaces.

The research highlighted the probable role of the interactions between LULC spatial distribution and water quality. This scale multiplicity suggests that, while water-monitoring and river restoration need to adopt a multi-scale perspective, particular attention should be paid to the watershed scale. In the context of population growth and increasing urban development continuing into the 21st century, preservation and restoration of vegetative LULC and the elimination of impervious surfaces within the watershed should be a primary concern for the general public, the scientific community, and public policy decision makers.

IMPACT OF LAND-USE LAND-COVER CHANGE ON STREAM WATER QUALITY IN THE REEDY FORK-BUFFALO CREEK WATERSHED, NORTH CAROLINA: A SPATIOTEMPORAL ANALYSIS

by

Frederick Ayivi

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DEDICATION

I dedicate this dissertation to my wife, Nancy, without whom this research and many other wonderful things would never have been possible, and to my children Donald, Brandon and Brianna, who helped me finally grow up. Also to my late mother, *Mrs. Celestina Abla Eva Gidiglo-Ayivi.*

APPROVAL PAGE

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CHAPTER I

INTRODUCTION

A high percentage of drinking water in the world comes from surface water bodies such as rivers, lakes, and streams. For the health and safety of the public, it is important that public water supplies or drinking water sources are kept free of pollution. Surface water quality is controlled by lots of natural and human factors. These factors can either be non-point sources (NPS) such as interflow through organic-rich soils, overland flow from extensive row crop cultivation or point source (PS) such as a Wastewater Treatment Plant (WWTP) outfall (Liu et al., 2002; Brabec, 2009). Calculating PS pollution is relatively simple as direct measurements can be made at the source, but attributing stream water quality to NPS is much more difficult (Baker, 2003). To address these water pollution issues, researchers have taken a landscape approach, dividing watersheds into various classes of LULC patterns for effective water quality monitoring. Numerous studies have identified the relationship between landscape pattern and river water quality. But in most of these studies, researchers use large aggregated LULC data in their work and consequently accept undesirable approximations and errors in their analyses and planning workflow (Beykaei et al., 2013). Previous researchers extract LULC information from widely available LULC data such as Cropland Data Layer (CDL), National Land Cover Database (NLCD) (Zhang, 2011; Sahu and Gu, 2009; Deng et al., 2005). However, these LULC data are aggregated and coarse. But, in LULC and water quality analysis in urban environments, detailed and up-to-date LULC data is necessary to provide the needed level of analyses required for an accurate result (Li et al., 2009).

Although the use of detailed and up-to-date LULC is recommended, it is not a common practice compared to the use of coarse LULC data in water quality research. Researchers that have used coarse aggregated LULC data have suggested that, in finding the relationships between LULC and water quality, the analysis should be done at the watershed scale (Jarvie et al., 2002; Woli et al., 2004). Others have also suggested the analysis be performed at the riparian buffer scales (Li et al., 2009; Sahu and Gu, 2009). The differing approaches themselves suggest that, different scales might display different results. According to Guo et al., (2010) and Zhang, (2011), LULC significantly governed river nitrogen loads and Total Phosphorous in a dynamic riparian width. Therefore, the important issue is that proper spatial scale should be selected when analyzing the relationship between landscape pattern and river water quality. Some recent studies advocated a multi-scale approach (Tang et al., 2005; Su et al., 2013) in which the impacts of landscape pattern were characterized and compared at different spatial scales. However, the temporal dimension was often ignored. Since landscape pattern change is one of the main causes of the serious environmental problem worldwide and poses a great threat to water quality, spatiotemporal information on landscape patterns is of vital importance to finding a solution to this problem. A multiple spatiotemporal scale approach uses the spatiotemporal information to provide insight into the prospective relationship between landscape pattern and river water quality.

Another discrepancy among previous research concerns which aspect of landscape pattern characteristics should be analyzed. Hundreds of landscape indices have been proposed by various researchers to analyze landscape structure. For example, no widely accepted conclusion has been reached regarding which land-use types should be used for metric calculation at class level, even though, different metrics have been performed for the description of landscape patterns in watersheds, such as areas of landscape elements and the distances of landscape elements to water bodies (Thierfelder 1998); the presence of riparian zones (Kuusemets and Mander 2001), wetlands (Trepel and Palmeri 2002) and various diversity indices (Jones et al. 2001; Chen et al. 2002; Gergel et al. 2002). Most previous studies just simply analyzed correlations between landscape patterns of one certain land-use type and water quality. Rare investigations have simultaneously analyzed metrics of different land-use types and compared the relative importance of their impacts, which could provide the implementations and applications for guiding landscape planning and water resource management (Lee et al., 2009).

Furthermore, stream flow is the main factor which influences the hydrological activities in lots of ways and shows their importance in a watershed. However, lots of watersheds are ungauged. The Reedy Fork-Buffalo Creek is an example of such watersheds. An ungauged watershed is a watershed with inadequate observed hydrological data (in both water quality and water quantity) (Cibin et al., 2013). The estimation of stream flow in the ungauged Reedy Fork-Buffalo Creek watershed is very critical if we are to better understand water quality issues in the watershed.

Though there have been many studies linking LULC spatial patterns to river water quality, little to no reseach is known to have been conducted in the Reedy Fork-Buffalo Creek watershed in Greensboro County (Fig. 1.1). Hence, the Reedy Fork Buffalo Buffalo Creek watershed makes a good test case for looking at how spatial patterns of developed area affect water quality because it resambles many other watersheds in the urban southern piedmont , and thus the results are likely to be usefull across the large populous region.

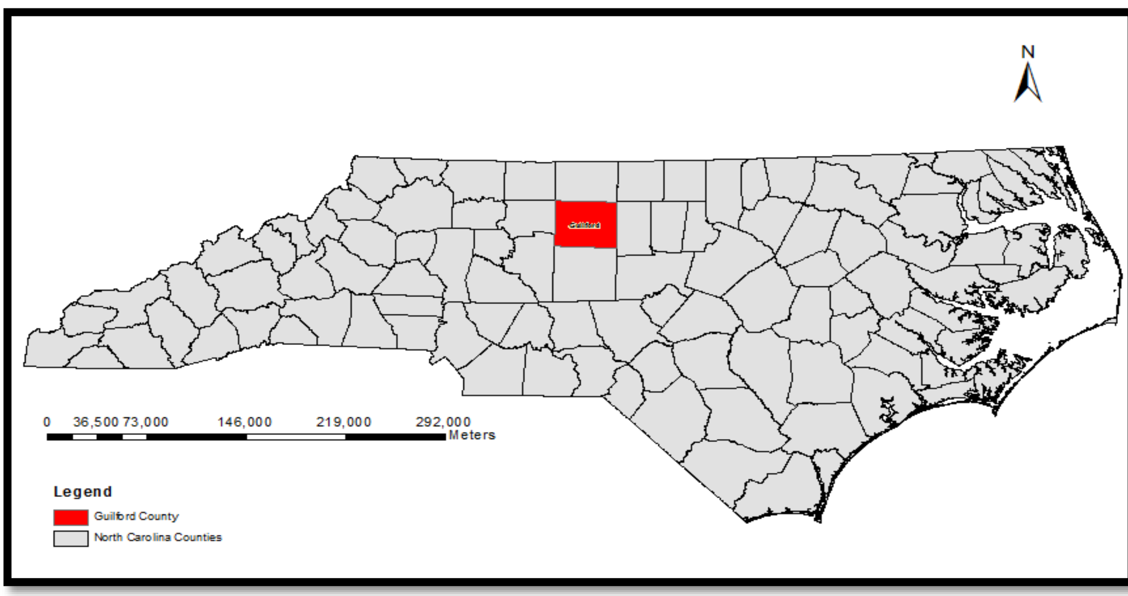


Figure 1.1. Guilford County, North Carolina: Location of Reedy Fork-Buffalo Creek Watershed.

The physiographic regions of the Reedy Fork-Buffalo Creek watershed may have a distinct interaction effect on the rivers and lakes as it moves from upstream to downstream. Most of the LULC within the watershed is made up of urban, forest, grass, and agricultural, hence, analyzing the spatial and temporal variation in water quality at multiple spatial scales is very crucial to aid in understanding how different LULC fragmentation affect water quality in the watershed.

The main purpose of this study is to apply a spatiotemporal scale approach to investigating the relationship between the change in LULC pattern distribution and river water quality, in the Reedy Fork-Buffalo Creek watershed from 2002 to 2013 at multiple spatial scales. To fully understand this relationship, this dissertation explores several questions specific to the LULC and water quality in the Reedy Fork-Buffalo Creek watershed. These questions include: what is the appropriate spatial scale at which landscape heterogeneity act to influence water quality and what components of the landscape pattern that are related to changes in water quality. An additional question will look to address if an increase in impervious surface (<10%) will cause a statistically significant increase in pollutant concentrations as established in other researchers (Schueler, 1994 and Brabec et al., 2002).

The previously natural vegetative areas in the Reedy Fork-Buffalo Creek watershed have seen a marked increase in some impervious surfaces as a result of urban development, and a corresponding reduction in areas of forest land cover resulting in a significant threat to the water quality of the Reedy Fork-Buffalo Creek watersheds. According to the City of Greensboro Water Resources Department annual report (Greensboro Water Resources Dept., 2012), the predominant factors determining the water quality characteristics of rivers and streams are the NPS pollutants washing off

Greensboro's urban landscapes rather than from just one identifiable source during a rain event (Greensboro Water Resources Dept., 2012). The majority of the pollution comes from fertilizer application to lawns and agricultural environments indirectly discharged into the creeks or rivers (Greensboro Water Resources Dept., 2012). With increasing concerns constantly on the rise from pollution in the watershed, it will be very important to understand the effect LULC spatial pattern plays in determining the quality of water in the study area.

In general, this research seeks to eliminate the gap in current literature relating to LULC spatial pattern distribution and scale of analysis that influences water quality. Geographers have for a long time been interested in the relationship between LULC spatial pattern and water quality. Taking a spatiotemporal approach to this topic presents an additional contribution to the literature since it enables one to understand the complex nature of the relationship that exists between highly detailed LULC spatial patterns and the chemical properties of water in the watershed.

CHAPTER II

LITERATURE REVIEW

To connect findings from this research to the research questions under investigation, literature on topics related to investigating the relationship between the spatiotemporal analysis of LULC patterns and water quality, as well as hydrologic modeling were reviewed. The purpose of this literature review is to highlight the interconnectedness between LULC pattern types at selected spatial scaled and water quality and to compare the findings to the results obtained in this dissertation. Also, hydrologic modeling will be incorporated to highlight how models can be utilized to simulate water quality and water quantity in relation to current and future LULC scenarios. In this manner, the literature review will aid in throwing more light on the gaps that exist in the literature so that a more detailed approach can be used to determine the spatiotemporal relationship between the LULC spatial patterns and water quality in the watershed. In doing so, the dissertation will aid in adding to the growing number of literature that seeks to understand how various LULC spatial pattern characteristics influence water quality in a watershed at multiple scales.

Importance of LULC Change in Water Quality Assessment

LULC change is one of the major natural changes happening around the world. Information on LULC change is constantly needed for policy making and management purposes. In hydrological setting, water quality is one of such variables influenced by

LULC change, since it is a key part of a healthy watershed where it coordinates imperative geomorphic, hydrologic, and a portion of the organic processes of a watershed (Hem, 1985). Modification of any of these procedures will influence at least one water quality parameters (Peterjohn and Correll, 1984).

Geographic Information System (GIS) and Remote Sensing Technologies for LULC Classification in Watershed Analysis

Remote sensing and GIS technologies have proved to be an efficient and effective way to analyze spatial information for LULC and watershed management (Tong and Chen 2002). These technologies have been useful in the quantification of LULC changes; especially from arable land to impermeable surfaces. LULC classification obtained from remotely sensed images aids in understanding the spatial arrangement and distribution of existing activities and changes in land development trends over space and time for water quality assessment and management in a watershed (Tong and Chen 2002). However, the use of these imageries such as Landsat is often regarded as too coarse for use in urban surface mapping because of the heterogeneity in the urban landscape (Jensen and Cowen 1999). With the development of High-Resolution (HR) satellite images, such as IKONOS, GeoEye-2, World-View1 and 2, and QuickBird, LULC classification can be determined very easily and quickly. Also, the ability to detect even small buildings, narrow roads and the avoidance of certain sources of false alarm and accuracy of detection can be ascertained (Cablk and Minor 2003). Welch (1985) stated that for urban LULC mapping, high-resolution images of about 0.5 m to 3 m are required for levels II and III classification proposed by Anderson et al. (1976). Though these HR images have proved to be a useful for providing detailed information and supplying recent information on activities within urban environmental setting (Etlers et.al., 1990; Foster, 1985), many issues still come into play during image classification (McGibbon and Eyton, 1996). Studies have shown that different variety of objects may have similar spectral signatures (Wang et al., 1999; Beykaei et al., 2010), and objects of the same type may appear with different spectral signatures especially with built environments, making LULC classification difficult. Hence, it is felt that, GIS technology, which allows an easy integrating of multi-source remote sensing information, as well as non-spectral data (ancillary data), will provide the needed detailed information and analysis capabilities of LULC classification purposes in urban areas and thus, be beneficial to land-use and environmental management (Welch et al., 1988; Nellis et. al. 1990; Mesev, 2005).

Studies (Quarmby and Cushinie, 1989; Forster, 1985; Welch, 1985) have shown that there are many advantages to combining remotely sensed data and spatial data using GIS technology, thereby maximizing the information upon which responsible decisions for LULC planning can be made. In their study of LULC mapping at the urban-rural fringe, Treitz et al. (1992) combined GIS data with LULC classes generated from Satellite Pour l'Observation de la Terre High-Resolution Visible (SPOT HRV) a zoning information using maximum-likelihood classification. The result produced an estimated accuracy of 78% as compared to 70.3% accuracy obtained from only SPOT HRV multispectral and panchromatic data. Li et al., (2004) also used GIS and remote sensing for land-use change analysis in Yulin Prefecture, Northwestern China. Their aim was to determine land-use transition rates among land-use types over a 14-year period (1986-

2000) using six land-use types: impervious, cropland, forestland, grassland, barren land, and water from a. These classes were obtained by visual interpretation and the digitization of High-Resolution (HR) satellite imagery. They observed that there was a significant change in land-use over the study period with cropland increasing by 3.39%. The increase was associated with conversions from barren land to grassland and concluded that integration of satellite remote sensing and GIS was an effective approach for classifying and analyzing the direction, rate, and spatial pattern of land cover over time.

Beykaei et al., (2013) in their quest to produce a highly accurate LULC, develop a hierarchical rule-based land-use extraction framework using geographic vector and remotely sensed (RS) data, in order to extract detailed sub-zonal land-use information, and residential land-use at a fine spatial level in their study area of the City of Fredericton, Canada. They used hybrid pixel- and object-based LULC classification system, coupled with a GIS post-classification correction process, to extract LULC, including vegetation, parking lot, and bare soil, required for land classification. They achieved an overall accuracy of 96.4%.

Classified Image Validation

While classified images may look pleasing to the eye, accuracy assessment is required to check the correctness of the information. Accuracy assessment involves the comparison of a classified imagery with ground-truth data to evaluate how well the classification represents the real world by allowing map producers to analyze the sources of error and weakness of a particular classification strategy (Powell et al., 2004) and compare two or more classification techniques (Foody, 2004).

There are a variety of methods for assessing the accuracy of classified image products of which the most common and popular one for LULC is the error matrix or the confusion matrix method (Foody, 2002). The Khat error matrix, which is a quantitative method for map comparison or accuracy assessment, is considered as the standard descriptive and discrete multivariate statistics when looking at spatial information in the field of remote sensing, (Congalton, 2004) summarizes the relationship between two datasets, often a classified map and a referenced map. The column mostly represents the referenced map, and the row represents the results from the classified maps from which the overall accuracy will be obtained (Foody, 2002). This matrix does not only presents a tabulated view of map accuracy, but also allows the calculation of specific accuracy measures such as the overall accuracy (dividing the total number of correct pixels by the total number of pixels in the error matrix), producer accuracy (how well a certain area can be classified), user accuracy (the probability that a pixel class on the map represents the category on the ground), and a measure of agreement between the classification map and the reference data (kappa coefficient). Previous studies have provided the meanings and methods of calculation for these statistical elements for judging the accuracy (Congalton 1991, Foody 2002). This method employs two approaches – random sampling or using reference data. The reference data approach requires a high-accuracy LULC data with the same number of classes which is sometimes difficult to obtain than the random sampling method for accuracy assessment which makes use of an error matrix based on stratified randomly sampling technique to select points across the classified image (Bock et al. 2005). This sampling technique is recommended so that the sampling points are fairly spread in each land-cover class, and a minimum of 50 samples should be collected for the kappa value to be obtained (Bock et al., 2005). Landis and Koch (1977) suggested the following guidelines: kappa values ≤ 0.40 represent poor-to-fair agreement; 0.41–0.60, moderate agreement; 0.61–0.80, substantial agreement; and 0.81–1.00, almost perfect agreement.

Landscape Metric for LULC Spatial Variation and Intensity

Variation in the extent and intensity of human land-use creates disturbance gradients that can potentially alter processes such as nutrient cycling, energy flows, and pollutant export in rivers and streams (Turner 1989; McDonnell et al. 1997). Numerous studies have linked land-use with water quality (e.g. Johnson et al. 1997) as the proportion, and spatial arrangement of LULC within watersheds can have significant impacts (Hunsaker and Levine 1995; Johnson et al. 2001). The field of landscape ecology provides a conceptual framework to understand these human influences because it is primarily concerned with land-use patterns within defined areas, interactions between different landscape elements, and the effects of changes in the spatial heterogeneity complex over time (Haines-Young et al. 1996).

In recent years, landscape ecology introduced the use of landscape ecological indices or metrics to quantitatively assess landscape fragmentation as a continuous surface, especially ecosystems and this, however, has become a trend in urban landscape change studies (Cushman, 2008). These metrics have been developed for landscape composition (relative amounts of different elements in the landscape) and configuration (arrangement of these elements) that aid in the analysis and interpretation of landscape processes (Turner 1989; Li and Wu 2004). Metrics can be calculated for individual patch, class (aggregation of the same type of patches) and overall landscape (Haines-Young and Chopping, 1996). Landscape metrics mainly fall into two general categories based on quantification of composition and spatial configuration. Composition refers to different and abundance of a specific pattern (patch and class) within the landscape, but without considering the relative orientation and structure of the features. Spatial configuration refers to aggregation, arrangement, position and orientation of patches within the class or landscapes. Landscape metrics can also be grouped according to their ability to measure patterns with explicit reference to structural and functional processes in a particular system (McGarigal and Marks, 2002). 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 Total Percentage Impervious Area (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.

Fragmentation Statistics (FRAGSTATS) for Landscape Analysis

One approach to quantifying landscape patterns as continuous surfaces have involved the use of moving windows, in which each cell in the landscape is assigned a value or a category based on the values of all cells within a kernel centered on the cell of interest. This approach can be computationally efficient for large areas, effective at capturing the context of a point relative to larger landscape neighborhood effects, and useful for examining the effects of scale on forest patterns. A fundamental concept in landscape ecology is that patterns influence processes and several studies have emphasized methods to quantify spatial heterogeneity (e.g., Forman and Godron 1986; O'Neill et al. 1988; Turner and Gardner 1991). In landscape ecology, the most widely used software package to calculate landscape metrics is FRAGSTATS. FRAGSTATS is a computer software program designed to compute a wide variety of landscape metrics for categorical map pattern either at the class or landscape level (McGarigal and Marks 1995). At the class and landscape level, some of the metrics quantify landscape composition, while others quantify landscape configuration (McGarigal, 2012). Changes of landscape pattern can be detected and measured by landscape metrics which quantified and categorized complex landscapes into identifiable patterns. Efforts to link landscape pattern through time to biotic responses have most commonly used metrics such as (1) patch area, edge density, and nearest neighbor distance, at the individual patch level; or (2) mean patch size, largest patch index, mean nearest neighbor distance, or cohesion, at the class level (Patterson and Malcolm, 2010; Scharine et al., 2009). However, many of them are highly correlated (Riitters et al., 1995). With regards to Class level, metrics like Total (Class) Area (CA), PLAND, LPI, Total Edge (TE), ED, NP, Patch Density (PD), Landscape Shape Index (LSI) and Euclidean Nearest-Neighbor Distance (ENN) are practical for analysis of urban areas (McGarigal, 2014). PLAND and Class Area (CA) give information about the area of settlements. NP and Patch Density (PD) focus on the subdivision of aggregation and are considerable for the number and density of settlements. The LPI gives information about the type and existence of a spatially dominant urban core (McGarigal, 2002).

Riitters and colleagues have used FRAGSTATS to quantify several aspects of landscape pattern (e.g. Riitters and Coulston, 2005; Riitters et al., 2009). Ting et al. (2012) used FRAGSTATS in assessing the effects of landscape pattern on river water quality at multiple scales in the Dongjiang River watershed, China. They analyzed how river flow and water quality variables were related to landscape attributes at three scales: subwatershed, catchment, and buffer. Their results show that the water quality of the Dongjiang River differed among the upper, middle, and lower reaches with LULC pattern having a major impact on the flow and water quality at multiple spatial scales. In investigating the relationship between land-use parameters, landscape metrics, and water quality indicators, multiple regression analysis results by Uuemaa et al., (2007) showed that, for BOD, Total-N and Total-P, the most important predictor was the proportion of urban areas, but landscape metrics also had a significant relationship with water quality. They concluded that, the knowledge that land-use and landscape configuration impact on water quality can be used in establishing and implementing water management plans in Europe.

Effects of LULC Change on Water Quality and Quantity

The quality of water availability for users downstream can change due to increasing modifications in the type and amount of surface vegetation, the porousness of soil and different surfaces, and the introduction of pollutants through anthropogenic activities (Foley et al. 2005, Brauman et al. 2007). Increases in the demand for water to address issues of expanding urban and rural development can add to water shortage. Specifically, redirections of surface water for farming and different uses can reduce flows and possibly cause a genuine alteration in the environment for fish and other aquatic organisms. Furthermore, industrial, and residential uses have reduced the elevation of the water tables and influenced discharges in numerous areas (Foley et al. 2005, Carlisle et al. 2010). Changes in vegetation can increase or decrease water availability. Likewise, changes in land-use influence to what degree pollutants can reach surface and groundwater, posing potential dangers to human wellbeing and biodiversity, as well as, increasing the treatment cost of water (where treatment is accessible). Anthropogenic activities, for example, intensive agriculture, urbanization, mining, or energy extraction can bring about nutrients, pesticides, industrial chemicals, heavy metals, and other pollutants to the landscape, with a variety of effects on the hydrology of the area. For instance, human-induced eutrophication, which is connected to exercises, such as, annual row-crop farming and concentrated animal feeding operations (Smith et al. 1999, Dodds et al. 2009, Rothenberger et al. 2009), can bring about lost assorted diversity and richness of life forms in waters, increase health risk of humans, and sometimes leads to the decrease in property values (Schilling and Spooner 2006, Dodds et al. 2009). Plants, soils, and organisms can filter a few contaminations from freshwater, yet the reducing or degradation of vegetation cover and the increase impervious surfaces due to development, for example, concrete or asphalt, compacted dirt, permit water to flow through the landscape relatively unhampered, thereby, reducing the chance of removing pollutants by means of filtring. (Brauman et al. 2007). Changing the characteristics of the ecosystem system can likewise alter the location and the timing or predictability delivery of water, with potential outcomes identified with drought or water mitigation. For instance, urbanization, and the related extension of impervious surface increases the recurrence and magnitude of discharge and resulting flooding (Brown 2000).

Urbanization and Urban Streams

In 1900, only 9% of the world's human population lived in "urban environments" (World Bank, 1984). This figure expanded to 40% in 1980, 50% in 2000, and is expected to increase to over 66% by 2025 (Rodick, 1995; Brockerhoff, 1996). The increase in population simultaneously leads in increased urbanization resulting in the threatening of water quality and biotic integrity of streams respectively. Covering land with impervious surfaces such as; roads, parking lots, buildings, and sidewalks, creates many direct and indirect deleterious impacts on aquatic ecosystems (Paul and Meyer, 2001). Impervious cover disrupts the natural hydrologic cycle (Booth, 1991), and often leads to unstable stream channel morphology (Leopold et al., 1964). The impervious cover problem, which will likely expand with the increase in sprawl around many cities in the United States (Ewing et al., 2002) is a continuing threat to aquatic ecosystems. Numerous studies have shown that water quality and stream habitats are sensitive to degradation with 10% impervious cover (Schueler, 1994; CWP, 2003; and Brabec et al., 2002). A degraded stream is difficult and very expensive to bring back to its original condition. Successful stream rehabilitation requires a shift from narrow analysis and management to combine understanding of the links between human actions and changing river health (Grimm et al.,2000; Booth et. al 2004) but any urban streams can, however, be rehabilitated – that is, their biological condition can be improved to some degree (Booth et. al 2004). Booth et al. (2004) conducted research in the Puget Sound lowlands of western Washington State to evaluate the health of the stream with changing levels of urban development taking into account the watershed landscape, hydrological, and biological. They found evidence that shows that, the impacts of urban development on the health of streams can be fully alleviated and stated that successful stream rehabilitation, thus requires coordinated diagnosis of the causes of degradation and integrative management to treat the range of ecological stressors within each urban area, and it depends on remedies appropriate at scales from backyards to regional stormwater systems. Others (Barker et al., 1991; Booth and Jackson, 1997; Jackson et al., 2001) came to a similar conclusion.

Thresholds of Impervious Surfaces Coverage and Urban Stream Hydrograph

Research in LULC and water quality has seen rising evidence that certain thresholds of the total percent impervious area exist at which water quality conditions in an area reach increasing levels of impairment. Studies have shown that changes in land-cover within a watershed can be used as water quality indicators of the extent to which surface waters will be impacted. Early research by Schueler (1994) suggested that a 10% - 20% total percent impervious area (TPIA) threshold exists for watersheds, beyond which streams become impaired. Arnold and Gibbons (1996), also stated in their review that as impervious surface reaches a threshold of 10 percent in a watershed, the health of the stream begins to be impaired, and at about 10% to 30%, the stream is impacted and becomes degraded when it is more than 30%. Others (Schiff and Benoit 2007) also stated that the quality of surface waters could be impacted at as low as 1% to 5% impervious surface. In his study between imperviousness and water quality in an urbanizing coastal zone of New Jersey, Conway (2007) determined that a threshold potentially exists between 2.4% - 5.1% of impervious surface cover resulting in the impairment of the stream. Further examination by Conway (2007) suggests that by 2020, water quality in more than 50% of the catchment in his study will be negatively impacted by non-point source pollution associated with impervious surfaces. These thresholds have been found to be a very reliable indicator of stream quality assessment. According to Beach (2002), an acre of impervious surface such as a parking lot produces 16 times more runoff than an acre of grassy land-cover such as a meadow or pasture.

In spite of the fact that total TPIA in a catchment has commonly been used as an indicator of hydrologic change, the influence of TPIA on stream hydrographs varies substantially with porousness of pervious parts of the catchment (Booth et al. 2004). TPIA also varies with how much of the impervious area draining directly to streams through pipes than to the surrounding pervious land (Walsh et al. 2005). The main feature of urbanization is a decrease in the perviousness of the catchment to precipitation, leading to a decrease in infiltration and an increase in surface runoff (Dunne and Leopold 1978; Paul and Meyer, 2001). As the percent impervious surface area in a watershed increases to 10–20%, runoff increases twofold; 35–50% impervious surface area increases runoff threefold; and 75–100% impervious surface area increases surface runoff more than fivefold over forested catchments (Arnold and Gibbons 1996). Impervious surfaces have become a reliable and accurate means of predicting urbanization and urban impacts on streams (McMahon and Cuffney 2000), and many thresholds of degradation in streams are associated with an impervious surface area of 10–20% (Booth and Jackson 1997; Yoder et al. 1999). Change in the impervious surface in watershed catchment changes the characteristics of stream hydrography.

Riparian Buffer and Watershed Spatial Scale

Landscape characteristics are some of the most important factors influencing nutrient and organic matter runoff in watersheds (Turner et al., 2003; Uuemaa et al., 2007). Therefore, there is increasing demand for indicators and methods that make it possible to evaluate the landscape factors influencing water quality in freshwater management (Griffith, 2002). Several studies have attempted to determine the relationship between land use and land cover and water quality but, most studies have largely relied on compositional landscape metrics (Kearns et al., 2005). It is, however, clearly important to understand not only the total area of sources and sinks in the landscape but also their spatial arrangement in relation to flow paths (Gergel, 2005). The importance of the spatial arrangement of land-cover within watersheds on water quality has been studied by King et al. (2005); Uuemaa et al. (2005, 2007). The spatial pattern of riparian zones is also an especially powerful landscape indicator of water quality because the variation in length, width, and gaps of riparian buffers influences their effectiveness as nutrient sinks (Gergel et al., 2002).

Riparian buffer refers to riparian zone measured from the stream centerline to the outer edge of the buffer. Riparian buffer plays an important role in the relationship between the percentage land-cover within an area and the water quality of local streams.

Results on the relationship between water quality and land-cover composition at various scales have been achieved through examinations of land-cover at the buffer and watershed scales. According to NCDWQ (2007b), the watershed can be defined as an element of the landscape that represents a single drainage basin with a single outlet point.

Research work by King et al. (2005), Lee et al. (2009), Alberti et al. (2007), Jones et al. (2001), Strayer et al. (2003), have found varying significance results between water quality and watershed as well as riparian buffers scales. 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. They found out that water quality 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. Weller et al. (1998) developed and analyzed models predicting landscape discharge based on material released by an uphill source area, the spatial distribution of a riparian buffer along a stream, and retention within the buffer, and found average width to be the best predictor of landscape discharge for an unretentive buffers. Maillard and Santos (2008) examined the relationship between LULC and water quality while modeling non-point source pollution effects in a Brazilian watershed. The research concluded that there were significant relationships between LULC and water quality at the 90m riparian buffer scale, but no significant relationships were found in 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.

Water Quality Parameters

A lot of parameters constituent pollutants that degrade the quality of streams. Pollution can put surface waters (river, lakes, and streams) at great risk. Pollution is a waste that originates from residential, industrial, municipal, and agricultural discharges to water (U.S. EPA, 2004d). Surface water contamination includes microbial, inorganic, organic, and radioactive contaminants (U.S. EPA, 2004c). Microbial contaminants are viruses, bacteria, and protozoa found in surface waters. Instead of measuring individual pathogens, indicator organisms such as E. coli and fecal coliforms are used to indicate the presence or absence of pathogens. Common inorganic contaminants found in source waters are nitrate and arsenic, originating from natural sources. In addition to naturally occurring inorganic contaminants, a number of inorganic contaminants originate from anthropogenic sources such as industrial and domestic waste discharges. Organic chemical contaminants are synthetic or volatile chemicals such as oil and grease. These are often a result of leaks from cars or automotive repair shops. Pesticides and herbicides are also a type of organic chemical contaminant typically transported to surface waters by runoff from agricultural areas. Home use of commercial pesticides and herbicides is another source of these contaminants.

Pollutants that originate from an established source are considered point source pollution. Point source pollution, as defined by the U.S. EPA, is “any discernible, confined and discrete conveyance, such as a pipe, ditch, channel, tunnel, conduit, discrete fissure, or container from which pollutants are or may be discharged” (U.S. EPA, 2004b). Wastewater facilities and industrial factories discharging waste directly into surface waters are a form of point source pollution. The second form of pollution to surface waters is through nonpoint source discharges. Nonpoint source pollution comes from many diffuse sources, where stormwater or snowmelt runoff transport contaminants on land surface into waterbodies. Examples of nonpoint source pollution include agricultural runoff and runoff from highly urbanized areas where the majority of the surfaces are paved. These sources of pollution are not regulated and are considered the leading remaining cause of water quality problems reported by state officials (U.S. EPA, 2004d). Effects of nonpoint source pollutants include excess sediment accumulating in water bodies, high levels of nutrients, and bacterial contamination. Sediment transport into water bodies is greatly affected by construction sites with little or no erosion control measures. High levels of nutrients are produced by runoff transporting pesticides, manure, and other nutrient-containing wastes into water bodies. Nutrients affect water quality by providing excess nitrogen or phosphorus, leading to extreme plant and algal growth. Bacterial contamination can result from wildlife, domestic, or livestock feces contaminating water, or from overburdened or deteriorating septic systems.

Choice of Water Quality Parameters

Though lots of parameters pollute the quality of surface waters, studies in water quality have shown that a limited number of important water quality parameters can be used to determine the health of a stream than had been previously used. Dow and Zampella (2000) carried out research in New Jersey, USA to examine the relationship between LULC using only two main water quality indicators, pH, and conductivity together with single LULC for their study. Their result indicated that there was a linear relationship between both pH and conductivity with LULC, with simple regression models indicating that LULC explained 48% of the changes in pH and 56% in conductivity, with 79% of the changes explained by a combined regression model of pH and conductivity. Li et al., (2009) also carried out research in the Han River basin of China to examine the impact of LULC on a wide variety of water quality variables. They took into consideration 17 physical and chemical indicators and determined that 8 of these parameters correlated most significantly with LULC, that is: conductivity, dissolved oxygen, temperature, suspended particulate matter, nitrate, pH, phosphates, and turbidity. Research conducted by Maillard and Santos (2008) in evaluating the effect of LULC on the quality of nearby stream water in a semiarid environment on a large watershed in Southeastern Brazil showed a strong relationship between LULC and turbidity, nitrogen and fecal coliforms. They also suggest that each of these parameters has a unique behavior when the distance from the stream is considered. Other researchers have indicated that conductivity, turbidity, nitrate, chloride, sulfate, and phosphates can be utilized as key water quality indicators for rapid assessment of stream system health (Tran et al., 2010; Tong and Chen 2002; Morse et al., 2003; Gergel et al., 2002).

Modeling the Hydrologic Response of an Urban Watershed

Hydrological modeling of watersheds with water quality issues is imperative for sustainable management of water resources. Most hydrological modeling is computer based. Hence, computer models for watershed hydrologic analysis have for some time now been an essential part of any water quality and water quantity assessment. Several watershed-scale hydrologic and water quality models have been developed that can estimate availability of water resources. For example, HSPF (Hydrological Simulation Program-FORTRAN), HEC-HMS (Hydrologic Modeling System), CREAMS (Chemical, Runoff, and Erosion from Agricultural Management Systems), EPIC (Erosion-Productivity Impact Calculator), and AGNPS (Agricultural Non-Point Source) have been developed for watershed analyses through the years (Jha, 2011). However, the kind of model to use depends on the intended hydrologic purpose by the user. To be able to reliably and accurately simulate environmental impacts (land-use) on hydrologic parameters, a large number of researchers are faced with the fact that no gauging stations exist in their study area of interest especially with small urban watershed Wagener (2007). Due to this, model adjustment and calibration need to be carried out on the observed hydrologic data for an efficient and reliable result to be obtained (Wagener et al., 2004; Beven, 2006; Gupta et al., 2008). Recent decades have seen a significant progress with regards to model calibration and adjustment in hydrologic modeling (Gupta et al., 1998; Vrugt et al., 2003; Beven, 2006). Most of these models require a large number of high-quality observed discharge data and other variables (spatial and temporal scale data) of interest, which in most situations is often very limited especially in ungauged watersheds (Sivapalan et al., 2003). More often, the calibrated models are user-dependent and are based on the model user's experience and knowledge about the watershed, model, chosen parameters, and their ranges (Harmel et al. 2006). However, uncertainties associated with the input data and measured hydrologic variables may lead to biased estimation of parameters calibrated using one or several stream gauges. Such uncertainties may result in errors in discharge measurements ranging from 6% to 16% (Harmel et al. 2006). A case study conducted by Zhang et al. (2008) in Reynolds Creek Experimental Watershed showed that a parameter set with high discharge simulation performance at the watershed outlet could have a much lower performance at some internal points within the watershed.

The SWAT Model

The SWAT model is an exceptionally flexible tool that has been used in numerous parts of the world to predict the effect of land-use management practices on water, sediments and chemical yields from urban and farming activities in small to vast complex basins over time (Eckhardt et al., 2005). Inside the SWAT model conceptual framework, the representation of the hydrology of a watershed is made up of two main parts: (a) the land phase of the hydrological cycle; and (b) the routing of water runoff through the stream system. In modeling the land phase, the river watershed is separated in sub-basins. Each sub-basin is further made up numerous Hydrological Response Units (HRUs), which are areas of moderately homogeneous LULC and soil types. The qualities of the HRUs characterize the hydrological reaction of a sub-basin. For a given time-step, the commitments to the discharge at every sub-basin outlet point is controlled by the HRU water balance calculation (land phase). The stream and river networks connect the different sub-basin outlets, and the routing phase decides on the movement of water through this network towards inner sampling locations, and eventually towards the watershed outlet (Neitsch et al., 2002).

For the water balance of the land phase, evapotranspiration can be calculated within SWAT model utilizing one of three strategies: Penman-Monteith, Hargreaves or Priestley-Taylor. The Penman-Monteith technique offers a superior procedure. However, it has a high demand of input information prerequisites which for pragmatic applications will be difficult to satisfy in numerous parts of the world. The Hargreaves or Priestley-Taylor techniques, although less physically based, have the benefit of less stringent information requirement. Under negligible conditions of data availability, the Hargreaves strategy can even be utilized with temperature time arrangement as the main required measured input (Heuvelmans et al., 2005). For estimations of surface runoffs, SWAT model gives the client two choices: (a) the utilization of the Soil Conservation Service Curve Number (SCS CN) procedure, and (b) the Green and Ampt infiltration technique. For the last strategy, input information at fine daily time resolutions are required, while the CN technique is lumped after some time (Johnson, 1998): the SCS CN methodology for water balance can typically be applied using daily precipitation (rainfall) values. Runoff commitments from snowmelt can be consolidated using temperature index, a technique ordinarily utilized as a part of water assets management applications (Walter et al., 2005). Because of this adaptability, SWAT model has been utilized in many towns and urban communities on the in the world (USA, Europe, India, New Zealand, and so forth; Tripathi et al., 2006). In any case, at present, almost no in-depth study uses of SWAT model in the study area watershed have been documented in research literature.

Predicting Water Yield of the Watershed

Water balance is the main driving force behind every one of the processes in SWAT model as a result of its effects on plant development and the movement of sediments, nutrients, pesticides, and pathogen within the watershed region (Arnold et al., 2012). The review of SWAT model application to various watersheds (Dilnesaw, 2006; Jha et al., 2007; Setegn, 2010) showed that the model is fit for simulating hydrological processes with high precision. In SWAT Model, a watershed is partitioned into various sub-basins, which are then further subdivided into hydrologic response units (HRUs) that comprise of homogeneous LULC, slope, and soil attributes (Neitsch et al., 2005). In the land phase of the hydrological cycle, SWAT reproduces the hydrological cycle taking into account the water balance formula in equation (1):

$$SW_t = SW_o + \sum_{i=1} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \ldots\ldots\ldots\ldots\ldots\ (1)$$

Where:

SW_t is the last soil water content (mm), SW_o is the underlying soil water content on day i (mm), t is the time (days), R_{day} is the measure of precipitation on day i (mm), Q_{surf} is the measure of surface spillover on day i (mm), E_a is the measure of evapotranspiration on day i (mm), W_{seep} is the measure of water entering the vadose zone from the dirt profile on day i (mm), and Q_{gw} is the measure of profit stream for day i (mm).

One of the critical parameters that should be evaluated for sustainable water resource management of the study area is the water yield. Water yield, therefore, is the aggregate sum of water leaving the HRU and entering principle channel during the time step (Arnold et al., 2011). Water yield of a waterway catchment is evaluated by the model using equation (2):

$$WYLD = SURQ + GWQ + LATQ - TLOSS \text{ ………………. } (2)$$

Where:

WYLD is the measure of water yield (mm H_2O), SURQ is the surface runoff (mm H2O), LATQ is the lateral flow contribution to stream (mm H2O), GWQ is the groundwater contribution to discharge (mm H_2O), and TLOSS is the transmission losses (mm H2O) from tributary in the HRU by means of transmission through the bed. The estimation of surface runoff can be performed by the model utilizing two strategies. These are the SCS bend number system by USDA Soil Conservation Service, equation (3) or the Green and Ampt penetration technique in equation (4).

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2)}{(R_{day} + 0.8S} \text{ ………………………… } (3)$$

In (5), Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), S is the retention parameter (mm). The retention parameter S and the prediction of lateral flow by SWAT model are defined in equation (4) and (5), respectively.

$S = 25.4\ [(100/CN) - 10]$ ………………………… (4)

$Q_{lat} = 0.024\ [(2SSC_{\sin\alpha}) / (\theta_d L)]$ ………………… (5)

Where:

q_{lat} = lateral flow (mm/day); S= drainable volume of soil water per unit area of saturated thickness (mm/day); SC= saturated hydraulic conductivity (mm/hr); L= flow length, α= slope of the land, θ_d= drainable porosity. The estimation of the base flow was done using equation (6):

$Q_{gwj} = Q_{gwj-1}.e^{(-\alpha gw\Delta t)} + W_{rchrg}\ (1 - e^{(--\alpha gw\Delta t)}$ ………… (6)

Where:

Q_{gwj} = groundwater flow into the main channel on day j; α_{gw} =base flow recession constant; Δt= time step.

Nutrients Modeling (Nitrogen-Nitrate)

Nitrogen management and movement are estimated in SWAT using the modeling approach of GLEAMS. SWAT assumes the movement and transformations of nitrogen for two mineral species (ammonium and nitrate) and three organic species (active, stable and fresh) in soil nitrogen pools (as N). The major in soil processes for nitrogen cycles in the SWAT model are Mineralization, decomposition, and immobilization. These processes are activated in model simulation when the temperature of the soil layer reaches above zero. SWAT estimates the nitrate load at various pathways e.g. export with runoff, lateral flow, and percolation and it is calculated as a function of the volume of water and the average concentration of nitrate in the soil layer. Instream Nutrient dynamics are replicated in SWAT model by incorporating the kinetic routines of QUAL2E model (Brown and Barnwell, 1987).

There are numerous studies that show the robustness in using SWAT for modeling nutrient losses. Santhi et al., (2001) and Saleh et al., (2000) used the SWAT model to evaluate nitrogen losses in watersheds in Texas. Their results show SWAT was able to predict nitrogen losses within reasonable limits of NSE value which was obtained as greater than 0.60. The NSE, which stands for 'Nash–Sutcliffe model efficiency' coefficient, is a widely used statistic to evaluate the efficiency in hydrologic predictions. Hanratty and Stefan (1998) also used data collected from Cottonwood River, Minnesota to calibrate the SWAT model and concluded that SWAT was a suitable model for simulating water quality variable under climate change. They simulated both nitrate-nitrogen and phosphorus for their study. Arabi et al., (2006) studied the effect of best management practices (BMPs) on nitrogen and phosphorus losses in two small watersheds in Indiana and found SWAT as an effective tool to do so. Jha et al., (2007 used SWAT for water quality modeling in the Raccoon River in West-Central Iowa. They found out that, model predictions performed very well on both an annual and monthly basis during the calibration and validation periods, with R2 and Nash-Sutcliffe efficiency (NSE) values exceeding 0.7 in most cases.

Scenario Analysis

Scenario analysis investigates directions of progress that diverges from current conditions, eventually leading alternative conceivable future events. In this manner, it gives a dynamic and adaptable approach to assessing strategy or management alternatives. Scenarios are not expectations or conjectures; yet rather, they are "conceivable and frequently streamlined depictions of how the future may develop in light of a reasonable and steady internal arrangement of presumptions about driving forces and key connections" (Houghton et al. 2001:796). Scenario analysis enables an investigation of the potential effects, dangers, advantages, and management opportunities originating from an assortment of conceivable future conditions. At the point when utilized in conjunction with modeling, scenario analysis can overcome any issues amongst science and decision making. This it does by throwing light on how land-use changes will influence hydrology over a wide range of spatial and temporal scales, thus allowing decision makers to viably get ready for such changes (Mahmoud et al. 2009). To give direction on the utilization of formal scenario analysis in environmental studies, Liu et al. (2008) and Mahmoud et al. (2009) proposed a guideline an iterative procedure for developing a scenario.

A scenario at first ought to be developed as images or narratives (Leney et al. 2004) that unmistakably and convincingly depict either the end condition of the situation or the procedures by which the end state could be accomplished (Liu et al. 2008). For instance, a map could demonstrate the area of local vegetation to remain in a watershed 20 years from the benchmark, or a narrative could depict policy changes anticipated to adjust future patterns of agricultural and urban land-use development. Scenarios in environmental science and decision making span a long period (20–50 years from the current situation) and utilize an extensive variety of spatial scales, from a watershed (e.g., Giertz et al. 2006, Mutiga et al. 2010). Some of the driving forces considered when carrying out scenario analysis with regards to hydrologic and other environmental services may include: rate of population, impervious LULC, housing densities, migration (domestic and foreign), Carbon emission, fertility rate, development plans, climate change, and environmental policies (UNEP 2002, MA 2005a, Mahmoud et al. 2011).

Secondly, researchers and partners flesh out scenario quantitatively or subjectively (Liu et al. 2008). Quantitative methodologies can give more prominent thoroughness, accuracy, and consistency and permit one to decide the impacts of option techniques or changes in suspicions. Qualitative methodologies, on the other hand, can capture perspectives motivation, qualities, and conduct (UNEP 2002, Liu et al., 2008, and Mahmoud et al. 2009). Water resources–related scenario analysis commonly utilize a quantitative modeling approach, which represents scenarios as information sets that can be utilized as inputs into a combination of land-use change and hydrologic process-based models (Kepner et al., 2008, Liu et al., 2008). A mix of qualitative and quantitative methodologies can permit one to capitalize on both methodologies (UNEP 2002).

A modeling based approach to deal with scenario development starts with the advancement of a reasonable model-an instinctive depiction or representation of what will be demonstrated and how and also the information prerequisites-to guarantee that decision makers and researchers share a typical comprehension of the quantitative model

(Liu et al. 2008). Researchers continue with scenario development by selecting or creating models or other information generating methods that can satisfactorily speak to the applied model, gathering and preparing model input information, running the models for every situation, and handling model yield information (situation results; Liu et al., 2008). In their utilization of this design, Mahmoud et al., (2011) gave a comprehensive description of the scenario development stage. In scenario analysis, analysts analyze scenario results and contrast them with gauge conditions utilizing statistical and other logical procedures, investigate the information for consistency with scenarios, and identify system conditions or practices, for example, patterns or triggers (Liu et al., 2008). Results are then introduced as narratives (e.g., Mahmoud et al., 2011) and in different forms, for example, maps, tables, or diagrams portraying examples of progress in different hydrologic or different endpoints for every situation contrasted with the standard (e.g., Hulse et al., 2004).

In general, hypothetical land-use scenarios have been constructed in SWAT and used to evaluate pollutant losses under different land-use or Best Management Practices. Borah et al., (2006) reviewed some recent applications of SWAT model in the United States that includes: Total Maximum Daily Load (TMDL) analysis, evaluate the effectiveness of conservation practices under the CEAP program. In one such study in Texas, Santhi et al., (2006) documented the impact of Best Management Practices on the water quality. Kirsch et al., (2002) reported that improved tillage practice, in a watershed in Wisconsin, reduced sediment yields by 20%. Vache et al., (2002) studied the effect of Best Management Practices in Walnut Creek watershed in Iowa and observed that suitable Best Management Practices could largely reduce the sediment load at the watershed outlet. In the same watershed, Chaplot et al., (2004) observed that land-use changes largely impacted nitrogen losses.

Studies That Have Used SWAT Model

The SWAT model has been adopted and applied worldwide in a wide range of applications and conditions (Gassman et al., 2010; Zhang et al., 2007; Watson et al., 2003; Tripathi et al., 2006; Behera and Panda, 2006; Barlund et al., 2007). Though most of the studies concluded that the SWAT model has a good potential for application in hydrology and water quality assessment in countries around the world under a wide variety of watershed characteristics, they do not mention the characteristics of the input data nor how data limitation was overcome. However, a few of them recommended further testing and customizing the SWAT model for different watershed conditions (e.g., Tripathi et al., 2006). Some articles indicated that the model performance efficiency is higher when coupled with the use of HR data sets. However, Tripathi et al., (2006) and Jha et al., (2004) have indicated that under different characteristics, HR spatial data does not necessarily improve the performance of SWAT.

Jha (2011) performed a sensitivity analysis on the Maquoketa River watershed, in northeast Iowa, the USA using an influence coefficient method to evaluate surface runoff and baseflow variations in response to changes in model input hydrologic parameters applied. The model was found to explain at least 86% and 69% of the variability in the measured discharge data for calibration and validation periods, respectively. Surface runoff was found to be sensitive, to runoff curve number (CN), Soil evaporation compensation factor (ESCO), available water capacity of the soil layer (SOL_AWC), and Soil evaporation compensation factor (EPCO) for the selected variation range. Jha concluded that the SWAT model could be an effective tool for accurately simulating the hydrology of the Maquoketa River watershed. However, accurate flow simulations are required to predict sediment loads and chemical concentrations accurately, and to simulate various scenarios related to crop and alternative management to mitigate water quality problems in the region. Studies by Arnold et al., (1999) and Spruill et al., (2000) also found the same top three parameters, CN, ESCO, and SOL_AWC, to be the most sensitive parameters to consider for the hydrological response of the watershed. Watson et al., (2003) also applied SWAT to the Woady Yaloak River watershed in Australia. Their model performed extremely well at predicting annual discharge (NSE 0.75 and 0.77) but indicated that problems with groundwater and eucalyptus growth (Leaf Area Index simulation) constrained the ability to model water balance accurately.

CHAPTER III

METHODS

Research Design

To evaluate the relationship between LULC spatial distribution and water quality at the selected spatial scales, and to assess the health of the urban streams in the Reedy Fork and Buffalo Creek watersheds of Guilford County, NC, this research project is designed with several objectives:

1. Develop a highly accurate LULC map through the integration of GIS vector data and HR orthophoto.
    1.1. Analytical study: Quantify and analyze the spatial and temporal patterns of four disturbance indicators (PLAND, NP, ED, and LPI) to determine the effect of their spatial distribution on LULC changes in the study.
2. Explore and evaluate key factors influencing LULC spatial pattern at the 100 m, 150 m, and watershed scales levels to determine if the disturbance indicators explain more of the variability in nutrient loads at the stream monitoring sites using statistical analysis.

A review of these primary objectives indicates that the research goals are somewhat hierarchical in nature, in that, objectives 1, and 1.1 serve as inputs for the second objective. The second objective is identified as providing the main aim of this research. This research allowed the development, analysis, and discussion of each of the individual research components while still retaining an emphasis on the primary purpose of determining the relationship between LULC spatial pattern and water quality in the Reedy Fork-Buffalo Creek watershed. To carry out this purpose, a diagnostic framework was established. Statistical analysis procedures, including descriptive statistics, FA, correlation analysis, and simple regression, were conducted using LULC spatial pattern composition data generated by this research along with 12 water quality data collected from 18 sampling outlets within the study area.

In addition to the first two objectives, a third objective (scenario analysis) was carried out to determine the impact of future LULC change on stream water quality in the watershed. Land-use changes (agricultural and urban), nitrate and discharge (flow) are the important factors influencing water quality and quantity in the study area watersheds, and the goal was to simulate and estimate the annual nutrient loads (Nitrate) and runoff under current and future urban land-use change situations using the SWAT model. It is believed that understanding of the outcomes from this research holds the potential to evaluate the appropriateness of this tool under comparative states of the watershed qualities and information accessibility for specific water resources applications.

Research Questions

The main purpose of this dissertation is to apply a spatiotemporal scale approach to investigate the relationship between the change in LULC pattern distribution and stream water quality in the Reedy Fork-Buffalo Creek watershed at multiple spatial scales. This research tends to close the gap in the growing literature related to changes in

LULC spatial pattern distribution and water quality by examining the following research questions:

- First, at what spatial scale does diversity in landscape act to influence water quality and what components of the urban watershed landscape spatial patterns are mostly related to changes in water quality at that scale?

Numerous studies have suggested analyzing the relationship between LULC and water quality at selected spatial scales (Jarvie et al., 2002; Woli et al., 2004; Li et al., 2009; etc.). Some have noted analyzing the relationship at the watershed scale, while others suggest the analysis of LULC at the riparian buffer scales. This is because different LULC components show different influences at different scales. This is expected because, for a specific scale of analysis, the captured LULC type features for urban areas will be different from those captured within agricultural and forested environments.

- Secondly, will a 10% or more increase in impervious surface cause a statistically significant increase in water quality concentrations?

As Dunne and Leopold (1978), Paul and Meyer (2001) and others have stated, the main features of urbanization are a decrease in the pervious surfaces of a watershed leading to decrease infiltration and increase surface runoff. With watershed impervious surface area increases to 10–20%, runoff increases twofold; and 35–50% impervious surface area increases runoff threefold over forested watershed (Arnold and Gibbons 1996). Urbanized areas with impervious surfaces such as roads, rooftops, sidewalks, patios, and parking lots, may exert significant stress on stream system health in the watershed. Hence it is very likely that urban areas with a high amount of impervious surfaces (<10%) at the selected spatial scales will show a high level of water quality degradation in comparison to areas with low impervious surfaces (<10%).

Study Area Description

The relationship between land-use and water quality, as well as, hydrologic modeling application performed in this study focuses on the Reedy Fork-Buffalo Creek watersheds. Geologically, the watershed is primarily located in Guilford County, North Carolina, but the north-western section extends a little into Forsyth County. The watershed is part of the headwaters of the Cape Fear River Basin, the largest of the 17 major basins in North Carolina. The watershed has an area of 603.4 km2 with an exceedingly urban environment in the south. The northern part of the watershed, which is in a somewhat urbanized or rural setting, has rich agricultural zones. The Reedy Fork Creek Buffalo Creek watershed (Fig. 3.1) is framed from precipitation that keeps running off, impervious and pervious surfaces, and from water that leaks up from nearby springs. This water eventually winds up in the Atlantic Ocean, only south of Wilmington, NC. The watershed is situated in a transition zone between warm and sub-tropical atmospheres and has a warm-temperate, semi-moist mainland atmosphere with cold and dry winters as well as warm and muggy summers. Its annual high and low temperatures range from 69.3°F to 48.8°F. The normal yearly precipitation is around 42.36inches (City of Greensboro Report, 2012).

The rivers and streams in the watershed serve as an essential water hotspot for the agricultural watering system, industrial and residential use, drinking water, and fishing.

However, the rivers, streams, and riparian environment of the watershed are in poor condition on account of escalated human exercises (e.g. far-reaching stream regulation, obstructions to fish development and inordinate toxin release). Contamination in the rivers and streams directly impacts the water quality of the primary rivers and lakes of the watershed.

Guilford County is one of the highly populated counties in North Carolina. According to the Piedmont Tried Regional Council (PTRC) 2012 report, the population of Guilford County in 2010 was 488,406 with an average population density of 286 people per square kilometers. Between 1990 and 2000, the population of Guilford County grew by 73,628 people, (about 21.2%) and between 2000 and 2010, the county's population raised by 67,358 people, or 16.0% (PTRC, 2012). It is estimated that from 2010 to 2020, the population will increase by 12.0% (58,778 people). Between 2020 and 2030, the total population is projected to increase by 10.5%, or 57,720 people (PTRC, 2012). In the past couple of years, six suburban towns, all within a 10-mile radius of Greensboro, have incorporated. These include Stokesdale, Whitsett, Summerfield, Pleasant Garden, Sedalia, and Oak Ridge. Many of these suburban (and recently incorporated) communities immediately surrounding Greensboro had significantly higher population growth rates. This is because people have been relocating from the city centers and other areas to the suburbs in the watershed. For example, Summerfield, which adjoins Greensboro's northwest border, had a population growth rate of 316.0 percent, while the town of Whitsett, east of Greensboro, experienced a 156.0 percent growth rate (Triad Region Report, 2013). The increase in population in and around Greensboro resulted in an increase in impervious surfaces of about 8 percent from 2002 to 2013. Such changes in the landscape pattern are usually accompanied by the conversion of forest and agricultural land to residential and commercial areas or from forested land to farmland.

As urbanization increases in the watershed due to increasing in population, it results in putting pressure on the available water resources. Also, the quality of water in the urban streams likewise gets to be poor, particularly amid storm events. Roadside dust and soil, anthropogenic activities, as well as, vehicular (rubber fragments, engine oils, cadmium, and nickel) contribute a high level of pollutants to streams in a watershed. At a point when combined with rain and snowfall, these poisonous and, sometimes, oxygen-demanding toxins will bring about a brief but radical water quality changes.

The ceaselessly developing pressure on the city's water resources, brought about by the changes in land-use, management practices, environmental conditions and nutrients transport, and the need to save its exceptional aquatic biodiversity, make it extremely hard to accomplish a satisfactory and manageable harmony between water quality, availability and demand, unless a superior understanding of the watershed hydrology and its sensibility to variation in climatic conditions and land-use can be provided. Therefore, progresses in the general understanding and the ability to describe and predict the effect of land types, LULC spatial pattern distribution, and effect of spatial scales on the hydrology of the Reedy Fork-Buffalo watershed is critically required.

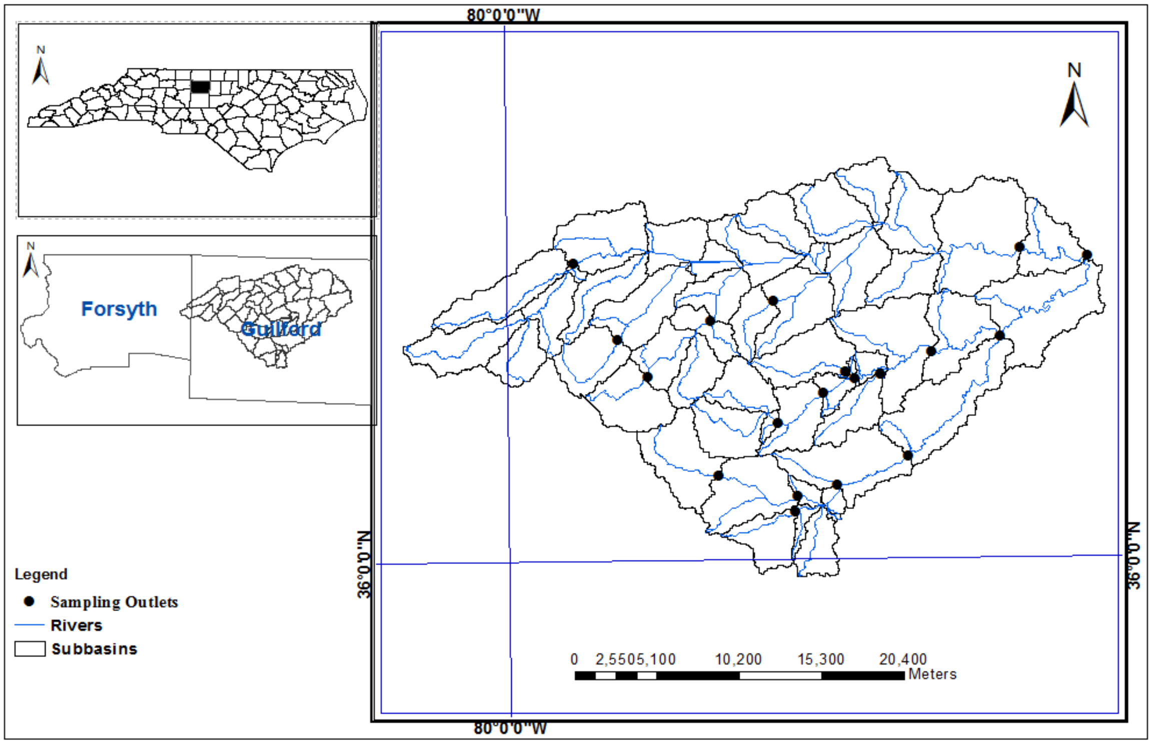


Figure 3.1. The Reedy Fork-Buffalo Creek Watershed.

Reason for Selecting the Study Area

The Reedy Fork-Buffalo Creek watershed is primarily characterized by urban, agricultural and forest land uses. It has 18 water quality sampling outlets established by the City of Greensboro Stormwater Division. Analyses in this study were limited to this watershed to correspond with the locations of water quality sampling outlet.

This study area was selected because of (a) input data availability and its representation of different types of LULC types within the watershed, (b) reduced amount of either hydropower base or significant irrigation system works; and (c) the lessened measure of snowfall in the watershed and its consequent reduced commitment of snowmelt to the overall discharge.

These last two viewpoints are viewed as a critical aspect of the study in that: the snowmelt commitments, as well as the presence of major flow deviations and reflections, would require exceptional consideration during the modeling process, because of their effect on the timing and magnitude of observed discharge values. This would require extra processes to be modeled, and in this manner further make the calibration and validation processes very complicated (the more the uncertainty included; the more parameters that must be tuned). This is not the case in the Reedy Fork-Buffalo Creek watershed. However, the selected watershed constitutes an interesting study area for evaluating the impacts land-use change have on watershed hydrology and water quality, as major conversions between agriculture and urban land-use have been experienced in this area over the past decades.

HR Orthophoto and GIS Ancillary Data

HR orthophotos and GIS data (Road centerlines, building footprints, and water layers) were acquired and used for the image classification. The HR orthophoto for 2002, 2008, 2010, and 2013 was downloaded from NC OneMap. These HR orthophotos had 3 spectral bands: Red, Green, and Blue, with a spatial resolution of 1/2 feet referenced to the State Plane Universal Transverse Mercator (UTM) Zone 17 projection. The orthophoto was resampled to a 0.5 m resolution so that its unit matches the units of the rest of the data. GIS vector files (non-spectral), referred here as “ancillary data” were obtained from The City of Greensboro Water Resources and GIS Department as road centerlines, building footprints. The ancillary data, which were in feet but having the same projection as the HR orthophoto were converted to meters using ArcMap. Taking into account previous works (Beykaei et al., 2010, Bahram et al., 2012, and Beykaei et al., 2013), the ancillary data (non-spectral GIS vector files) were used together with the HR orthophoto for the LULC classification. This was done to aid in the reduction of the significant time required for the orthophoto processing and to accurately classify surfaces that have similar spectral signatures (buildings, road network, pavements, walkways, etc.). The road centerlines were selected because it could be buffered based on the existing road width and together with the water and building footprint vectors can be inserted in the final classification with high precision.

Digital Elevation Model (DEM) and Soil Data

The Digital Elevation Model (DEM) used for this research was obtained from the U.S. Geological Survey (USGS), EROS Data Center and has a spatial resolution of one-third arc-second (10-meter resolution).

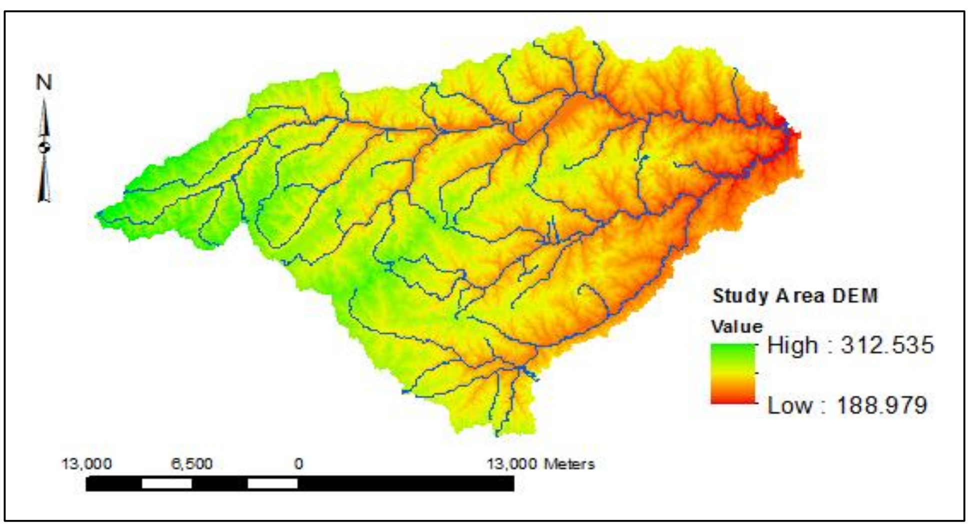


Figure 3.2. Slope for the Reedy Fork-Buffalo Creek Watershed

The layer representing the different soils in the basin is a Soil Survey Geographycal (SSURGO) data, Fig. 3.3, obtained from the Web Soil Survey of the Department of Agriculture Natural Resources Conservation Service (USDA-NRCS). Both the soil and DEM were referenced to the UTM Zone 17 projection.

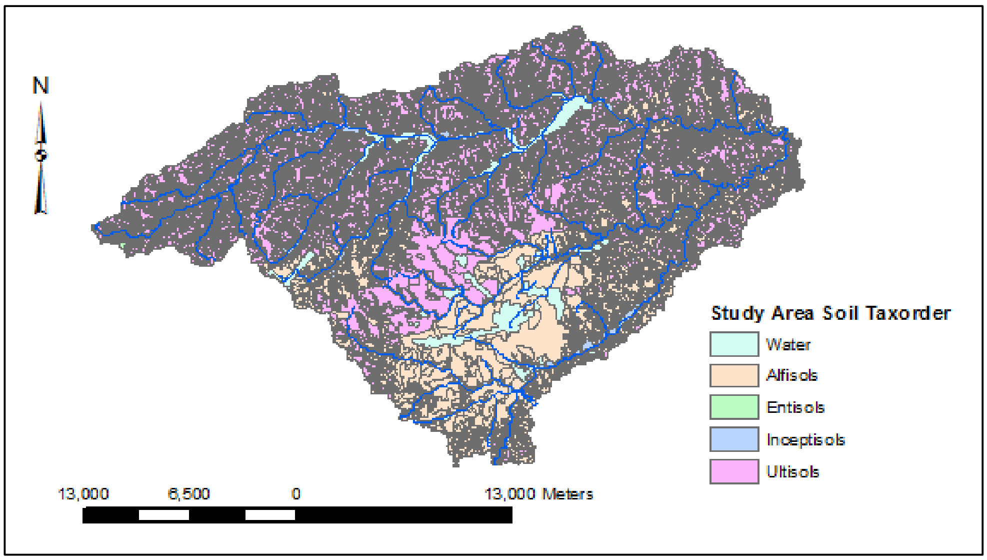


Figure 3.3. Soil Types for the Reedy Fork-Buffalo Creek Watershed.

Weather Data

Metrological data sets available for the study is made up of 16 years of time series (1998–2013) daily precipitation and temperature information, observed at 2 weather stations close to the study area (Fig. 3.4). This was obtained from the Climate Retrieval and Observations Network of the Southeast (CRONOS, 2016) Database for meteorological stations in the study area. In correspondence with the available data, the SCS CN approach and the Hargreaves technique were utilized for ascertaining runoff and evapotranspiration, respectively.

Discharge and Water Quality Data

There are 18 sampling sites within the Reedy Fork-Buffalo Creek watershed managed by the Stormwater Division of the City of Greensboro Water Resources Department. Twelve (12) water quality and flow data, grab-sampled monthly and bi-monthly were obtained from the department for our purpose. These includes: Total Suspended Solids (TSS, mg/L), Total Kjeldahl Nitrogen (TKN, m/L), Chemical Oxygen Demand (COD, mg/L), Biochemical Oxygen Demand (BOD5, mg/L), Total Dissolved Solids (TDS, mg/L), Total Phosphorus (TPhosphorus, mg/L), Turbidity (NTU), Nitrite (NO_2, mg/L), Nitrate (NO_3-, mg/L), Fecal Coliform (F.Col,CFU/100 ml), Hardness (m/L), and Conductivity (Cond., ohms/cm). Although there was adequate water quality sampled data over the 18 sites, not much flow data was available. Hence, modeled flow data based on two sampling stations (Friendship Church Road and Mcleansville Road) with enough flow data were used to fill this gaps. The modeled flow was done in SWAT model domain to aid effective statistical analysis.

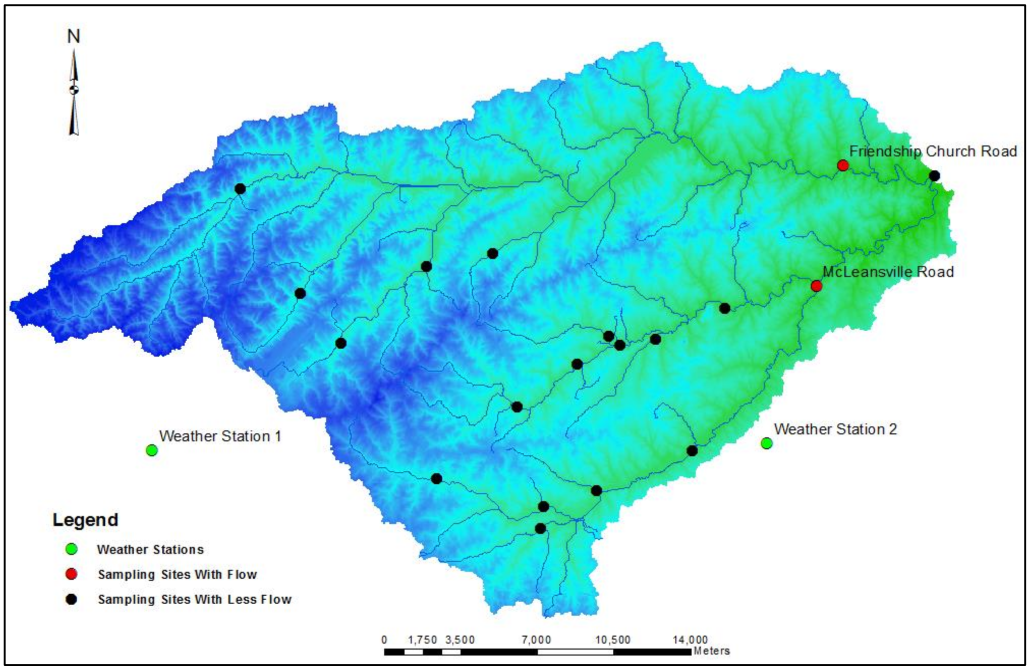


Figure 3.4. Location of Sampling Sites within the Reedy Fork-Buffalo Creek Watershed Used for the Calibration and Validation of the Model.

LULC Classification

Classified LULC map used in this research was based on the integration of ancillary data and HR orthophoto. Accurately classified data is very important because it serves as the basis for the landscape disturbance quantification and its relationships with water quality data. This section focuses on LULC classification. The procedure was based on Joined Pixel-Object Based Methodology taking after the Anderson et al., (1976) classification scheme. This was done using the Environment for Visualizing Images (ENVI) and ArcMap 10.3 software.

Processing of GIS Ancillary Data

To be able to perform an effective classification in this section of the research, it was necessary to fulfill all the needed processes related to the ancillary data usage the image classification. That is, the creation binary map representing impervious, water and vegetative environment using the building footprints, road centerline buffers, and water files. To extract features for binary data creation, the water vector file was overlaid on the 2002 orthophoto and examined for positional accuracy. Spatially mismatched areas were correctly adjusted and the result transformed into a binary image with values 0 and 1, where 0 is water, and 1- land. In a lot of traditional classification processes, close to 100 percent accuracy classifiers are always obtained when classifying the "water" class, but usually lots of problems are encountered in areas presenting a mixture of uses (mostly in urban environments), often referred to as 'mixels' (Beykaei et al., 2013). Hence, in these situations, it is prudent to use the already existing GIS water vector data. For the impervious binary, the road centerlines and building footprints were examined cleaned, and areas missing data were digitized accordingly to represent existing impervious features correctly. The road centerlines were buffered based on existing road width in the study area. The buffered roads and building footprints were merged and the result transformed into a binary image with '1' and '0' representing impervious and land areas respectively. Because the impervious and water will be included in the final classes, the final stage in the ancillary data processing is the creation of a single band ancillary data. This was achieved by combining the two binary files using the raster calculator in

ArcMap 10.3. The result was a single image file with assigned values of 1 for impervious, 2 for vegetation, and 3 for water.

Pixel-Object-Based Classification

The methodology used for the LULC classification is structured based on the following layered image classification approach: Pre-classification extraction; Pixel-based classification (maximum likelihood); Post-classification Extraction; Post-classification smoothing and data integration; and Accuracy Assessment. In the use of ancillary data in image classification, common approaches make use of the ancillary data either before, during, or after the processing stages (Beykaei et al., 2010, Bahram et al., 2012, and Beykaei et al., 2013). In this work, the initial and final steps make use of the ancillary data.

Pre-Classification Extractions

First, pre-image classification extraction was carried out in ArcMap 10.3. The objective at this stage is to use the ancillary data to extract objects in the orthophoto, thereby, creating a 'hole' in the orthophoto. Preliminary investigation indicates that extraction of features in the HR orthophoto before image classification does reduce not only the size and processing time of the orthophoto but also maintain a high level, all the properties inherent in the orthophoto for an accurate result to be obtained. Also, it reduces the misclassification of parking lots, driveways, and pavements, which have similar spectral signatures as roads and roof on buildings. This makes it easy for an accurate classification to be obtained in a highly urban environment. Based on this, the binary ancillary files were used as a mask to extract the impervious (roads and buildings) and water environment from the orthophoto before classification. The result is an orthophoto with only vegetation, parking lots, driveways, and pavements for the pixel-object based classification.

Pixel-Based Classification – Bare Earth, Parking Lots, Pavements, Driveways, Vegetation

After the pre-classification extraction, what remained was areas comprising vegetation, bare earth, parking lots, and driveways. The pixel-based land-cover classification was then performed to classify these land-covers using Maximum Likelihood (ML) image classification technique. The classes were then extracted after the ML classification. Because of the similarity in composition and spectral characteristics of bare earth, its extraction did not pose much of a problem. Also, since the ancillary data (building footprint, water, and road buffer) were initially masked-out from the orthophoto during the pre-image classification stage, it made it easier to subtract the vegetation and bare earth leaving parking lots, driveways, and pavements classes. The extracted results from the pixel-based classification were assigned values based on the individual land-cover and mosaicked. Parking lots, driveways, and pavements were assigned a value of ‘1’, bare earth and grass ‘4’, and forest a value of ‘5’.

Shadows

Shadows are dark features in an orthophoto or imagery, which tends to influence the surrounding area object or structures. Shadow reduces the spectral values of the shaded objects and as such influences the land-cover classification (Lu et al., 2010). In the creation of the classified map, shadows were treated as a separate class, extracted and later added to the impervious classes. To be able to know the class to assign the extracted shadow, visual inspection shows that a good percentage of shadow was casted on roads and parking lots. Since pavements, driveways, parking lots, buildings, and roads fall under one LULC class in the study area, the extracted shadow was assigned to the impervious land cover class in the final result.

Post-Classification Extractions

The aim is to have agricultural, forest and grass as separate classes. However, classifying agricultural was a bit of a challenge. Hence, the Cropland Data Layer (CDL) was used. Here, all the croplands within the study area in the CDL data were grouped as one layer, extracted from the forest and grass class obtained from the pixel-based classification and assigned a value of 2 representing agricultural classes.

Post-Classification Smoothing and Data Integration

The image classification procedures for extracting the urban LULC, though produced a great result, came with some slight "noisy" patches. To do away with this, a post-classification smoothing was carried out in ArcMap using defined threshold of less than (<) 50 to determine the patches to be cleaned. This threshold was chosen based on the knowledge and continued work carried out in the study area. Since the idea is to develop 5 LULC classes, the binary ancillary data (road buffer and building footprint) and the classified parking lots, pavements, shadow, and driveways were merged into a single class (impervious) and assigned a value of '1'. Agricultural from the CDL was assigned a value of 2. Water a value of ''3', bare earth and grass were merged as grass and assigned a value of '4'and forest were assigned values of ''5. Finally, the layered classes were mosaicked using the image analysis tool in ArcMap10.2 and reclassified (Table 3.1).

Table 3.1 LULC Classification Code.

Code	LULC Classes	Description
1	Impervious	Residential and industrial building areas and transportation.
2	Agricultural	Irrigated and unirrigated land, animal rearing, vegetable land, and fruit land
3	Water	Lakes, rivers, reservoirs, and ponds
4	Grass	Sparse woodland, rangelands in water deficit, and other grasslands
5	Forest	Arboreal forest, shrubbery area, and economic forest

Accuracy Assessment

Verifying the accuracy of classified maps before its use in any study is very important (Jensen, 2005). Jensen maintains that when a classified map is used for any research work and policy-making purposes, a statistical figure explaining the reliability of the data is required. However, if the data will not be used for such purposes, visual inspection of the data’s reliability is adequate.

Accuracy assessments were undertaken in this study to determine how well the classified image performed against the orthophoto using statistical figures. However, before this could be executed accurately, the right numbers of samples have to be used for the needed accuracy to be obtained. In practice, the required number of samples (ground truth) is limited by the extent of the study area. According to Congalton and

Green (1999); and Jenson (2005), the evaluation of the number of points required to validate the results of an image is based on several criteria, including the number of classes, and their proportion. From a statistical perspective, the number of samples to be validated must be adequate for measuring the variability associated with the variable tested.

Hence, the number of sample size needed to validate the classified map was obtained based on a multinomial distribution equation by Jenson (2005) in equation (7) below.

$$N = \frac{B\prod_i (1 - \prod_i)}{b_i^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where;

N is the number of sample size, $\prod_i$ is the proportion of a population in the ith class out of k classes that has the proportion closer to 50%, b_i is the desired precision for the class, B is the upper $(\alpha/k) \times 100^{th}$ percentile of the chi square (X^2) distribution with 1 degree of freedom and k is the number of classes.

In this research, the desired precision was 95% for all classified data. Based on the calculated number of sample, stratified random sampling technique was employed to distribute the samples based on the size of each class in the classified map. Placement of random points throughout the study area will give a correct representation of the surfaces to be assessed for accuracy. The stratified random sampling was done with the Hawth tool, an extension for ArcGIS. An on-site inspection was also done to check the accuracy of some of the randomly generated points for the 2013 data since it was the closest year to current year.

Accuracy assessment was then performed in ArcMap resulting in an error matrix. Error matrix represents a systematic comparison between the classified image pixel and the ground reference for the same location. It also provides information about the error inherent the data (commission and omission) and helps refine classification output. In the error matrix, rows indicate derived class information and columns indicate the reference image. Pixels classified accurately are the diagonal values of the matrix, and the others represent pixels that have been misclassified pixels. Accuracies obtained from the error matrix includes: Overall accuracy (the ratio of correctly classified sample pixels to the total number of samples used for the assessment); producer's accuracy (the number of accurately classified pixel of a class divided by total number of pixel in that column and it shows how accurately an area could be classified using this particular classification). User's accuracy which corresponds to the probability that classified map matches the reference data is obtained when the correct number of pixels in a row is divided by row total for a category. Kappa statistics, which represent the agreement between the reference data and classified results (Congalton, 1981) is also obtained from the matrix. Landis and Koch (1977) suggested the following guidelines: kappa values ≤ 0.40 represent poor-to-fair agreement; 0.41–0.60, moderate agreement; 0.61–0.80, substantial agreement; and 0.81–1.00, almost perfect agreement. Accuracy assessment results are provided in the result section, Chapter IV.

Relative Change and Dynamic Index of LULC

Relative change and dynamic index of the classified LULC maps were quantified to give an insight of the changes that have occurred over time. The relative change indicates the absolute change as a percentage of the value of the LULC in the earlier period. The dynamism of LULC describes the conversion between the areas of types of LULC in a locality (Wang et al., 1999). The dynamic of LULC classes was quantitatively monitored based on the intensity of one type of land-cover using the dynamic index (Wang et al., 1999) with results being displayed in two dimensions. The relative change A and dynamic index B, of a LULC type, were calculated based on equation (8) and (9).

$$A = \frac{Y_b - Y_a}{Y_a} (100\%) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$B = \frac{Y_b - Y_a}{Y_a} (1/T)\,(100\%) \ldots\ldots\ldots\ldots\ldots (9)$$

Where Y_a and Y_b represent the beginning and the end of a LULC type respectively. T is the length (period) of time; A is the relative change, and B represents the rate of change of a certain LULC type per year. The equations above were used in this study to examine the degree and directions of change in LULC in the Reedy Fork-Buffalo Creek watershed. The relative change was calculated for 2002 and 2013 to determine the change in 2013 LULC in relation to 2002 LULC.

Stream and Watershed Delineation

The mainstream and watersheds of the Reedy Fork-Buffalo Creek were delineated from the DEM using SWAT2012 model. The model was set up using a threshold of 800 ha as a drainage area for delineating the watershed. This resulted in 55 subdivisions of the watershed. For ease of analysis, the 55 were aggregated into 18 so as to match with the sampling sites in the watershed. The model also generated stream centerlines. A series of riparian buffers of different widths, ranging from 100 m to 150 m on each side of the river buffers were derived based on the derived stream centerlines in ArcMap domain.

Quantifying Classified LULC Change Map

Landscape indicators provide information on the condition of landscapes (Dale 2001; Bolliger 2007) and multiple indicators addressing different aspects of land-use change can help to reveal broader impacts of human disturbance. In LULC analysis, softwares have been developed which quantifies and categorizes complex landscapes into identifiable patterns. Notable among them is FRAGSTATS. Therefore, in this section, LULC patterns were quantified from the classified orthophoto using FRAGSTATS (McGarigal and Marks 1995), developed to calculate landscape metrics, which can be useful in understanding LULC changes in watersheds

LULC Patterns Spatial Scale of Analysis

The influence of land-cover composition at various spatial scales represented an additional area of investigation for this research. A review of 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 (Smart et al., 2001; Sponseller et al., 2001; Sliva and Williams 2001; Griffith 2002; Strayer et al., 2003; King et al., 2005; Alberti et al., 2007; Xiao and Ji 2007; Maillard and Santos 2008; Lee et al., 2009; Tan et al., 2010; Jones et al., 2001).

Contradictory results had been obtained in several of these studies. Therefore, to contribute to the literature regarding the effects of scale on land cover and water quality relationships, an examination of LULC composition at select scales in the Reedy Fork-Buffalo Creek was undertaken.

The following spatial scales were selected for analysis for the analysis: watershed; 100 m buffer, and 150 m buffer. The create buffer tool in ArcMap 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, had to be extracted from each of these buffers and watersheds, its area value exported, and the percent coverage calculated. With the 100 m and 150 m spatial scales and 18 individual watersheds, this required about 36 different stream buffer runs, followed by area calculations. The created buffers were measured from the delineated stream centerline to the outer edge of the buffer. Therefore a 100 m buffer has a total edge-to-edge width of 200 m, and a 150 m buffer has a total width of 300 meters. The stream centerlines were delineated with the aid of the SWAT model. The 100 m buffer was chosen based on a review of the existing scientific literature (Maillard and Santos, 2008; Li et al., 2009), 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 m 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 increasing riparian buffer zone scales, so 150 m was selected to test whether this trend would continue or change above the 100 m buffer distance.

The riparian buffers were created using the final derived stream centerlines. Using this 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 the land-cover composition. The delineated watershed and stream centerline buffer images are displayed in Fig. 4.1 to Fig. 4.3. For simplicity, the names of the sub-watersheds were abbreviated. These are Sixteenth St (16^{th} St), Aycock St. (AS), Battleground Ave. (BA), Bluff Run Rd. (BRR), Church Rd. (CR), Fieldcrest Dr. (FD), Fleming Rd. (FR), Friendship Church Rd. (FCR), McConnell Rd. (MCCR), Mcleansville Rd. (MCLR), Meritt Dr. (MD), Old Oak Ridge Rd. (OORR), Pleasant Ridge Rd (PRR)., Randleman Rd. (RR), Rankin Mills Rd. (RMR), Summit Ave.(SA). West JJ Dr.(WJJD), and White St. (WS).

Landscape Metrics Derivation

The final procedure undertaken in this section of the research component involved the quantification of landscape indexes for Impervious, Agricultural, water, grass, and forest at the watershed, subwatershed, and riparian buffer spatial scales. PLAND, NP, ED, and LPI of impervious, agricultural, water, grass, and forest LULC coverage were calculated for the entire Reedy Fork-Buffalo Creek watershed, sub-watersheds, as well as their spatial buffers so that more detailed and comprehensive statistical analyses could be undertaken on them. FRAGSTATS (McGarigal and Marks 1995) designed specifically as an ESRI ArcGIS extension tool, provides an integrated user interface that enables metrics to be calculated for LULC layers at both landscape and class levels was used in this study. Landscape-level metrics calculate values with all classes included (e.g., mean patch size within a watershed) while class-level metrics calculate values for specific classes (e.g., the number of patches of impervious areas). For each of the four LULC maps in this study (i.e., 2002, 2008, 2010, and 2013), the spatiotemporal changes were examined and quantified for four class level metrics (PLAND, NP, ED, and LPI) in the Reedy Fork-Buffalo Creek Watershed Table 3.2. The class level metrics has spatial features which allow it to represent each LULC classes and aids in assessing the transformation types which affects the landscape spatial patterns (McGarigal and Marks 1995).

Table 3.2. Description of Landscape Configuration Metrics (Class level) Used.

Structural category	**Landscape metrics**	**Description**	**Units**	**Range**
Area/Density/Edge	Percentage of Landscape (PLAND)	Measures the percentage of landscape	Percent	0 < PLAND ≤ 100
	Number of Patches (NP)	The number of patches in each land-use	None	NP ≥ 1, no limit
	Largest Patch Index (LPI)	Equals the percentage of the landscape comprised by the largest patch.	Percent	0 < LPI ≤ 100
	Edge Density (ED)	Total length of all edge segments per hectare	Meters per hectare	ED ≥ 0, no limit

Exploring and Evaluating the Relationships between LULC Patterns on River Water Quality at Multiple Scales

Completion of the HR orthophoto classification, LULC pattern quantification, as well as water quality data acquisition, provided the inputs required to explore the relationships between LULC patterns and water quality variables in this research using statistical techniques. However, the main concern in water quality research and analyses is the selection of right statistical, presentation, and analytical methods to determine the relationships between LULC and water quality parameters (Carpenter et al., (1989). Due to the spatial autocorrelation and non-independence of sampling site issues that often accompany research into water quality and LULC, the selection of appropriate statistical techniques is especially important (King 2005; Griffith 2002; Hunsaker and Levine 1995). There are many different types of statistical analysis that can be performed on water quality data for reporting and interpretation purposes. Some of the commonly used statistics include; Principal Component Analysis (PCA), Factor Analysis (FA), Correlation analysis, and Regression Analysis. Johnson and Gauge (1997) reviewed statistical methods and different landscape approaches to study linkages between landscape factors and stream, river, or lake ecology. The authors stated that LULC factors that affect water bodies occur at multiple levels. Initially, Hynes (1975) mentioned a strong influence of valleys on streams. However, he stated that it is very difficult to analyze such a heterogeneous system in order to understand complex processes. After the emergence of remote sensing and GIS technology, it has become possible to capture heterogeneous spatial systems at various scales with relative ease (Johnson, 1990).

Hence, the quantitative assessment of landscape factors has become possible because through the combination of these technologies and statistical analysis packages (Petts et al., 1995; Puckett, 1995).

In this work, FA, Correlation, regression analysis, and descriptive statistics were used to explore the relationship between the data.

Descriptive Statistics

Though not critical in ecological studies, many inferences can be made from simple descriptive statistics such as mean, minimum, maximum, median, range, and standard deviation with respect to the variables under study. Li and Migliaccio (2011) emphasized the importance of presenting the common data measures most often used in descriptive statistics as the primary step in any water quality analysis. Most of these statistics are self-explanatory. The minimum and maximum give the lowest value and the highest value in a dataset respectively. The range is the difference between the minimum and the maximum. The median value of water quality variables is often used to remove the undesirable effects of outliers on water quality datasets. The mean value, which is one way of finding the center value of a data set, is still a useful measure of central tendency, along with mode, but can be skewed by the existence of outliers (set of extremely high and low values). The distribution or normality of water quality datasets is also very important, along with statistical indices of variables such as range, variance, and standard deviation. Graphical representations of descriptive and other statistical analysis are also often needed and summarizing analysis results in tables, graphs, or charts for reporting purposes can be very helpful to the reader.

Descriptive statistics were carried out on the water quality variables to help present the data in a more meaningful manner for simple interpretation. The mean value for each water quality variable for each sampled site was calculated over the entire study period. These values were organized within an Excel spreadsheet and an SPSS domain.

Factor Analysis (FA)

FA is a multivariate statistical method that has been utilized effectively in water quality research for many years and is well described in the literature (Praus, 2005). The FA allows the derivation of hidden information from a data set linking the influences of environment factors on water quality (Spanos et al., 2003). In FA, attempts are made to explain the connection between the underlying factors of data, which are not directly observable (Yu et al., 2003). According to Gupta et al., (2005), three phases are involved in performing FA: generation of a correlation matrix for all variables, extracting of factors from the correlation matrix based on correlation coefficients of the variables, and rotation of the factors to maximize the relationship between some of the factors and variables. The first step is the determination of the parameter correlation matrix. It is used to account for the degree of mutually shared variability between individual pairs of water quality variables. Then, eigenvalues and factor loadings for the correlation matrix are determined. Eigenvalues correspond to an eigenfactor which identifies the groups of variables that are highly correlated among them. Lower eigenvalues may contribute little to the explanatory ability of the data. Only the first few factors are needed to account for much of the parameter variability. Once the correlation matrix and eigenvalues are obtained, factor loadings are used to measure the correlation between the variables and factors. Rotation of factors is used to facilitate interpretation by providing a simpler factor structure (Zeng and Rasmussen, 2005). Some studies that have used FA for water quality analysis are, Liu et al., 2000, Yidana et al., 2007; and Millard and Neerchal, 2001).

In this section, the water quality variables were subjected to FA to extract the most influential factors affecting water quality in the study area. The stream water was pretreated before undergoing statistical analysis. Monthly specific water quality values were entered into Excel and SPSS. To avoid the influence of occasional extreme pollution events during the period of study, outliers were screened, and each parameter data was log transformed using the base-10 logarithm to avoid misclassification of the water quality variables.

Similarly, the suitability of the water quality data for FA was examined using the Kaiser–Meyer–Olkin (KMO) and Bartlett's test. KMO is a measure of sampling adequacy and data suitability for FA. KMO values range from 0 to 1. High values (close to 1) indicate that FA may be useful. Bartlett's sphericity test of indicates tests whether the data for FA comes from a multivariate normal distribution with zero covariance's. For FA to be recommended suitable, the Bartlett's Test of Sphericity must be less than 0.05. (Nair et al., 2010). The communality of the variables, which is the portion of the variance that a variable share with the common factors, is important to obtain accurate and stable solutions. Like KMO, communality values ranges from 0 to 1. Communality values close to 1 indicates an accurate and stable solution in the interpretation (Mahloch, 1974).

These factors obtained from the FA were applied to identify groups of related stream chemistry parameters so that their relationships with LULC characteristics could be analyzed.

Correlation and Regression Analysis

Regression analysis is also frequently used to provide greater explanatory power of 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, Sliva and Williams (2001) utilized a similar methodology for their research in Ontario, Canada. Maillard and Santos (2008) also made use of regression analysis in their research regarding land cover and water quality in Brazil, in order to help establish the relative importance of various LULC compositions regarding their explanatory value for water quality. 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 before regression is presented by Jones et al., (2001), who employed log transformations to produce more accurate regression results from their analysis regarding landscape metrics and water quality.

Pearson correlation and regression analysis were performed after the extraction of the most influential water quality parameters using FA. This involved statistical analyses of annual mean values for each water quality variable and the LULC composition variables. Annual mean values for the water quality variable for the Reedy Fork-Buffalo Creek watershed were grab sampled at the 18 outlets the 12 water quality variables for the year 1999-2002, 2003-2008, 2009-2010, and 2011-2013 respectively. The 18 watersheds were each represented by 12 distinct combinations of LULC: PLAND impervious, PLAND agricultural, PLAND grass, and PLAND forest cover at the watershed scale, the 100 m buffer, and the 150 m buffer. PD, NP, and LPI at the various spatial scales with landscape metrics composition were also obtained and used in the analysis. Correlation analyses and simple regression analyses were undertaken on the $\log_{10}(x)$ transformed values for these variables to determine the correlation coefficients, p-values and R-squared values for each pair of log-transformed variables. The regression methods were employed to identify a final model with only significant ($p < 0.05$) independent variables included. Water quality variables were considered as dependent variables, while variables, including PLAND, ED, NP, and LPI of each LULC type (e.g., impervious, grass, forest, agriculture) were treated as independent variables. Water was not considered because there was no significant change in its values over time. A comparison was made regarding how the correlations between river water characteristics and landscape pattern varied with the spatial scale of analysis using the coefficient of determination R^2. Average R^2 of the buffers of 100 m and 150 m were calculated to represent narrow and median scale respectively, and the average value in the watershed to represent wide scale. For each water quality sampling site in this study, the values of each variable were averaged for four time periods: 1999–2002, 2003-2008, 2009-2010 and 2011-2013. The grouping was done corresponded to the approximate dates of the HR orthophoto used to generate the LULC maps. This phase was undertaken with the intention of providing a more temporally detailed and comprehensive examination of the relationship between water quality and LULC data.

Modeling the Effect of LULC Changes on Discharge and Water Quality

Data used for SWAT modeling was made up of spatial and temporal data. Spatial data includes DEM, Soil, Land-use (2010 data) and temporal data includes weather, discharge, and nitrate data. Discharge and nitrate data were adequately sampled at two sampling stations located in the watershed at Friendship Rd. and Mcleansville Road near the outlet of the watershed. These are very important in the modeling approach.

SWAT Model Setup

The widely used SWAT model is a watershed scale continuous model that works on a daily time series and assesses the effect of management practices on water, sediment and farming chemical yields in ungauged watershed. The model's real components incorporate climate, hydrology, erosion, soil temperature, plant development, nutrients, pesticides, land-use management, channel and reservoir routing.

One of the first steps in setting up SWAT model is to identify the calculation units or the Hydrological Response Units (HRUs) for the water balance. For this purpose, the Reedy Fork-Buffalo Creek watershed was extracted from the DEM, using standard analytical techniques contained in the ArcSWAT interface (a minimum upstream contributing area of 800 ha was used as a threshold value for defining river cells). In total 55 sub-watersheds were defined and 333 HRUs. These units comprise of homogeneous land use, slope and soil properties. The water balance of each HRU in the watershed is represented by four storage volumes; snow, soil profile, shallow and deep aquifer. In this study, the choice of predominant land-use and soil in the sub-basins was utilized to lessen the substantial computational time required. The SCS curve number method was also chosen to recreate surface runoff, and the Hargreaves approach to predict the evapotranspiration. The lateral subsurface discharge in the soil profile was calculated at the same time with percolation. To predict the lateral flow in each soil, the kinematic storage routing based on slope, the length of slope, and saturated hydrologic conductivity was utilized. In the model, lateral flow occurs when the storage capacity in any layer surpasses field limit after permeation. Groundwater discharge contribution to discharge originates from the storage of shallow aquifer (Arnold and Allen 1996). Movement of water from the surface to the base of the root zone is considered as recharge to the shallow aquifer and water is directed to the channel system utilizing the variable storage routing strategy. The simulation period for these study was from 01 January 1998 to 31 Dec. 2013. All necessary files needed to simulate SWAT were written at this level, and the appropriate selection of weather sources was done before running the SWAT executables.

Sensitivity Analysis, Calibration, and Validation of Discharge

Incorporated into the SWAT model is an extensive number of parameters which portray the diverse hydrological conditions and attributes across the watershed. Amid calibration procedure, model parameters are liable to different sorts of alterations, with a specific end goal to acquire model results that relate better to observed data. The scope of parameter values utilized as part of the calibration procedure must be physically conceivable (Eckhardt et al., 2005) so that the model can be used later to assess the effect of change scenarios.

The selection of the “most suitable” calibration and uncertainty techniques for the SWAT model depends on the expected results, the hypothesis behind it, its simplicity, its computational proficiency, data accessibility and the modeler's abilities (Yang et al., 2008). Calibration of the model parameters can be done manually (inside SWAT model) or using semi-automated software. Some of the available semi-automatic software includes Parameter Arrangement (ParaSol) and General Likelihood Uncertainty Estimation (GLUE), Sequential Uncertainty Fitting (SUFI-2) just to mention a few. Though there are various kind of software for calibration and validation, the SWAT model calibration and validation in this research were performed with sequential uncertainty fitting (SUFI-2).

The Sequential Uncertainty Fitting (SUFI-2) algorithm created by Abbaspour (2008) was chosen as the most adapted algorithm for the calibration of the discharge in the study area watershed. The algorithm used by SUFI-2 is added in SWAT Calibration Uncertainty Procedures (SWAT-CUP) tool. It uses as an input, the output from the SWAT model for calibration and uncertainty prediction. The uncertainty of inputs parameters in the SUFI-2 is represented by uniform distributions, while model output uncertainty is evaluated by the 95 Percent Predicted Uncertainty (95PPU). Also, two efficiency criteria, P and R factors, that give a measure of the model's capacity to determine uncertainties and a measure of the quality of calibration, respectively were introduced in the SUFI-2. Specifically, the P component is the percentage of measured data sectioned by the 95PPU and should have a value of 1, which is 100%. The R component, on the other hand, shows the thickness of the 95PPU band and it is computed as the mean separation between the upper and lower 95PPU separated by the standard deviation of the observed data (Abbaspour, 2008). The R variable ought to be preferably close to zero, in this manner harmonizing with the measured data. In assessing these two variables, SUFI-2 evaluates the best parameter values through an interactive methodology, maximizing or minimizing the objective function (Abbaspour, 2008).

The SUFI-2 was selected and used for this work because it has been broadly utilized as part of the calibration of the SWAT model at the watershed scale due to its simple usage and the reduced number of model runs expected to accomplish great prediction (Yang et al., 2008). Also, in comparison to other the other methods, SUFI-2 is portrayed by a high flexibility in the choice of different components, for example, parameters and ranges, the time scale and the determination of gauged sub-basins to be calibrated (Yang et al., 2008).

For the model calibration in this research, time series of monthly discharge data from 2002 to 2013 from the two stations (Friendship Church Road and Mcleansville Road Rd) were used. These two stations and their nested sub-watersheds together cover about 96% of the entire drainage area of the Reedy Fork-Buffalo Creek watershed (Fig. 3.4). For the calibration period, the model was run using precipitation and temperature information from 1998–2010 as input with the initial four years of the modeling period used for the "model warm-up." Before the calibration procedure was done in SWAT-CUP using SUFI-2, a sensitivity analysis was carried out for each station, keeping in mind that, the end goal is to decide on the parameters to which the calibration results are most sensitive. The nine "most sensitive" parameters, considered and used in the calibration, was determined by Latin Hypercube Sampling- One-at-A-Time analysis (LH-OAT) (van Griensven et al., 2006).

Validation process which also considers the “most sensitive” discharge parameters followed the calibration process. The validation process was performed taking into account discharge for the 2011-2013 period.

Sensitivity Analysis, Calibration, and Validation for Nitrate Load

Like discharge, SUFI-2 in SWAT-CUP was again used determine the “most sensitive” parameters for nitrate load calibration and validation at the Friendship Church Rd. and the Mcleansville sampling sites within the Reedy Fork-Buffalo Creek watershed.

Calibration and validation of nitrate using the SWAT model are important because of the complexity of the nitrogen components and its intensive input data requirements. The nitrogen model development for the Reedy Fork-Buffalo Creek watershed was made after calibration and validation of SWAT’s hydrology components since hydrology is the main driving force behind every one of the processes in SWAT model. This is because hydrology affects plant development and the movement of sediments, nutrients, pesticides, and pathogen within the watershed region (Arnold et al., 2012). Monitoring results for Nitrate nitrogen collected through by the City of Greensboro water quality department for the year 2002-2010 and 2011-2013 were used for the calibration and validation of the model respectively. Monthly calibration and validation were made for the watershed. Procedures similar to those used in hydrology predictions were applied for sensitivity analysis and calibration and validation of nitrate nitrogen.

Performance Evaluation of the Model (Discharge and Nitrate)

In most simulation studies, model performance evaluation is necessary for the verification of the robustness of the model by comparing simulated output and observed measurements (Moriasi et al., 2007). In general, no comprehensive standardization is available for model evaluation. However, Moriasi et al., (2007) presented several model evaluation statistics for model calibration and evaluation. To evaluate the performance of the model, according to Haan et al., (1982), graphical representation of the result could easily be interpreted if the calibration is done for only one watershed at one stream gauging location. Time series plot of the observed and simulated data and a scatter diagram of observed data plotted against simulated data were used in this study for a graphical representation of the result. Though scatter diagram method does not show the flow sequence contained in the time series plots, it shows the difference between a simple regression line through the plotted points, and this line helps identify errors that can be used with these graphical displays.

In this research, besides the graphical representation of the output, several statistical outputs were also used to provide useful numerical measures of the degree of agreement between the simulated and observed values.

Evaluation of the performance of the model was done by comparing the observed and simulated monthly data at the Friendship Church Road and Mcleansville Road station for both the calibration and validation periods. The accuracy of SWAT model simulation results, obtained in this research was determined by examining four quantitative statistical parameters; mean, standard deviation (SD), coefficient of determination (R^2) and Nash and Sutcliffe Efficiency (NSE). The mean and standard deviation indicate whether the frequency distribution of model results is similar to the measured frequency distribution. The R^2, on the other hand, indicates the strength of the linear relationship between the observed and simulated values. This R^2 value is most often used in linear regression. Linear regression gives a formula for the line most closely matching with a set of data points, in this case, the simulated and observed values. It also gives an R^2 value to say how well the resulting line matches the original data points. The values range from $0 < R^2 < 1$ where higher values indicate less error variance. The value of Nash and Sutcliffe model coefficient determines the efficiency at which the model performs. The value ranges from 0 to 1.0 and the higher the value, the better the model prediction output. The R^2 and NSE values were obtained based on the following equations (10) and (11):

$$R^2 = \frac{[\sum_i (Q_{m,i} - \bar{O}_m)(Q_{s,j} - \bar{O}_s)]^2}{\sum_{m,j} (Q_{m,i} - Q_m)^2 \sum_i (Q_{s,i} - Q_s)^2} \qquad \ldots\ldots\ldots\ldots\ldots (10)$$

$$NSE = 1 - \frac{\sum_i (Q_{m,i} - Q_m)_i^2}{\sum_{m,j} (Q_{m,i} - \bar{O}_m)^2} \qquad \ldots\ldots\ldots\ldots\ldots (11)$$

Where:

Q_m is the deliberate release, Q_s is the reenacted release, $\bar{O}_m$ is the normal measured release and $\bar{O}_s$ is the normal mimicked release.

Estimation of Water Balance

To be able to manage water issues, it is important to break down and measure the diverse components of hydrological procedures happening inside the range of interest. Some of these components comprise water yield, runoff, Evapotranspiration, etc. Understanding the spatial and temporal variety and interaction of these hydrologic parts could be instrumental in helping water management organizations in the detailing of methodologies for water protection. In this manner, as a further examination, SWAT model was utilized to evaluate each of the hydrological forms happening in the study area watershed considered in this research.

Scenario Constructs for Land-Use Change

As an important part of the Cape Fear River basin, the Reedy Fork-Buffalo Creek Watershed currently provides water for many industries and residences and is a valuable fish and wildlife habitat and an aesthetic landscape. In 2010, only 24.2% (or 145.9 km^2) of the watershed had been converted to urban or suburban use (Impervious). The remainder consists of forest (42.7%); agricultural uses (5.8%); and water (2.7%), and grass (24.6%).

To predict the future changes in water quality conditions in the Reedy Fork-Buffalo Creek watershed, some kind of future and land-use scenarios had to be developed. In this study, the 2010 land-use map was used for the current scenario. The future land-use scenario was developed to determine the long term effect of increased impervious LULC change on runoff and water quality with particular emphasis on nitrate nitrogen. Nitrate was considered because previous statistical analysis indicated that nitrate loads are the dominant nutrient in the study area for the 2002-2013 study year. The effect of impervious surfaces on water quality has been well documented. Arnold and Gibbons (1996) characterized streams within watersheds containing <10% of impervious cover as protected, 10-30% as impacted, and greater than 30% as degraded. Linking an imperviousness threshold to water quality can be challenging. However, many studies do not differentiate between total and effective impervious cover within watersheds because of ease of analysis (Brabec et al., 2002). The initial LULC analysis shows that there is a continual increase in impervious surfaces in the study area watershed (Table 4.5). Based on these, the question is; how does an alternate change (Increase) in the impervious area affect the hydrology and water quality in the long run? To answer such question, a scenario was constructed to understand the impact of an expansion of impervious surface.

To conduct the scenario analysis, ultimately, three scenarios of land use change were considered. The past land-use (2002), present land-use (2010) and future land-use (2030). Under the current land-use (1): 24.2% of the watershed is developed (impervious). For the past land-use scenario (2): impervious land-use was 18.01% (Table 3.3). For the future land-use Scenario (3): LULC for the study area was created from 2011 National Land Cover Data (NLCD) over the next 20 years' period using an Integrated Climate and Land-use Scenarios (ICLUS). ICLUS is a GIS-based tool and Datasets for Modeling US Housing Density Growth. The output from ICLUS was modified to create scenarios representing changing levels of LULC for the 2030 period. ICLUS was developed by the EPA-ORD-Global Change Research Program at the National Center for Environmental Assessment (ICLUS, 2010). It has multiple scenarios for housing density and population. However, the scenario giving the highest population was selected. For 2030, the ICLUS output, which consists 15 land-use classes of the NLCD data was aggregated into 5 LULC classes to match with the current and past LULC data.

The main aim of this part of the research was to quantify the impacts of an increase in impervious land-use on water quality and quantity in Reedy Fork-Buffalo Creek watershed. The Soil and Water Assessment Tool (SWAT) model was used to evaluate the overall impacts of an increase in imperviousness on water quality regarding nutrient loads and runoff. The simulation was made based on the temporal variation of weather (temperature, precipitation, solar radiation, and humidity conditions), soil and management conditions for the eight years' simulation from 2002 to 2010. These scenarios were constructed by assuming current climatic conditions for the past and future LULC.

Table 3.3. Structure and Changes in LULC for the Past (2002) and Current (2010) Year.

LULC Type	**2002**		**2010**	
	Area (km^2)	%	Area (km^2)	%
Impervious	120.3	20	145.9	24.2
Agricultural	32	5.3	35.0	5.8
Water	15.2	2.5	16.1	2.7
Grass	149.6	24.8	148.1	24.6
Forest	285.3	47.4	257.2	42.7

CHAPTER IV

RESULTS

LULC Classes and Spatial Pattern Analysis

Qualitative and visual assessments of the classified 2002 to 2013 orthophoto indicated that high accuracy levels had been achieved. The integrated GIS ancillary data and HR 0.5m orthophoto had enhanced the level of detail in the LULC classification, particularly in edge-zones and transition areas. Particularly impressive was the detail observable in a small forest, residential and road developments, where even relatively small features such as buildings and impervious pathways were properly classified as impervious surfaces and properly delineated. The integration of ancillary and HR orthophoto in ArcMap produced excellent results regarding differentiation of agricultural from forest from grass areas Fig. 4.4 through 4.7.

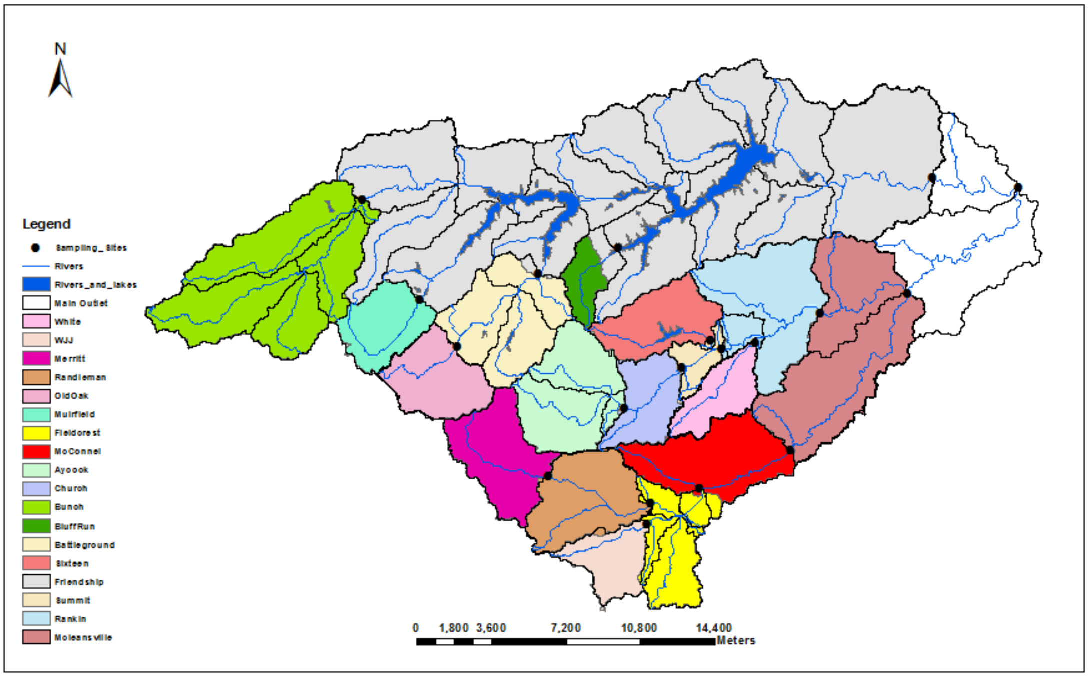


Figure 4.1. Delineation of Sub-Basins of the Reedy Fork-Buffalo Creek Watershed

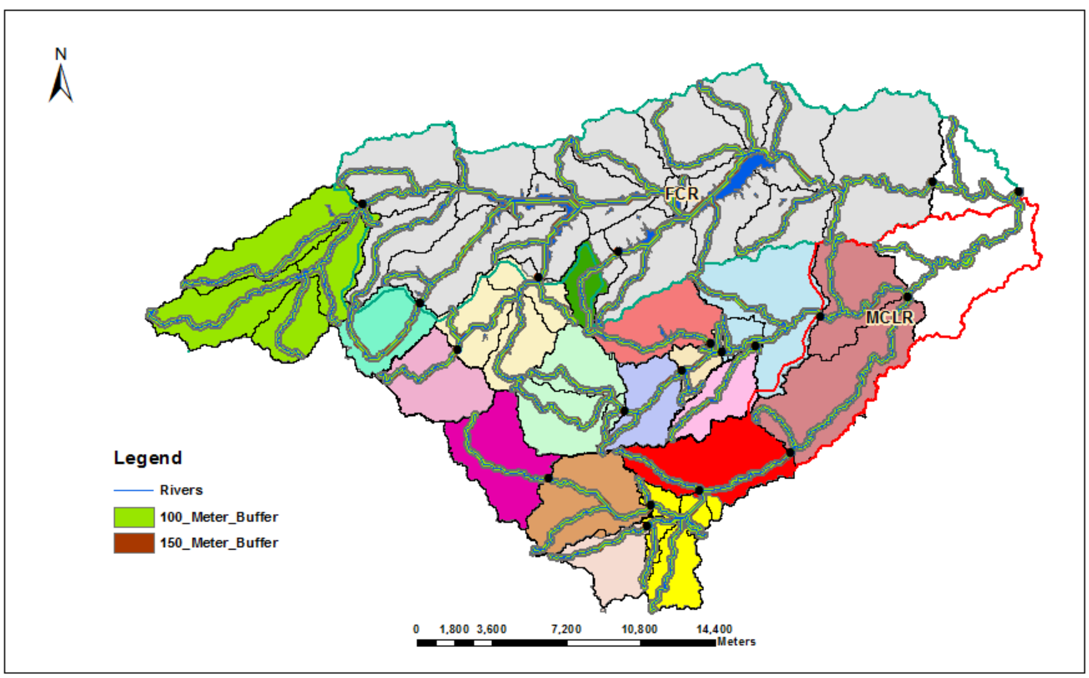


Figure 4.2. Riparian Buffer Zones with 50 m, 100 m, and 150 m Distances from the Centerline of Derived Drainage Lines

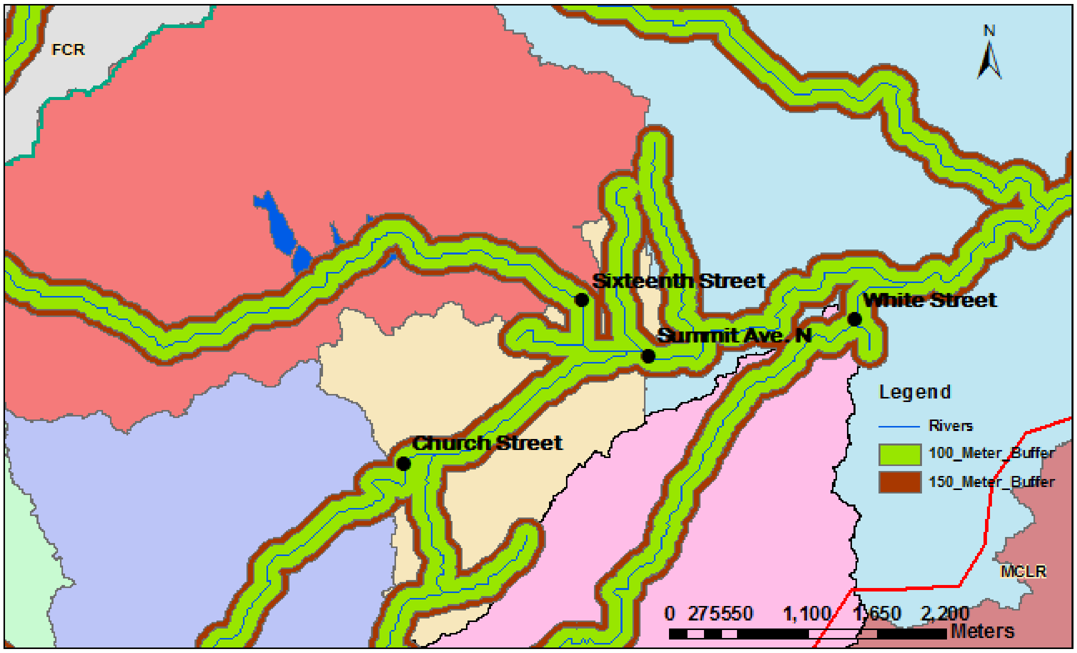


Figure 4.3. Details of Riparian Buffer Zones draped over some Selected Sub-Watersheds

Using the formula by Jensen, (2005) for sample point determination resulted in 664 samples for the 2002 and 637 for 2008, 2010, and the 2013 classified map. For consistency, the number of samples was rounded up to 600 for all classified images. The results of each of the producers, users, and overall and kappa accuracies presented as error matrices are shown in Tables 4.1 through 4.4. The assessment was very robust, indicating success in generating highly accurate, HR LULC map. The overall accuracy for each classified map was approximately 95%, 93%, 95% and 94% for 2002, 2008, 2010, and 2013 respectively. Kappa statistics were also calculated for each classified map. The Kappa statistic for the classification was robust with 0.93, 90, 0.93, and 0.92 for 2002, 2008, 2010, and 2013 study years respectively. The overall accuracy and Kappa statistics are an indicating of excellent results from the classification procedure.

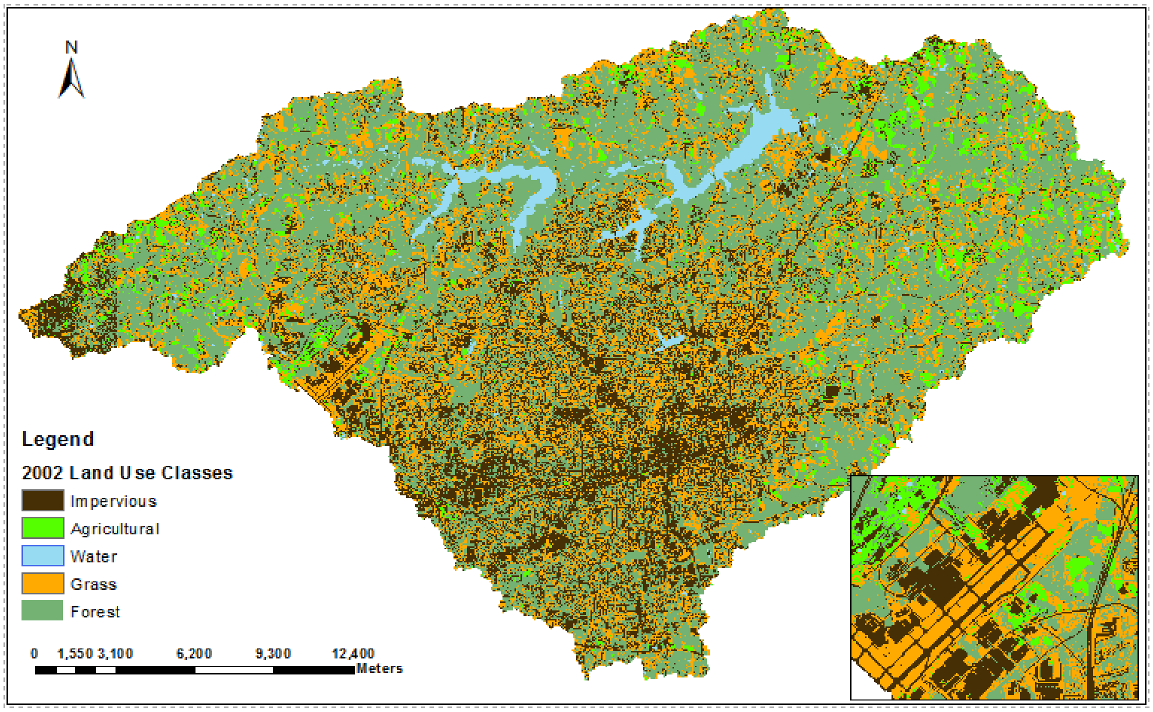


Figure 4.4. Classified LULC Map for 2002

Table 4.1. LULC Classification Map Error Matrix from Accuracy Assessment for 2002.

Class Name	Impervious	Agricultural	Water	Grass	Forest	Column Total
Impervious	139	2	0	3	3	147
Agricultural	0	51	0	2	4	57
Water	0	1	32	1	4	38
Grass	3	1	1	139	2	146
Forest	0	0	3	1	208	212
Row Total	142	55	36	146	221	600
Overall Accuracy =						95%

	Producer' Accuracy	**User's Accuracy**
Impervious	98%	95%
Agricultural	93%	89%
Water	89%	84%
Grass	95%	95%
Forest	94%	98%
Kappa = 93% = 0.93		

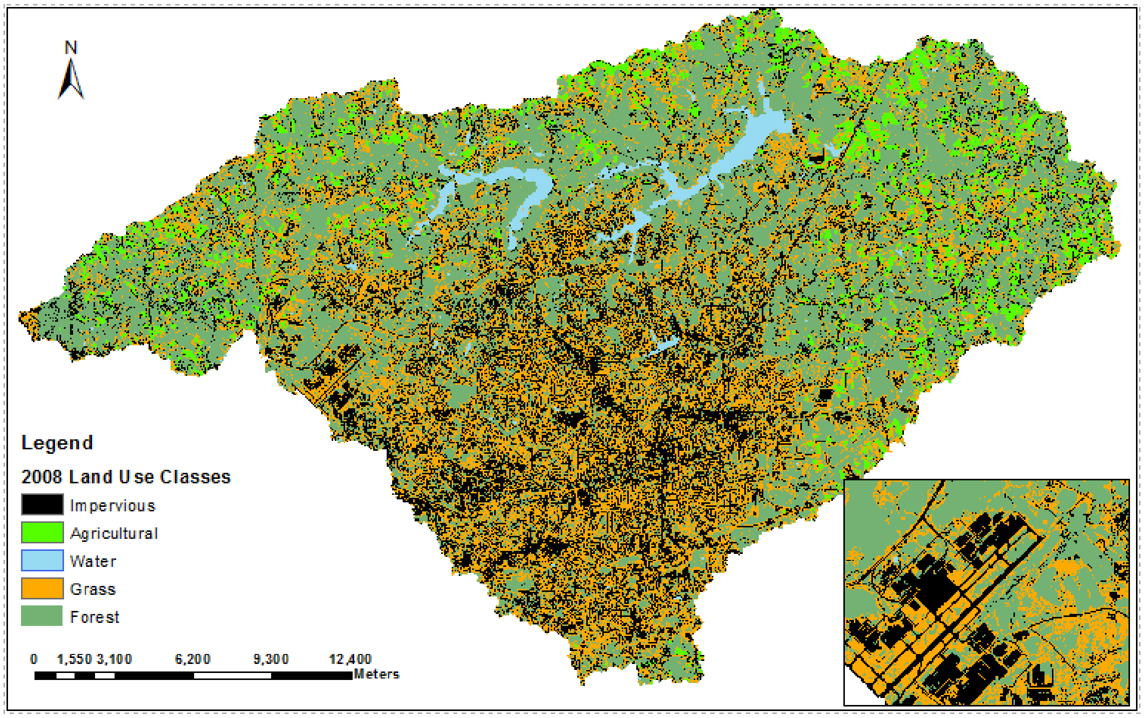


Figure 4.5. Classified LULC Map for 2008

Table 4.2. LULC Classification Map Error Matrix from Accuracy Assessment for 2008.

Class Name	Impervious	Agricultural	Water	Grass	Forest	Column Total
Impervious	114	5	0	2	1	122
Agricultural	5	52	0	4	5	66
Water	0	0	28	0	0	28
Grass	2	2	0	157	4	165
Forest	8	1	2	3	205	219
Row Total	129	60	30	166	215	600
Overall Accuracy =						93%
	Producer's Accuracy	**User's Accuracy**				
Impervious	88%	93%				
Agricultural	87%	79%				
Water	93%	100%				
Grass	95%	95%				
Forest	95%	94%				
Kappa = 90.4% = 0.90						

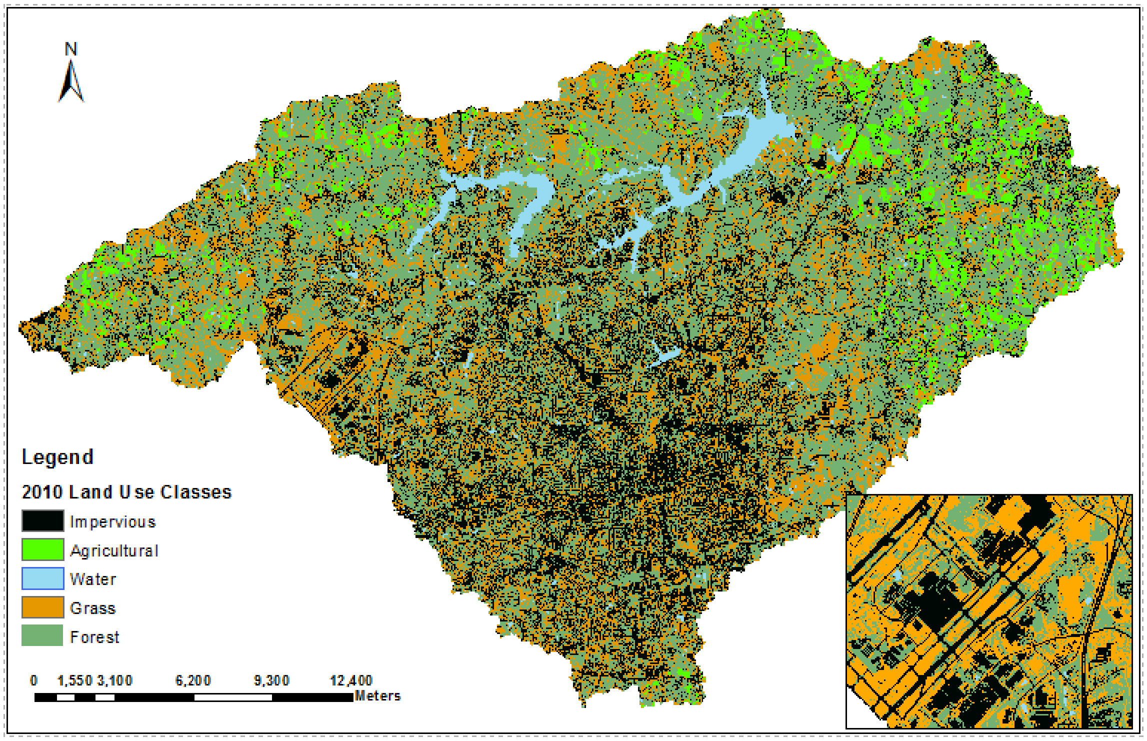


Figure 4.6. Classified LULC Map for 2010

Table 4.3. LULC Classification Map Error Matrix from Accuracy Assessment for 2010.

Class Name	Impervious	Agricultural	Water	Grass	Forest	Column Total
Impervious	139	2	0	3	3	147
Agricultural	0	51	0	2	4	57
Water	0	1	32	1	4	38
Grass	3	1	1	139	2	146
Forest	0	0	3	1	208	212
Row Total	142	55	36	146	221	600
Overall Accuracy =						95%

	Producer's Accuracy	**User's Accuracy**
Impervious	98%	95%
Agricultural	93%	89%
Water	89%	84%
Grass	95%	95%
Forest	94%	98%
Kappa = 93.02% = 0.93		

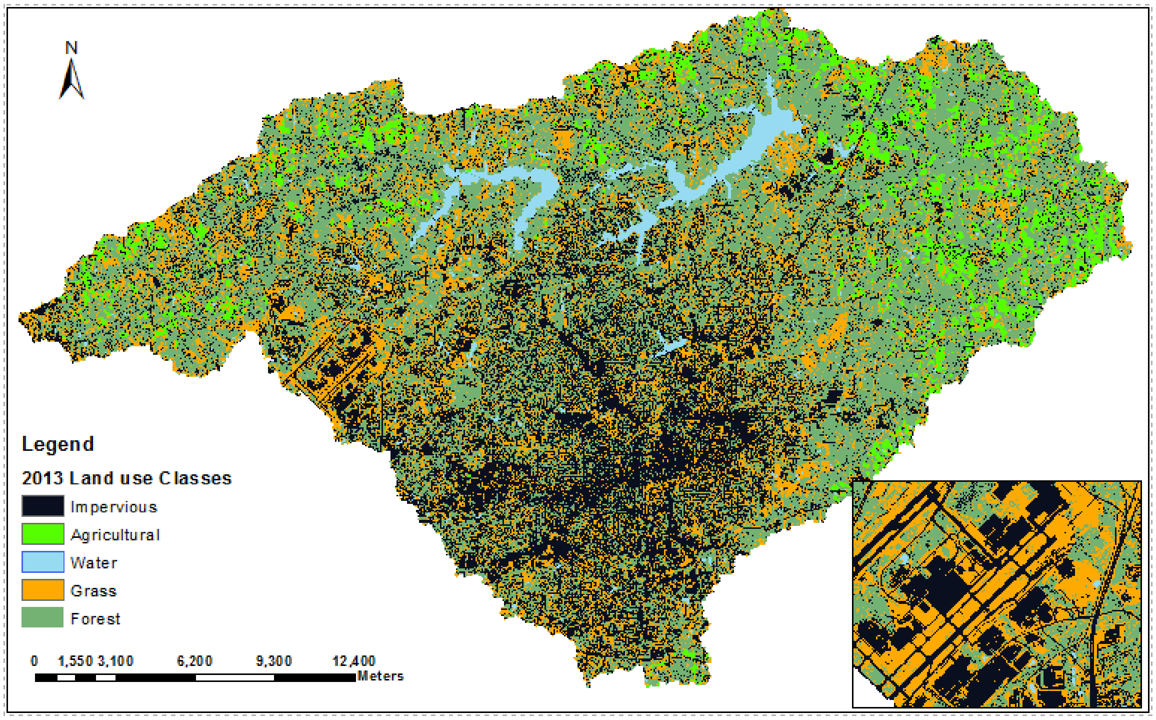


Figure 4.7. Classified LULC Map for 2013

Table 4.4. LULC Classification Map Error Matrix from Accuracy Assessment for 2013.

Class Name	Impervious	Agricultural	Water	Grass	Forest	Column Total
Impervious	161	0	0	3	3	167
Agricultural	1	54	1	3	2	61
Water	1	2	37	1	3	44
Grass	5	0	0	113	7	125
Forest	0	2	0	4	197	203
Row Total	168	58	38	124	212	600
Overall Accuracy =					94%	

	Producer' Accuracy	User's Accuracy
Impervious	96%	96%
Agricultural	93%	89%
Water	97%	84%
Grass	91%	90%
Forest	93%	97%
Kappa	= 91.5%	= 0.92

Percent LULC Change for Entire Watershed

Table 4.5 illustrates the LULC structure and its relative changes in the Reedy Fork-Buffalo Creek watershed over the 2002-2013 study period. The result shows that forest land is the primary LULC type in the LULC structure and accounted for more than 40% of the total watershed at all studied years, which is approximately one-third of the total study area. The relative change rate of forest land cover during the 2002-2013-year period was only -10.9%. Grass land-cover following forest cover accounted for 20% to 27% of the total watershed with a relative change of -17.3% from 2002 to 2013. Impervious land class following grassland in the area accounted for a constant 20% to 28% of the total watershed, and the relative rate of change was 40.7% from 2002 to 2013. Agricultural land covers about 5% to 6% with a relative change of 21.4%. The water area has the least land surface among all the classes with percentages ranging between 2% and 2.7% and its relative change from 2002 to 2013 was 8.7%. However, water did not experience much dynamic change throughout the years; it was excluded from further analysis.

Generally, high relative change of a LULC type refers to an increase in percent area of the current LULC type compared to past LULC type and vice versa. This is evident in the relative change values in Table 4.5.

Table 4.5. Structure and Changes in LULC from 2002 to 2013.

LULC Type	**2002**		**2008**		**2010**		**2013**		**Relative Change 2002-2013**
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	%
Impervious	120.3	20.0	129.6	21.5	145.9	24.2	169.3	28.1	40.7
Agricultural	32.0	5.3	38.8	6.4	35.0	5.8	38.8	6.4	21.4
Water	15.2	2.5	12.1	2.0	16.1	2.7	16.5	2.7	8.7
Grass	149.6	24.8	165.9	27.6	148.1	24.6	123.6	20.5	-17.3
Forest	285.3	47.4	255.8	42.5	257.2	42.7	254.0	42.2	-10.9

The transition area of the LULC classes for the study area from 2002 to 2013 was also calculated (Table 4.6.). The transition matrix provides important information about the nature and spatial distribution of changes in LULC (Shalaby and Tateishi, 2007). Table 4.6 illustrates that new impervious areas in 2013 were mostly derived from forest cover, whereas new agricultural land cover from grassland. Likewise, new water from the forest, new grassland from the forest and new forest land from grassland. The changes LULC in the Reedy Fork-Buffalo Creek watershed are related to the rapid urbanization process in Greensboro between 2008 and 2013.

Table 4.6. LULC Transition Matrix from 2002-2013.

		2002					
2013	**LULC Type**	**Impervious**	**Agricultural**	**Water**	**Grass**	**Forest**	**Total**
	Impervious	106.1	3.8	0.5	21.1	37.8	169.4
	Agricultural	1.2	14.4	0.1	17.5	5.7	38.8
	Water	0.3	0.2	11.9	1.4	2.7	16.5
	Grass	7.2	9.2	0.8	69.1	37.3	123.7
	Forest	5.5	4.3	1.9	40.5	201.7	254.0
	Total	120.4	32.0	15.2	149.6	285.3	602.3

The dynamic index of the LULC change of the entire study area is indicated in Fig. 4.8. The dynamic index of the impervious area is the largest out of the five LULC types, and it illustrates the characteristics of rapid expansion in the developed area in the watershed. The dynamic index of grassland changed greatly from 2002 to 2013; the value of the index was 1.7% during 2002 to 2008 and decreased to -5.3% during 2009-2010 periods. However, the grassland index increased to 2.1% during the 2011-2013 periods. Dynamic indices of the other LULC types changed slightly and remained within the interval of −2.0% to 2.0%. Since the index of water did not experience any significant change throughout the years, it was excluded from further analysis.

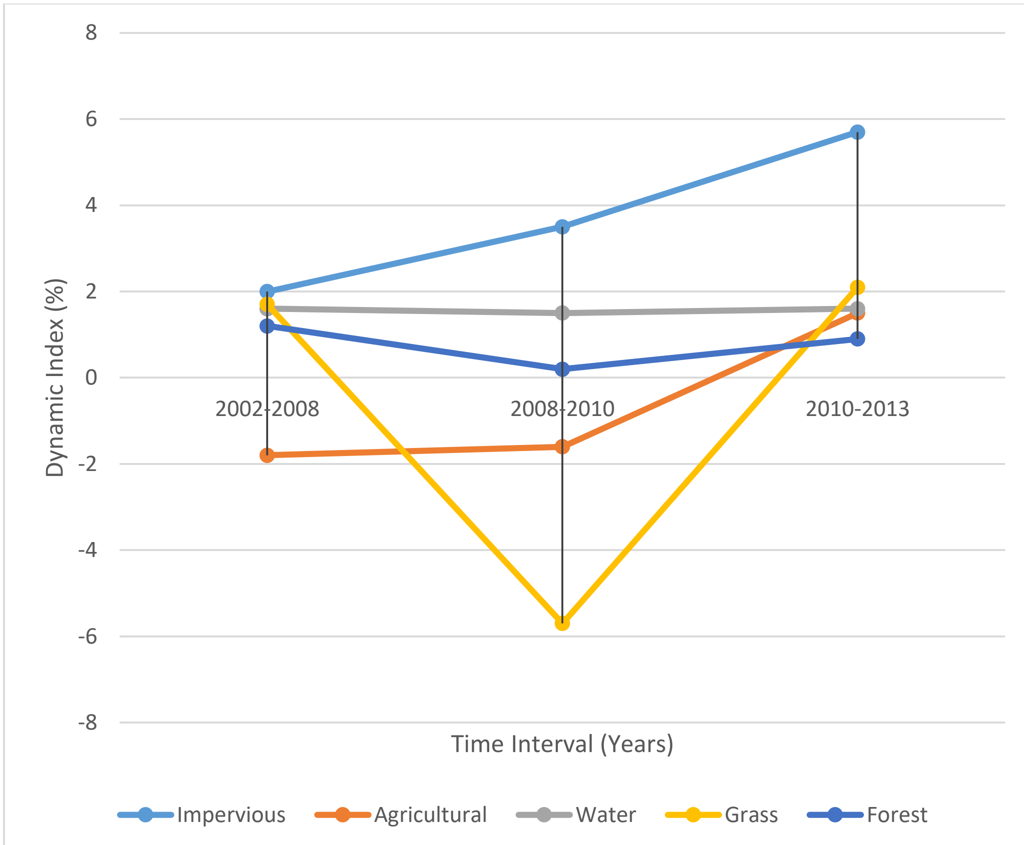
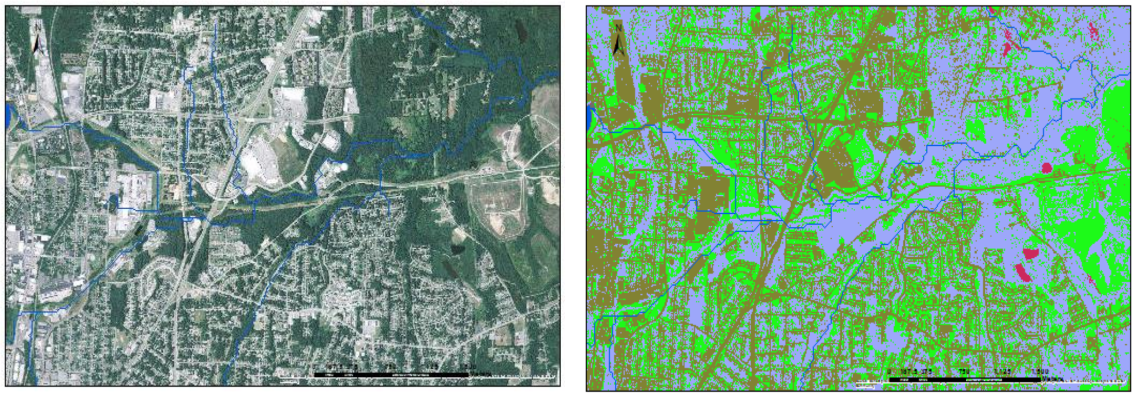


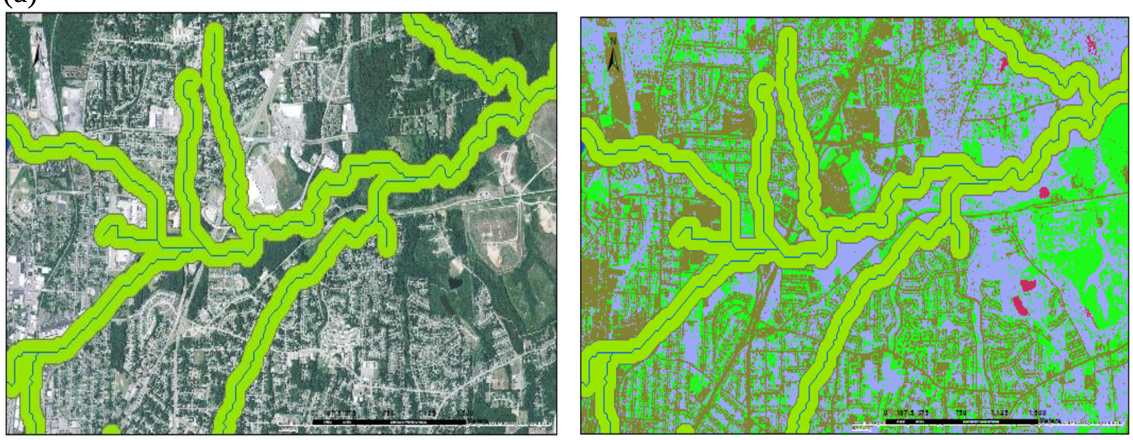
Figure 4.8. Dynamic Index of LULC of the Classified Maps for the Study Period.

Landscape Metrics

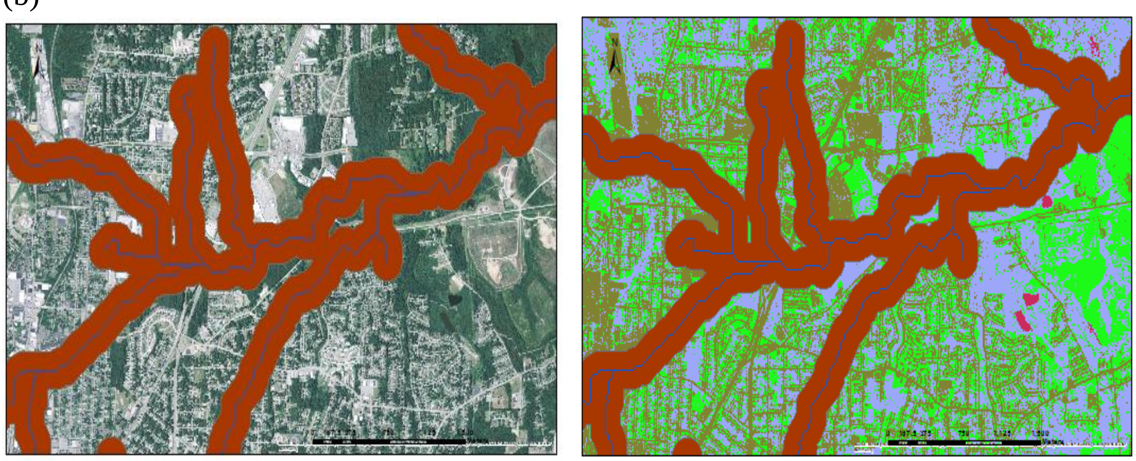
The landscape metrics component involved in this research, NP, ED, and LPI together with PLAND at the various spatial scales (watershed and riparian buffer) are shown in Table 4.10 through 4.21. Results from the Fragstats analysis showed differing changes in the fragmentation of LULC areas at the watersheds and buffer scales between the years.



(a)



(b)



(c)

Figure 4.9. Watershed (a), 100 m (b), and 150 m (c) Scales draped over 2010 HR Orthophoto to the Left and Classified 2010 Map to the Right

Landscape Metrics Dynamics for Entire Watershed

The landscape metrics shown in Fig. 4.10 to 4.13 indicate the dynamic trend of the spatial pattern of the changing landscape of the entire Reedy Fork-Buffalo Creek watershed landscape from 2002 to 2013. The landscape metrics used in this study were calculated based on the LULC classified data (Fig. 4.4 to 4.7).

Here, the change in the shape and spatial distribution pattern of all the LULC types were examined. Fig. 4.10 illustrates the dynamics of the landscape metrics of the impervious area from 2002 to 2013. The impervious PLAND increased from 32.5%, 33.9%, 35.6%, and 43.8% for 2002, 2008, 2010, and 2013 respectively indicating the expansion of impervious cover into forest cover and grassland in the watershed. The NP value increased slightly from 2002(9562.7) –2008(11789.7) and from 2008(11598.7) to 2010(15408.8) and leveled off to a slower, steady growth level since 2010(15408.8) to 2013(15521.8).

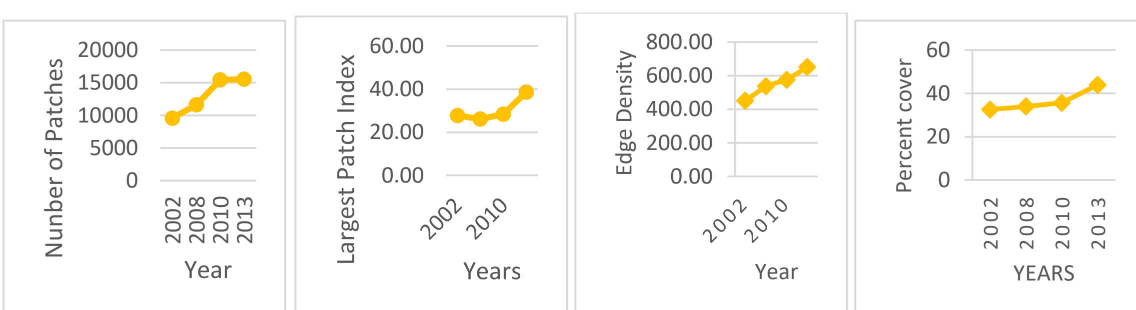


Figure 4.10. Dynamics of the Landscape Metrics of Impervious Areas

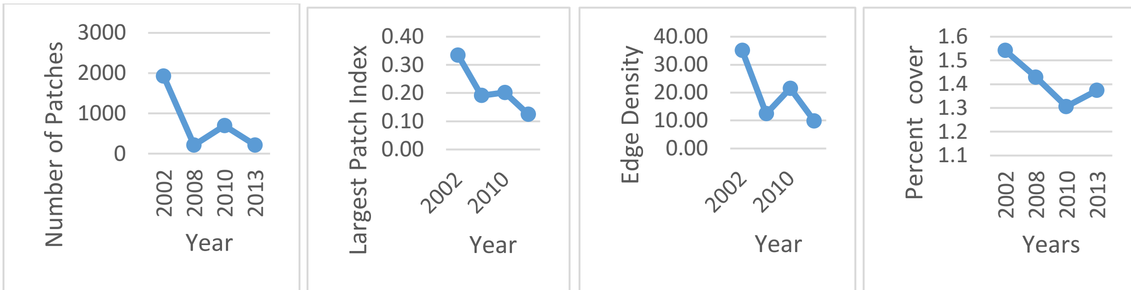


Figure 4.11. Dynamics of the Landscape Metrics of Agricultural Lands

Correspondingly, continuous growth in the ED value was also observed from 2002(450.0), 2008(537.2), 2010(575.1) to 2013(650.0). The increase in NP and ED is due to the increase in impervious cover patches and edge complexity. The LPI of impervious land-use decreased from 2002 to 2008. It then increases gradually from 2008 to 2010 and sharply from 2010 to 2013.

The general trend in PLAND of agricultural (Fig. 4.11) shows a decrease from 2002(1.54%) to 2008(1.42%). It further decreased to 2010(1.3%) and increased from 2010(1.3%) to 1.37%% in 2013. Some obvious change in NP, LPI, and ED of agricultural land were also observed during the 2002-2013 study period. The NP value of agricultural land decreased sharply from 2002(1924.8) to 2008(214.7) and then slightly increased after from 2008(214.7) to 2010(700). From the 700 in 2010, it decreased to 2013(219.5) (Fig. 4.11). The same pattern with different values was recorded for the ED and LPI.

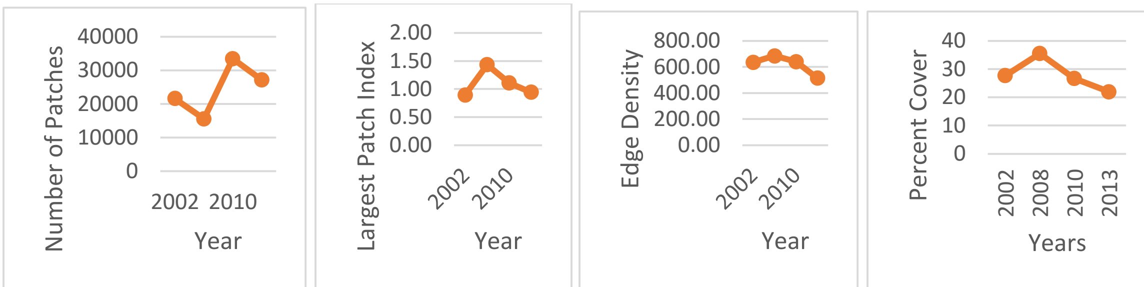


Figure 4.12. Dynamics of the Landscape Metrics of Grasslands

Variations in PLAND of grassland were also examined (Fig. 4.12). In 2002, grass PLAND was 27.8%, and it increased to 35.5% in 2008. It then dropped gradually from 35.5% in 2008 to 26.7% in 2010 then to 21.9% in 2013.The NP of grassland changed from 2002(21609) to 2008(15557), 2008(15557) to 2010(33483), and 2010 (33483) to 2013 (27157). The LPI greatly increased from 2002(0.89) to 2008(1.43) and gradually decreased to 0.94 in 2013. The density of the LULC edges also increased from 2002 to 2008 and gradually dropped to 514 in 2013.

Figure 4.13. Dynamics of the Landscape Metrics of Forest Lands

Both PLAND of forest cover and ED fluctuated from 2002 to 2013. Both decreased from 2002 to 2008, and increased in 2010 and decreased in 2013, Fig. 4.13. However, the NP of forest cover increased from 15566 in 2002 to 20740 in 2008. It then gradually decreased to 19388 in 2010 to 14562 in 2013. The LPI also increased slightly from 2002(3.03) to 2008 (3.92) and dropped slightly to 2.85 and remained almost the same in 2013 (2.75).

Dominant Landscape Metrics at the 100 m, 150 m and Watershed Scales

The final procedure undertaken for the LULC research component involved the calculation of landscape metrics at the various spatial scales for each LULC class, Table 4.7 to 4.17. Different individual watersheds within the study area recorded different values of landscape metrics at spatial scale level of analysis. High values were observed in 9 out of the total 18 sites in the Reedy Fork-Buffalo Creek watershed, and these values together make up about 89.1% of the total watershed. These individual watersheds include the: 16th St., AS, BA, CR, FCR, OORR, PRR, WJJD, and WS **(**Figure 4.14).

Percent Land (PLAND)

For PLAND, at the sub-watershed scale, impervious cover was the most dominant among all LULC types with WS having the highest values of 54%, 43%, 49%, and 63% for 2002, 2008, 2010, and 2013 respectively. Agricultural was high in PRR watershed with 2002(9.61%), 2008(10.95%), 2010(7.55%), and 2013(8.26%). OORR had the most grassland PLAND with 2002(37.9%), 2010(35.29%), and 2013(32.34%). WJJD had 43.13% grass cover for 2008, whereas, PLAND of forest was dominant at FCR with 2002(51.32%), 2008(49.71%), 2010(46.10%), and 2013(45.97%). A similar trend in PLAND was exhibited at the 100m and 150m riparian buffer scales for 2002 to 2013 (Table 4.7 to 4.9).

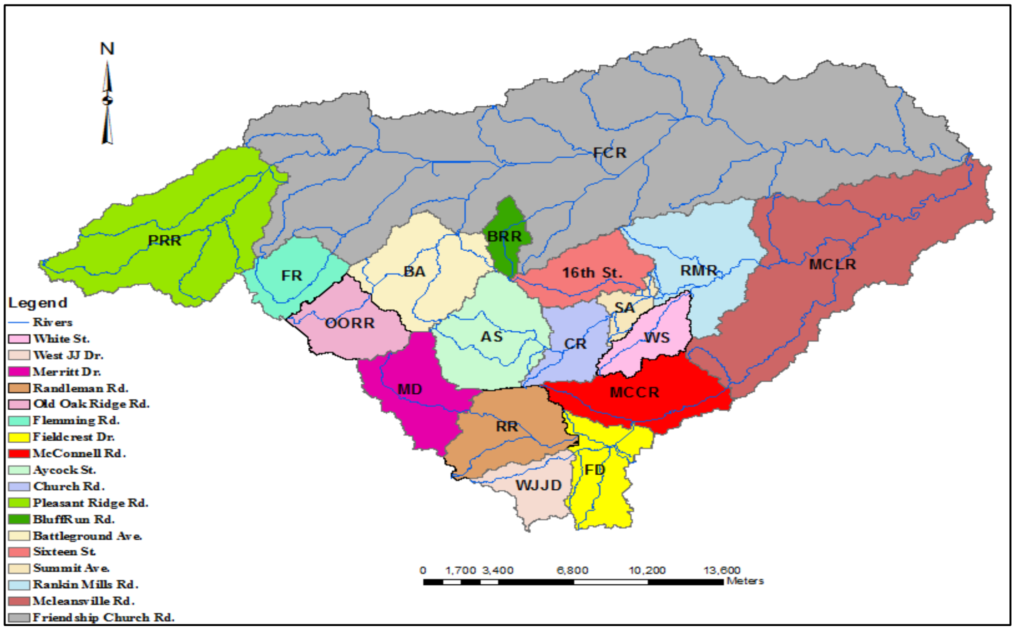


Figure 4.14. Reedy Fork-Buffalo Creek Watersheds.

Largest Patch Index (LPI)

The area of the LPI of LULC was also analyzed. The large LPI of impervious cover at the watershed scale were observed in WS with 2002(47.85%), 2008(37.71%), 2010(45.91%), and 2013(66.06%). Agricultural cover LPI was 2002(3.72%), 2008(0.33%) at FR and 2010(0.45%), and 2013(0.52%) at PRR. For grass, 2002(3.15%) and 2008(4.77%) were recorded at OORR and 2010(7.06%) and 2013(5.08%) at FR. BRR was dominated by forest cover in at this scale, decreasing from 2002 to 2013 with 2002(12.49%), 2008(12.19%), 2010(11.46%), and 2013(10.78%). The impervious cover was high for both AS and WS at the 100m scale. AS recorded 9.44% during the 2008 period, and WS recorded 2002(14.27%), 2010(12.20%), and 2013(31.28%). The agricultural cover was maximum with 2002(3.39%), 2008(0.98%) at FR, whereas high values were obtained for 2010(0.81%), and 2013(0.85%) at PRR. LPI for grass was maximum at OORD with 2002(2.44%), WJJD with 2008(8.57%) and FD with 2010(3.09%), and 2013(2.44%). For the 150m scale, apart from LPI of grass, all the other LULCs exhibited a similar trend, but with different values of imperviousness at WS, agricultural cover at FR and PRR, and forest cover at FR, PRR, and WJJD. The highest LPI of grass within the 150m buffer was 2002(3.89%), 2010(2.78%), and 2013(3.69%) at OORR and 2008(8.29%) at WJJD (Table 4.10 to 4.12).

Number of Patches (NP)

NP which estimates the degree of aggregation a LULC class was maximum for impervious cover for FCR with 2002(35979), 2008(55921), 2010(92647), and 2013(99358). In the same regards, agricultural cover was 2002(8268), 2008(911), 2010(926), and 2013(551) at FCR; grass recorded 2002(76331), 2008(73677), 2010(94004), and 2013(81228); and forest 2002(45200), 2008(63917), 2010(63035), and 2013(43973) at the watershed scale. The same format was observed for at the 100m and 150m scale Table (4.13 to 4.15).

Edge Density (ED)

The last landscape metrics to examine was the ED for individual LULC type. CR dominated the impervious cover ED for 2002, 2008, 2010, and 2013. The highest densities of agricultural edges were observed at FR with 2002(148.8). ED of grass was high in four different watersheds; 16th St. was 2002(801.6), WS was 2008(823.2), AS 2010(734.2), and WJJD 2013(598.3). Maximum forest cover was accounted for at AS with 2002(620.6) and 2010(796.3), 16^{th} St. 2008(535.1), and BA with 2013(701.0). The 100m and 150m exhibited the same trend with different values (Table 4.16 to 4.18).

Table 4.7 Percentage Land (PLAND) Total Area Calculations Matrices of Land-Cover Composition at the Watershed Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

		PLAND Impervious			PLAND Agricultural				PLAND Grass				PLAND Forest			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	33.28	35.99	39.35	46.16	0.75	0.00	0.00	0.00	31.40	34.14	20.68	18.08	32.20	27.48	37.12	32.87
AS	39.24	38.50	41.74	52.27	0.37	0.00	0.00	0.00	30.35	42.04	23.76	18.42	29.91	19.16	33.81	28.59
BA	27.83	28.89	30.08	35.80	2.84	0.13	0.00	0.07	32.93	32.55	29.82	27.21	36.00	38.01	38.71	35.48
BRR	24.46	29.47	27.56	36.50	0.54	0.00	0.00	0.00	27.51	31.85	23.39	20.08	46.83	38.08	47.45	41.80
CR	42.71	40.80	44.86	56.64	0.35	0.00	0.00	0.00	29.45	41.14	22.64	17.84	27.39	17.86	32.00	25.01
FD	36.93	36.41	38.23	50.01	0.96	0.47	0.50	0.55	24.63	39.82	26.55	20.95	37.29	23.16	34.08	27.77
FR	24.04	20.42	24.50	31.17	10.73	1.08	0.00	0.00	24.89	25.62	39.50	30.99	39.78	52.60	35.35	37.19
FCR	17.58	16.12	18.13	20.99	6.09	7.60	6.57	6.89	23.78	23.13	24.87	21.74	51.32	49.72	46.10	45.97
MCCR	35.62	34.98	39.33	48.74	1.05	0.39	0.37	0.41	25.76	39.87	26.78	22.02	37.40	24.66	32.95	28.19
MCLR	30.38	30.58	34.58	41.28	2.31	2.53	1.49	2.32	26.74	35.11	25.41	19.97	40.19	31.47	37.81	35.68
MD	42.14	39.88	38.21	49.75	1.30	0.00	0.00	0.03	23.26	37.98	25.63	18.40	33.22	22.10	35.54	31.12
OORR	32.56	30.36	32.59	40.92	3.51	0.00	0.00	0.00	37.99	37.66	35.29	32.34	25.76	31.81	31.09	25.69
PRR	16.81	15.54	15.80	20.31	9.61	10.95	7.55	8.26	21.04	19.99	30.51	26.03	51.86	53.14	45.44	44.64
RR	40.23	38.83	38.70	52.43	1.00	0.00	0.00	0.02	23.61	39.84	25.75	19.55	35.11	21.27	35.06	27.46
RMR	35.07	34.66	38.08	46.44	1.34	0.77	0.00	0.31	29.55	35.50	24.35	20.05	33.54	28.58	36.79	32.40
SA	40.52	39.63	43.50	54.12	0.47	0.00	0.00	0.00	30.07	39.07	22.37	18.26	28.24	20.52	33.03	26.50
WJJD	31.64	33.22	36.12	49.24	0.73	0.30	0.00	0.06	28.25	43.13	30.78	24.84	39.11	23.29	32.46	25.15
WS	50.93	43.92	49.25	63.22	0.17	0.00	0.00	0.00	27.64	41.30	21.67	18.51	21.26	14.78	29.09	18.27

Table 4.8. Percentage Land (PLAND) Total Area Calculations Matrices of Land-Cover Composition at the 100 m Buffer Scale in the Study Area for the2002, 2008, 2010, and 2013 Classified Map.

	PLAND Impervious				**PLAND Agricultural**				**PLAND Grass**				**PLAND Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	26.86	28.94	32.03	40.21	0.56	0.00	0.00	0.00	27.74	30.56	17.67	14.29	33.79	29.44	38.04	33.21
AS	35.58	34.43	37.49	48.66	0.24	0.00	0.00	0.00	30.36	41.18	25.43	20.00	33.39	23.43	35.26	29.47
BA	21.88	24.10	24.67	29.89	1.81	0.05	0.00	0.12	32.63	32.66	30.16	26.53	42.86	42.18	42.63	40.87
BRR	25.28	30.39	28.44	39.41	0.52	0.00	0.00	0.00	28.82	36.76	24.83	21.01	43.21	31.31	43.55	36.38
CR	37.71	35.87	39.68	52.05	0.23	0.00	0.00	0.00	31.29	42.25	25.24	20.00	30.47	21.22	33.79	26.63
FD	31.64	30.65	32.53	46.10	0.47	0.14	0.44	0.55	23.51	41.87	25.58	19.60	44.03	27.11	40.29	32.42
FR	18.90	14.21	19.94	28.04	10.04	1.74	0.00	0.00	21.75	23.87	36.28	27.75	48.64	59.85	42.58	43.01
FCR	8.36	11.06	12.02	18.45	2.72	3.34	2.64	2.80	14.69	16.68	19.30	14.78	59.47	56.65	51.63	49.44
MCCR	29.84	29.80	34.29	44.22	0.62	0.24	0.42	0.47	24.77	40.66	26.13	20.71	44.43	29.05	38.14	33.47
MCLR	24.10	24.08	28.73	35.89	0.92	0.72	0.76	1.34	22.90	33.36	22.98	17.87	51.11	40.82	45.90	43.22
MD	36.97	34.56	33.99	45.17	0.35	0.00	0.00	0.18	23.04	41.45	25.86	17.09	39.65	23.99	39.20	36.60
OORR	25.50	24.94	26.80	33.83	2.36	0.00	0.00	0.00	40.93	39.79	37.53	33.43	30.97	34.91	34.21	31.25
PRR	12.06	11.98	12.00	23.51	4.37	6.18	3.27	3.52	14.33	15.44	27.27	21.71	68.17	66.06	56.82	50.56
RR	31.70	30.75	31.42	45.87	0.35	0.00	0.00	0.09	23.99	42.15	25.17	18.18	43.90	26.86	41.94	34.32
RMR	29.98	29.29	32.68	41.98	1.00	0.47	0.00	0.06	27.59	34.76	23.65	18.73	39.74	33.66	41.38	36.90
SA	35.72	34.58	38.20	49.73	0.34	0.00	0.00	0.00	30.47	39.58	23.73	18.93	30.84	22.93	34.47	27.71
WJJD	26.38	27.10	29.46	44.99	0.25	0.00	0.00	0.00	28.47	48.36	30.60	25.02	43.45	24.54	38.69	28.49
WS	42.52	35.49	39.75	55.24	0.43	0.00	0.00	0.00	30.66	45.33	23.72	19.82	26.39	19.18	36.53	24.95

Table 4.9. Percentage Land (PLAND) Total Area Calculations Matrices of Land-Cover Composition at the 150 m Buffer Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	PLAND Impervious				**PLAND Agricultural**				**PLAND Grass**				**PLAND Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	28.97	31.17	34.50	42.24	0.78	0.00	0.00	0.00	28.47	31.62	18.35	14.99	32.78	28.26	37.24	32.85
AS	36.81	35.60	39.06	50.12	0.31	0.00	0.00	0.00	30.58	41.54	24.51	19.43	32.00	22.20	35.11	29.07
BA	23.71	25.48	26.38	31.69	2.07	0.12	0.00	0.08	32.94	32.30	30.40	27.30	40.47	41.25	41.10	38.72
BRR	26.13	31.40	29.49	39.75	0.51	0.00	0.00	0.00	28.53	35.46	24.44	21.02	43.26	32.01	43.74	36.88
CR	39.03	37.17	41.25	53.49	0.28	0.00	0.00	0.00	31.07	42.26	24.30	19.45	29.42	20.12	33.52	26.08
FD	34.01	32.58	34.93	47.88	0.54	0.13	0.44	0.54	23.90	41.26	25.88	20.29	41.27	25.86	37.85	30.24
FR	20.23	14.75	20.61	27.99	10.64	1.87	0.00	0.00	21.25	23.61	38.03	28.54	47.31	59.52	40.50	42.61
FCR	9.39	11.86	13.00	18.65	3.27	3.87	3.17	3.37	15.70	17.07	19.98	15.59	58.47	56.20	50.92	49.36
MCCR	31.60	31.29	35.87	45.66	0.76	0.27	0.45	0.51	25.25	40.52	26.56	21.33	42.10	27.71	36.21	31.51
MCLR	26.00	25.88	30.40	37.51	1.12	1.02	1.00	1.60	23.72	33.54	23.31	18.24	48.29	38.70	43.91	41.23
MD	39.72	36.78	36.69	47.81	0.50	0.00	0.00	0.16	23.53	39.73	26.02	17.61	36.20	23.49	36.62	33.72
OORR	27.47	26.37	28.29	35.65	2.78	0.00	0.00	0.00	40.62	38.82	37.66	34.06	28.83	34.45	32.69	28.92
PRR	13.07	12.63	12.87	22.98	5.56	6.68	3.70	4.10	15.10	15.81	28.26	22.45	65.45	64.59	54.58	49.79
RR	34.47	33.13	34.11	48.04	0.51	0.00	0.00	0.08	24.12	41.07	25.40	18.77	40.85	25.63	39.42	31.97
RMR	31.62	30.91	34.41	43.50	1.10	0.49	0.00	0.07	28.24	35.16	23.83	19.09	37.64	31.99	39.92	35.47
SA	37.32	36.11	40.04	51.36	0.41	0.00	0.00	0.00	30.39	39.70	23.15	18.68	29.76	21.89	33.97	27.09
WJJD	26.90	27.39	30.22	45.03	0.52	0.03	0.00	0.00	29.36	48.32	31.57	26.60	42.09	24.25	37.29	27.26
WS	44.59	37.64	42.05	57.06	0.34	0.00	0.00	0.00	30.42	44.23	23.62	19.87	24.65	18.13	34.33	23.07

Table 4.10. Largest Patch Index (LPI) Matrices of Land-Cover Composition at the Watershed Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	LPI Impervious				**LPI Agricultural**				**LPI Grass**				**LPI Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	26.96	30.20	33.86	41.56	0.07	0.00	0.00	0.00	0.56	0.60	0.44	0.57	2.41	1.75	3.99	1.52
AS	32.11	31.98	35.85	48.91	0.03	0.00	0.00	0.00	1.53	1.96	1.26	1.38	0.66	0.72	0.51	0.60
BA	23.26	23.38	23.94	30.62	0.21	0.07	0.00	0.03	1.26	1.79	1.04	1.04	3.42	2.91	3.27	3.31
BRR	17.75	24.11	22.22	28.96	0.06	0.00	0.00	0.00	0.54	1.95	0.50	0.44	12.49	12.19	11.46	10.78
CR	36.46	34.60	39.76	53.73	0.02	0.00	0.00	0.00	1.02	1.31	0.84	0.92	0.44	0.48	0.34	0.40
FD	30.86	29.36	30.02	44.41	0.08	0.14	0.15	0.16	0.17	0.59	0.17	0.14	1.53	1.07	1.08	1.19
FR	18.89	11.84	17.96	24.96	3.72	0.33	0.00	0.00	2.48	2.71	7.06	5.08	7.62	23.79	8.29	8.82
FCR	10.90	10.05	11.54	13.08	0.15	0.29	0.20	0.24	0.29	0.30	0.39	0.28	1.97	1.88	1.72	1.79
MCCR	30.42	28.90	32.69	43.53	0.06	0.10	0.11	0.12	0.31	0.44	0.48	0.44	1.15	1.06	0.83	0.89
MCLR	25.94	25.08	28.43	36.55	0.13	0.12	0.09	0.10	0.30	0.21	0.45	0.32	1.96	1.56	1.54	1.93
MD	33.97	30.81	26.49	41.29	0.13	0.00	0.00	0.03	0.61	1.32	0.61	0.34	2.03	0.88	2.43	2.33
OORR	28.62	23.91	25.05	36.01	0.55	0.00	0.00	0.00	3.35	4.77	2.76	2.76	2.52	7.74	1.92	2.49
PRR	11.64	6.50	7.19	7.91	0.41	0.40	0.45	0.52	0.44	0.57	0.75	0.56	6.37	6.36	4.28	4.76
RR	33.48	31.73	29.80	46.44	0.12	0.00	0.00	0.02	0.29	0.79	0.29	0.21	0.98	1.28	1.18	1.13
RMR	30.05	29.00	32.94	42.38	0.10	0.11	0.00	0.09	0.72	0.50	1.08	0.78	3.39	3.72	3.39	3.44
SA	34.52	33.80	38.50	50.89	0.02	0.00	0.00	0.00	0.66	0.84	0.54	0.60	0.65	0.47	1.08	0.41
WJJD	25.64	25.86	29.51	43.86	0.15	0.16	0.00	0.06	0.76	3.73	0.75	0.82	3.62	2.10	2.35	2.27
WS	47.85	38.71	45.91	61.06	0.03	0.00	0.00	0.00	0.82	1.40	0.57	0.33	1.36	0.51	1.56	1.36

Table 4.11. Largest Patch Index (LPI) Matrices of Land-Cover Composition at the 100 m Buffer Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	LPI Impervious				**LPI Agricultural**				**LPI Grass**			**LPI Forest**				
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	5.10	9.15	7.23	13.67	0.07	0.00	0.00	0.00	1.56	1.86	0.62	0.99	3.63	3.03	6.71	2.73
AS	10.42	9.44	7.69	27.10	0.07	0.00	0.00	0.00	1.20	1.59	1.12	1.06	2.73	2.95	1.61	2.45
BA	2.18	2.16	1.78	2.36	0.17	0.05	0.00	0.05	1.09	1.93	1.17	0.77	6.68	4.38	4.26	3.73
BRR	5.35	6.21	6.58	10.06	0.06	0.00	0.00	0.00	1.18	4.22	1.16	0.93	7.11	7.14	6.81	5.46
CR	9.89	9.18	8.12	27.19	0.04	0.00	0.00	0.00	0.84	1.09	0.77	0.73	1.87	2.02	1.10	1.68
FD	3.58	2.52	2.74	5.59	0.13	0.09	0.17	0.26	0.45	1.46	0.63	0.36	3.02	2.21	3.30	1.81
FR	3.29	5.20	3.75	3.26	3.39	0.98	0.00	0.00	1.34	1.47	3.09	3.85	6.75	15.95	6.56	6.28
FCR	0.57	0.39	0.39	0.48	0.12	0.21	0.23	0.25	0.54	0.46	0.44	0.45	3.01	2.70	2.59	2.74
MCCR	1.78	1.31	1.41	5.41	0.09	0.08	0.08	0.13	0.55	0.78	0.56	0.49	2.58	2.46	2.32	2.21
MCLR	1.34	0.95	1.26	3.13	0.07	0.09	0.10	0.25	0.33	0.44	0.34	0.30	4.61	3.67	4.34	4.34
MD	11.96	4.77	4.39	14.51	0.06	0.00	0.00	0.18	1.49	4.42	1.28	0.45	4.36	3.27	4.42	4.51
OORR	4.89	4.85	3.66	5.29	0.38	0.00	0.00	0.00	2.44	4.32	2.61	1.72	3.78	3.73	3.61	3.42
PRR	3.21	0.59	0.59	1.22	0.37	0.89	0.81	0.85	0.86	1.01	1.50	1.01	12.70	9.10	5.53	7.86
RR	5.74	2.28	2.10	8.94	0.03	0.00	0.00	0.09	0.72	2.11	0.61	0.57	4.70	3.42	5.13	2.81
RMR	4.23	3.92	3.47	11.62	0.19	0.16	0.00	0.06	0.54	0.46	0.54	0.41	7.83	5.91	7.52	7.36
SA	7.00	6.49	5.74	19.23	0.03	0.00	0.00	0.00	0.59	0.77	0.54	0.51	1.32	1.43	1.46	1.19
WJJD	10.63	8.10	10.43	12.01	0.06	0.00	0.00	0.00	2.42	8.87	2.57	3.00	9.64	3.54	7.98	4.24
WS	14.27	8.63	12.26	31.28	0.14	0.00	0.00	0.00	1.61	2.97	1.29	0.92	5.59	1.98	6.46	5.57

Table 4.12. Largest Patch Index (LPI) Matrices of Land-Cover Composition at the 150 m Buffer Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	LPI Impervious				**LPI Agricultural**				**LPI Grass**				**LPI Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	6.74	10.09	8.22	14.59	0.17	0.00	0.00	0.00	1.39	1.72	1.03	1.03	5.00	2.82	5.91	2.62
AS	23.31	21.76	23.33	40.46	0.05	0.00	0.00	0.00	0.93	1.24	0.85	0.81	1.93	2.09	1.16	1.75
BA	2.25	2.29	1.73	2.53	0.19	0.08	0.00	0.04	1.72	2.53	1.23	1.63	5.51	3.51	3.78	3.63
BRR	6.88	10.18	9.22	11.73	0.05	0.00	0.00	0.00	1.17	3.49	1.07	0.78	8.17	8.10	7.14	5.81
CR	25.05	21.88	25.03	47.53	0.03	0.00	0.00	0.00	0.82	0.85	0.67	0.55	1.32	1.43	0.79	1.20
FD	3.64	2.79	2.91	6.68	0.09	0.06	0.12	0.26	0.45	1.34	0.55	0.32	2.54	1.77	2.74	1.73
FR	3.69	5.56	3.56	3.56	3.22	0.86	0.00	0.00	1.60	1.66	5.94	3.57	6.44	16.21	6.30	6.14
FCR	0.60	0.44	0.43	0.53	0.13	0.19	0.34	0.37	0.45	0.39	0.35	0.35	3.14	2.58	2.48	2.60
MCCR	1.87	1.63	1.80	7.06	0.14	0.06	0.07	0.13	0.52	0.67	0.53	0.47	2.38	2.31	2.06	1.98
MCLR	4.32	3.87	4.91	9.10	0.08	0.08	0.11	0.25	0.31	0.41	0.32	0.28	4.22	3.32	4.18	4.03
MD	12.12	9.31	8.66	15.00	0.10	0.00	0.00	0.16	1.51	3.36	1.20	0.44	3.81	2.77	3.78	3.28
OORR	5.09	5.17	3.49	5.71	0.31	0.00	0.00	0.00	3.89	5.72	2.78	3.69	3.23	4.76	2.96	2.81
PRR	3.39	0.61	0.61	0.98	0.42	0.69	0.82	0.85	1.01	1.00	1.51	1.07	11.76	8.76	5.08	8.25
RR	5.80	4.45	4.12	9.10	0.13	0.00	0.00	0.08	0.72	1.61	0.58	0.42	3.94	2.82	4.26	2.70
RMR	10.66	9.31	10.65	21.39	0.16	0.18	0.00	0.07	0.52	0.36	0.71	0.59	7.06	5.48	6.94	6.78
SA	17.63	15.39	17.61	35.36	0.04	0.00	0.00	0.00	0.57	0.60	0.47	0.39	1.09	1.01	1.29	0.84
WJJD	8.71	6.59	8.53	10.95	0.41	0.03	0.00	0.00	1.93	8.29	2.50	2.86	8.31	3.47	6.78	4.45
WS	32.31	24.42	30.05	41.53	0.10	0.00	0.00	0.00	1.15	2.59	1.16	0.64	4.24	1.58	4.89	4.26

Table 4.13. Number of Patches (NP) Total Area Calculations Matrices of Land-Cover Composition at the Watershed Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	NP Impervious				**NP Agricultural**				**NP Grass**				**NP Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	3265	3230	3390	3320	485	0	0	0	6500	4743	11016	8571	5600	6959	5806	4813
AS	5201	4907	4422	3926	586	0	0	0	11321	5948	17931	14292	9846	12420	11109	8961
BA	4829	6332	7393	8657	1833	2	0	9	13168	10442	20291	16625	10474	12992	13105	8554
BRR	953	1015	831	1669	175	0	0	0	2445	1457	3759	3078	1685	2058	1848	1642
CR	7113	7016	6216	5201	752	0	0	0	17155	9964	26570	20453	15176	18653	17123	14289
FD	11397	12137	14734	13439	1391	34	31	29	27485	16507	34834	30104	17582	25090	23470	17535
FR	1389	1695	1466	2839	978	8	0	1	3073	2862	3910	3827	2137	2570	3394	2237
FCR	36979	55921	92647	99358	8268	911	926	551	76331	73677	94004	81288	45200	63917	63035	43973
MCCR	14809	15956	19477	18305	1643	36	31	36	35603	21228	47919	40235	24221	34190	31457	23275
MCLR	36059	42594	58857	52805	5061	308	408	349	82585	55148	72564	90127	60125	81615	73540	55525
MD	3205	3152	4313	3540	708	0	0	1	8310	5129	10439	8780	5440	7515	7322	4565
OORR	1512	1853	2729	2802	744	0	0	0	4093	2927	6101	4856	3557	4657	4800	2971
PRR	7036	11269	17307	20067	2583	351	599	390	11149	12568	20753	17069	7353	8461	9456	7470
RR	7494	7271	8273	6954	1075	0	0	1	17515	10225	21982	18855	11479	15820	14986	10781
RMR	16901	18839	20912	19374	2477	76	0	46	37835	25865	59900	47077	31481	39665	35811	28403
SA	11107	11119	10378	9142	1286	0	0	0	25437	15845	39972	30917	22348	27660	24897	20678
WJJD	1974	2220	2352	2319	110	3	0	1	4342	2531	5244	5131	2723	4167	3574	3349
WS	1545	2088	1661	1445	80	0	0	0	4620	2955	6378	4787	3754	4915	4243	3087

Table 4.14. Number of Patches (NP) Matrices of Land-Cover Composition at the 100 m Buffer Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	NP Impervious				**NP Agricultural**				**NP Grass**				**NP Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	502	613	578	722	85	0	0	0	1180	832	1746	1373	826	1043	814	761
AS	1126	1084	1252	1395	95	0	0	0	2895	1669	4186	3224	2250	2848	2587	2334
BA	1320	1929	2417	3271	425	2	0	7	3793	2877	5736	4731	2574	3493	3414	2176
BRR	385	381	331	607	48	0	0	0	780	498	1264	1048	657	743	688	638
CR	1599	1634	1726	1883	134	0	0	0	4171	2547	5986	4607	3438	4287	3905	3562
FD	1579	1851	2136	2742	148	6	14	7	3939	2646	4880	4240	2245	3629	3087	2364
FR	418	501	445	1034	307	4	0	0	779	760	990	1003	452	586	749	523
FCR	4043	6818	14517	16644	1050	155	207	190	8534	11831	19588	14518	3844	5962	6109	5267
MCCR	3182	3730	4963	5775	283	11	22	17	7698	5176	10492	8878	4909	7254	6424	4909
MCLR	4502	5757	10432	11154	504	45	80	53	11345	8351	17629	13763	6721	9982	8855	6677
MD	454	497	605	782	67	0	0	1	1191	766	1473	1228	724	1186	1143	603
OORR	500	641	925	1208	206	0	0	0	1428	1045	2064	1691	1069	1603	1529	952
PRR	963	1669	3434	3685	219	56	67	55	1534	2054	3791	2882	837	922	1105	1375
RR	1130	1144	1264	1614	106	0	0	1	2562	1668	3259	2856	1566	2393	2094	1614
RMR	3297	4061	5192	5843	400	12	0	6	8362	5806	12516	9838	6063	7794	7009	5955
SA	2213	2391	2433	2797	239	0	0	0	5642	3534	8081	6297	4483	5678	4974	4567
WJJD	189	295	250	355	11	0	0	0	451	247	521	507	231	417	283	306
WS	332	498	463	590	24	0	0	0	935	639	1349	1023	787	1034	906	650

Table 4.15. Number of Patches (NP) Area Calculations Matrices of Land-Cover Composition at the 150 m Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	NP Impervious				**NP Agricultural**				**NP Grass**				**NP Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	733	854	792	958	126	0	0	0	1674	1207	2568	2043	1240	1590	1304	1122
AS	1696	1679	1734	1775	175	0	0	0	4043	2270	6087	4763	3332	4115	3742	3300
BA	1809	2587	3268	4244	643	2	0	7	5196	4008	7953	6486	3652	4891	4862	3049
BRR	501	485	418	795	59	0	0	0	1062	673	1712	1443	866	1023	904	822
CR	2364	2458	2361	2323	230	0	0	0	5921	3467	8747	6743	5035	6190	5624	5120
FD	2252	2562	2937	3455	236	7	14	8	5564	3596	6971	6076	3402	5104	4611	3534
FR	559	699	609	1325	416	6	00		1083	1005	1347	1405	631	772	1079	703
FCR	5827	9732	19923	23143	1728	227	303	280	12736	16029	27798	20926	5741	8866	9033	7274
MCCR	4526	5211	6777	7410	440	16	22	17	10921	7095	14802	12690	7293	10431	9438	7239
MCLR	6554	8267	13873	14214	820	65	102	64	16141	11466	24990	19638	10252	14585	13173	9984
MD	637	696	857	990	120	0	0	1	1672	1119	2131	1768	1129	1695	1716	931
OORR	657	831	1252	1473	317	0	0	0	1886	1398	2822	2255	1511	2156	2157	1298
PRR	1412	2372	4558	5097	394	69	79	71	2232	2847	5211	4028	1243	1361	1644	1805
RR	1626	1609	1766	2036	179	0	0	1	3651	2288	4722	4114	2359	3387	3136	2418
RMR	4835	5900	6966	7357	633	15	0	6	11818	8024	17947	14149	9024	11491	10375	8694
SA	3268	3519	3348	3510	386	0	0	0	8034	4917	11851	9237	6650	8270	7359	6618
WJJD	278	406	364	449	12	1	0	0	643	336	762	729	364	592	429	451
WS	487	713	633	709	34	0	0	0	1306	911	1918	1456	1132	1525	1316	946

Table 4.16. Edge Density (ED) Calculations Matrices of Land-Cover Composition at the Watershed Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	ED Impervious				**ED Agricultural**				**ED Grass**				**ED Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	584.8	642.8	672.8	745.1	23.1	0.0	0.0	0.0	801.6	723.6	630.9	528.2	617.8	535.1	704.9	694.8
AS	648.6	662.1	695.9	738.2	13.6	0.0	0.0	0.0	792.3	818.9	734.2	534.5	670.6	593.9	796.3	675.8
BA	414.3	461.0	474.6	522.6	46.8	0.5	0.0	0.7	648.6	608.7	641.7	531.4	494.2	509.5	639.1	542.1
BRR	463.2	556.7	489.7	687.4	20.2	0.0	0.0	0.0	703.6	648.5	684.7	538.1	580.6	454.9	679.8	701.0
CR	649.8	669.2	693.3	776.9	12.7	0.0	0.0	0.0	755.3	819.3	685.0	508.3	646.7	485.9	770.4	626.1
FD	530.9	566.9	619.8	657.0	18.2	2.7	2.8	2.6	613.1	737.4	676.5	531.6	531.6	439.8	614.4	550.8
FR	316.3	302.8	314.6	400.1	148.8	5.3	0.0	0.0	436.4	489.5	519.9	481.3	379.8	422.7	470.9	474.9
FCR	265.9	329.7	397.2	452.3	157.6	31.7	38.7	37.4	422.1	462.1	499.8	435.8	373.2	416.6	542.7	538.5
MCCR	525.8	553.6	636.4	654.0	16.9	2.2	2.1	2.0	622.4	738.8	659.1	532.2	522.7	443.1	608.0	545.0
MCLR	469.4	514.5	600.3	592.9	24.2	11.0	9.0	11.4	608.1	678.3	605.7	489.8	500.9	450.4	632.3	550.3
MD	557.2	575.3	634.4	607.9	30.3	0.0	0.0	0.2	627.8	708.1	705.2	513.1	543.6	454.5	656.8	527.8
OORR	388.5	384.5	465.4	495.2	55.7	0.0	0.0	0.0	594.6	591.7	608.0	500.1	414.3	477.6	572.8	448.6
PRR	308.6	355.9	394.1	519.8	83.6	52.9	55.0	51.7	358.5	424.8	534.5	476.4	376.1	450.5	537.3	604.5
RR	577.7	591.7	636.6	659.8	22.4	0.0	0.0	0.1	631.1	750.4	705.6	532.6	562.8	447.2	653.3	543.3
RMR	548.0	588.2	629.8	647.0	23.8	4.2	0.0	2.0	700.6	724.7	634.7	516.8	555.6	483.3	683.5	589.7
SA	627.2	655.4	683.8	714.7	15.2	0.0	0.0	0.0	764.4	787.6	664.9	515.6	624.6	495.7	738.2	631.6
WJJD	533.4	596.0	620.6	770.5	12.3	1.7	0.0	0.4	656.1	787.0	730.9	598.3	542.3	454.7	584.1	601.8
WS	630.5	664.5	692.4	651.4	6.0	0.0	0.0	0.0	707.2	823.2	608.8	492.1	476.1	435.8	606.6	445.6

Table 4.17. Edge Density (ED) Calculations Matrices of Land-Cover Composition at the 100 m Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	ED Impervious				**ED Agricultural**				**ED Grass**				**ED Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	433.3	494.7	509.4	650.9	19.9	0.0	0.0	0.0	726.7	618.8	527.2	426.9	584.3	486.4	601.2	662.1
AS	528.4	539.1	578.3	679.3	8.4	0.0	0.0	0.0	713.9	729.3	799.8	511.0	608.1	490.9	755.1	651.7
BA	318.9	387.1	395.9	477.9	31.7	0.3	0.0	1.6	572.0	551.7	601.8	488.6	455.5	473.1	608.9	550.1
BRR	492.4	585.5	521.9	768.2	17.6	0.0	0.0	0.0	725.0	693.4	731.0	569.2	586.9	448.3	703.6	751.3
CR	542.4	598.8	586.9	872.7	8.4	0.0	0.0	0.0	703.6	751.4	670.7	502.8	599.6	487.5	734.7	625.7
FD	412.4	464.1	484.8	643.5	11.3	1.5	3.6	2.9	554.0	717.2	619.7	483.4	480.3	469.8	577.5	619.5
FR	239.2	248.6	236.2	392.4	153.1	6.5	0.0	0.0	341.0	449.7	481.5	422.9	347.0	388.6	450.4	497.2
FCR	146.9	227.8	310.9	469.9	27.3	14.7	15.6	15.6	261.1	357.2	413.4	320.7	276.6	357.6	518.7	598.6
MCCR	421.1	467.4	550.4	642.8	10.9	1.6	3.4	3.0	561.8	702.1	616.4	496.4	473.7	448.7	592.2	604.2
MCLR	338.2	388.6	509.6	568.3	13.6	3.9	5.8	6.1	506.1	594.9	562.2	442.1	437.0	433.4	636.4	603.2
MD	426.0	460.9	510.4	534.0	12.0	0.0	0.0	0.9	582.9	685.6	671.9	478.6	483.0	467.8	628.5	535.6
OORR	319.2	333.7	395.4	470.3	37.9	0.0	0.0	0.0	547.2	568.3	572.5	474.6	394.6	475.1	535.9	477.1
PRR	224.5	286.5	374.9	668.4	36.8	30.3	22.8	25.9	242.4	337.6	515.5	413.0	325.4	388.3	616.0	787.2
RR	449.6	482.9	506.0	650.3	11.1	0.0	0.0	0.4	582.2	719.6	653.7	491.4	507.1	462.1	606.8	616.3
RMR	433.6	474.3	525.9	605.4	16.6	2.1	0.0	0.4	621.4	646.9	589.5	469.9	508.1	458.4	650.7	603.6
SA	508.3	529.6	556.1	661.0	12.1	0.0	0.0	0.0	698.5	715.4	627.4	482.4	582.7	483.3	687.1	623.5
WJJD	423.3	514.1	499.4	818.1	9.0	0.0	0.0	0.0	632.8	706.5	675.2	573.8	477.5	510.7	538.7	694.5
WS	521.9	556.0	598.8	647.4	13.0	0.0	0.0	0.0	680.3	793.0	600.7	488.6	442.3	455.0	578.8	516.4

Table 4.18. Edge Density (ED) Calculations Matrices of Land-Cover Composition at the 150 m Scale in the Study Area for the 2002, 2008, 2010, and 2013 Classified Map

	ED Impervious				**ED Agricultural**				**ED Grass**				**ED Forest**			
Sites	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013	2002	2008	2010	2013
16th St	467.5	535.2	541.9	667.9	23.1	0.0	0.0	0.0	731.6	643.8	543.3	445.1	589.3	499.5	627.5	668.8
AS	571.5	582.4	623.6	705.7	10.9	0.0	0.0	0.0	745.8	764.1	737.7	523.8	632.1	495.7	776.7	662.4
BA	344.6	404.3	418.8	485.4	34.8	0.5	0.0	1.1	588.7	560.1	611.5	501.6	462.9	480.6	620.1	538.5
BRR	499.5	602.5	531.0	758.1	18.1	0.0	0.0	0.0	733.5	689.7	728.9	576.4	602.0	457.0	707.7	742.0
CR	586.1	596.2	631.2	695.7	10.2	0.0	0.0	0.0	730.2	782.0	678.3	513.7	620.8	489.0	754.6	630.8
FD	445.5	491.4	516.3	638.4	12.3	1.5	3.7	3.2	566.1	721.7	631.7	497.0	490.4	455.4	577.6	588.9
FR	257.8	250.2	252.2	390.5	159.8	7.0	0.0	0.0	350.3	445.0	499.6	445.5	362.1	389.3	458.7	498.0
FCR	167.3	244.1	322.6	462.2	32.9	16.7	17.4	17.9	283.9	363.6	422.6	338.2	291.4	358.5	513.9	582.8
MCCR	451.5	493.4	571.8	642.2	12.3	1.9	3.5	3.1	580.6	714.6	628.2	509.8	488.8	444.2	590.1	581.9
MCLR	373.7	422.3	528.7	570.3	15.6	5.3	6.6	7.0	529.8	613.9	570.0	451.7	452.2	434.3	628.9	582.2
MD	459.8	487.3	546.6	547.7	16.3	0.0	0.0	1.0	588.3	685.6	681.5	484.6	487.0	458.8	628.3	524.1
OORR	339.0	346.2	417.1	469.3	43.2	0.0	0.0	0.0	551.5	569.9	580.8	480.6	393.4	474.3	552.6	457.4
PRR	248.9	306.4	382.7	648.3	49.5	31.0	26.3	29.6	259.1	352.7	521.4	430.7	339.7	402.5	600.9	734.7
RR	484.6	514.9	542.2	649.2	13.6	0.0	0.0	0.5	595.5	725.9	669.2	507.2	517.7	451.0	612.0	588.9
RMR	472.7	512.8	558.6	619.8	18.3	2.3	0.0	0.4	648.9	674.5	600.2	483.5	523.8	465.0	659.9	598.3
SA	549.9	571.9	598.0	680.7	13.6	0.0	0.0	0.0	721.0	743.8	636.0	494.2	598.1	486.2	706.3	626.2
WJJD	451.1	529.2	521.3	800.3	8.4	0.5	0.0	0.0	644.3	803.1	698.0	589.4	500.6	485.6	546.9	668.5
WS	566.9	599.2	643.4	661.4	11.0	0.0	0.0	0.0	701.9	809.6	618.4	501.6	449.8	457.5	588.8	495.6

Statistical Relationship between LULC Spatial Patterns and Water Quality Variables - Descriptive Statistics

In this section, the descriptive statistics results for the water quality variables are presented to give a general insight into the nature of the water quality data. The means and standard deviations of the water quality dataset for the study period year groups; 1999-2002, 2003-2008, 2009-2010, and 2011-2013 were obtained from the log-transformed data to examine the effects of the data transformation on the normality of the distributions. The log-transformed data demonstrates the improvement in the normality of the data distribution. Table 4.19 to 4.26 summarizes mean and standard deviation results of the water quality variables under study for all sites in the Reedy Fork-Buffalo Creek watershed.

In general, the descriptive statistics shows that high water quality values were associated with FD. The Fecal Coliform exhibited the greatest trend in water quality variables for the analyzed years. An indication of a substantial amount of waste from animal and human sources.

Table 4.19. Descriptive Statistics for 1999-2002 Water Quality Variables with Flow at the Reedy Fork-Buffalo Creek Watershed

Parameters	Descript	BRR	FR	FCR	OORR	PRR	BA	AS	CR	FD
Flow-cms	Mean	0.84	0.70	20.97	1.27	2.67	3.35	4.01	6.12	8.84
	Std. Dev.	0.66	0.68	19.38	1.09	2.75	2.77	2.69	4.13	6.37
BOD-mg/l	Mean	2.24	2.52	2.20	2.38	2.05	2.15	2.26	2.71	2.34
	Std. Dev.	0.84	1.13	0.57	1.03	0.27	0.41	0.51	0.86	0.84
COD-mg/l	Mean	22.49	19.67	21.99	22.44	20.58	20.29	23.53	23.55	23.71
	Std. Dev.	7.70	0.80	5.06	5.88	2.66	0.83	9.97	7.60	7.82
F. Col-CFU/100ml	Mean	907.8	199.7	201.2	354.9	159.1	534.57	1613.9	1189.5	2447.4
	Std. Dev.	1503.	225.6	192.6	227.2	141.9	1,265.6	2367.7	2227.5	2708.9
Hardness- mg/l	Mean	46.24	38.64	42.40	74.09	34.11	56.11	72.84	81.98	151.29
	Std. Dev.	17.24	10.82	19.20	14.46	11.1	15.04	25.24	30.71	36.87
Nitrate- mg/l	Mean	0.21	0.25	0.22	0.38	0.29	0.30	0.27	0.29	0.26
	Std. Dev.	0.10	0.16	0.11	0.20	0.13	0.13	0.25	0.28	0.24
Nitrite- mg/l	Mean	0.12	0.14	0.12	0.12	0.14	0.12	0.12	0.12	0.12
	Std. Dev.	0.09	0.12	0.09	0.09	0.12	0.09	0.09	0.09	0.09
TDS- mg/l	Mean	91.24	84.24	93.95	112.2	82.1	99.12	135.8	142.6	246.6
	Std. Dev.	32.76	38.75	37.49	41.19	34.3	32.01	67.90	32.30	81.59
TSS- mg/l	Mean	4.26	6.44	3.55	4.34	7.18	5.88	4.81	3.91	6.98
	Std. Dev.	3.75	5.19	3.02	3.62	5.19	4.83	3.72	2.05	9.28
TKN- mg/l	Mean	0.43	0.61	0.44	0.45	0.42	0.48	0.78	0.81	0.60
	Std. Dev.	0.23	0.77	0.16	0.18	0.19	0.24	1.13	0.99	0.43
T. Phos- mg/l	Mean	0.04	0.05	0.02	0.06	0.03	0.05	0.08	0.07	0.09
	Std. Dev.	0.02	0.04	0.02	0.07	0.01	0.06	0.07	0.06	0.03
Turbidity- NTU	Mean	5.75	17.07	8.74	7.67	13.6	11.85	9.45	7.86	10.42
	Std. Dev.	4.25	15.17	4.89	2.81	9.51	8.72	13.51	9.72	16.19
Cond.- ohms/cm	Mean	115.62	102.5	103	183.14	95.3	148.57	198.10	228.00	422.05
	Std. Dev.	8.38	15.12	14.21	17.92	7.15	15.51	44.88	47.08	105.7

Table 4.20. Descriptive Statistics for 1999-2002 Water Quality Variables with Flow at Reedy Fork-Buffalo Creek Watershed

Parameters	**Description**	**MCCR**	**MD**	**16TH ST**	**RR**	**RMR**	**WJJD**	**WS**	**MCLR**	**SA**
Flow-cms	Mean	11.93	2.32	2.12	5.86	13.15	1.46	1.80	28.10	2.16
	Std. Dev.	8.67	1.71	1.47	4.03	9.46	1.07	1.21	21.48	1.49
BOD-mg/l	Mean	2.37	2.21	3.14	2.53	3.31	2.30	2.22	2.97	2.61
	Std. Dev.	0.88	0.52	1.41	1.19	2.15	0.73	0.58	2.11	0.82
COD-mg/l	Mean	22.53	23.56	28.42	22.56	31.71	24.90	21.38	24.70	23.27
	Std. Dev.	3.68	6.32	13.57	5.75	13.54	6.78	2.75	8.76	10.53
F. Col-CFU/100ml	Mean	201.38	720.60	3167.71	528.91	866.81	710.67	853.57	1410.86	1178.30
	Std. Dev.	178.3	977	11125	702	1115	1356	1472	1590	1585
Hardness-mg/l	Mean	94.60	72.01	76.07	79.39	74.87	77.14	110.3	88.25	75.23
	Std. Dev.	25.78	17.26	35.27	23.26	33.44	22.61	31.61	32.25	27.17
Nitrate- mg/l	Mean	0.38	0.25	0.27	0.26	9.57	0.20	0.40	3.62	0.32
	Std. Dev.	0.35	0.19	0.11	0.18	6.48	0.16	0.41	6.68	0.27
Nitrite- mg/l	Mean	0.12	0.12	0.12	0.12	0.23	0.14	0.12	0.11	0.11
	Std. Dev.	0.09	0.09	0.08	0.09	0.35	0.14	0.09	0.04	0.02
TDS- mg/l	Mean	169.3	127.5	166.65	143.3	277.5	147.1	193.7	219.3	146.6
	Std. Dev.	46.12	40.26	171.42	35.08	65.54	49.70	63.28	95.17	136.6
TSS- mg/l	Mean	2.76	8.08	10.75	3.39	4.13	12.66	2.55	3.33	5.75
	Std. Dev.	1.97	7.15	9.66	3.68	2.59	11.66	1.76	2.89	5.36
TKN- mg/l	Mean	0.54	0.57	0.74	0.53	2.04	0.65	0.53	1.29	0.77
	Std. Dev.	0.26	0.32	0.52	0.33	1.51	0.27	0.22	1.61	0.64
T. Phos- mg/l	Mean	0.05	0.06	0.06	0.09	0.83	0.07	0.06	0.34	0.07
	Std. Dev.	0.03	0.03	0.05	0.19	0.22	0.06	0.03	0.45	0.07
Turbidity-NTU	Mean	9.20	34.07	21.76	12.60	7.30	28.30	8.34	14.39	16.11
	Std. Dev.	9.03	56.86	13.18	16.21	6.36	33.96	22.63	30.89	16.99
Cond.-ohms/cm	Mean	278.95	203.40	191.58	221.43	438.81	216.57	326.43	362.43	199.70
	Std. Dev.	73.98	42.21	32.40	38.90	97.90	67.60	88.34	142.3	56.29

Table 4.21. Descriptive Statistics for 2003-2008 Water Quality Variables with Flow at the Reedy Fork-Buffalo Creek Watershed

Parameters	Description	BRR	FR	FCR	OORR	PRR	BA	AS	CR	FD
Flow-cms	Mean	1.28	1.35	37.6	1.95	5.42	5.17	4.81	7.34	11.38
	Std. Dev.	1.13	1.48	38.7	1.74	6.13	4.63	3.09	4.69	8.04
BOD-mg/l	Mean	2.09	2.28	2.16	2.39	1.99	2.17	2.18	2.15	2.87
	Std. Dev.	0.32	1.22	0.49	1.86	0.07	0.84	0.56	0.50	4.93
COD-mg/l	Mean	10.7	13.9	14.9	13.56	12.5	13.6	15.6	13.6	25.3
	Std. Dev.	7.63	14.3	13.5	9.64	8.53	8.64	11.6	14.8	52.8
F. Col-CFU/100ml	Mean	843.	329	199	642.1	282	428	859.3	506	1459
	Std. Dev.	2122.	690.4	422	816.6	633.0	925.9	1452.	620	2087
Hardness- mg/l	Mean	39.1	37.5	33.2	75.48	32.1	53.9	72.2	82.2	129
	Std. Dev.	4.66	7.36	5.43	9.29	3.78	5.84	11.4	8.85	20.6
Nitrate- mg/l	Mean	0.27	0.23	0.18	0.32	0.28	0.25	19.50	0.22	0.26
	Std. Dev.	0.17	0.17	0.16	0.19	0.18	0.15	115	0.21	0.22
Nitrite- mg/l	Mean	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.03	0.05
	Std. Dev.	0.04	0.04	0.04	0.04	0.04	0.04	0.09	0.04	0.09
TDS- mg/l	Mean	86.7	84.2	69.8	124.9	71.4	98.6	137	165	239
	Std. Dev.	14.5	17.7	15.8	13.73	16.9	13.5	30.8	58.6	85.0
TSS- mg/l	Mean	7.45	12.1	4.06	7.11	5.92	6.19	3.78	5.60	5.75
	Std. Dev.	12.1	14.9	3.85	4.84	4.12	4.34	3.29	5.28	5.77
TKN- mg/l	Mean	0.36	0.30	0.42	0.38	0.26	0.43	0.76	16.9	16.58
	Std. Dev.	0.35	0.18	0.20	0.30	0.16	0.61	1.40	89.93	97.10
T. Phos- mg/l	Mean	0.04	0.04	0.03	0.07	0.03	0.04	0.05	0.05	0.11
	Std. Dev.	0.03	0.03	0.02	0.14	0.04	0.04	0.03	0.03	0.11
Turbidity- NTU	Mean	6.09	23.1	7.89	9.75	29.5	9.76	4.75	6.27	5.77
	Std. Dev.	3.10	23.3	4.46	6.08	117.	3.93	2.32	4.00	3.55
Cond.-ohms/cm	Mean	104	113	99.8	177.1	97.3	144	216	234	364
	Std. Dev.	24.7	22.1	15.3	45.12	9.83	30.4	56.6	67.9	58.1

Table 4.22. Descriptive Statistics for 2003-2008 Water Quality Variables with Flow at Reedy Fork-Buffalo Creek Watershed

Parameters	Description	MCCR	MD	16^{TH} ST	RR	RMR	WJJD	WS	MCLR	SA
Flow-cms	Mean	15.3	3.00	2.74	7.26	17.01	1.90	2.15	37.92	2.78
	Std. Dev.	10.9	2.20	1.93	4.86	12.05	1.34	1.35	28.51	1.96
BOD-mg/l	Mean	2.08	2.33	2.40	2.12	2.65	2.18	2.24	2.32	2.33
	Std. Dev.	0.34	1.00	1.08	0.29	1.07	0.60	0.67	0.81	1.10
COD-mg/l	Mean	16.5	16.1	14.15	16.11	21.91	19.07	16.81	16.77	20.40
	Std. Dev.	13.2	15.5	8.40	9.79	17.44	11.36	11.63	12.88	8.55
F. Col-CFU/100ml	Mean	183	209	1078	739.9	664	1340	738.6	642.6	1113
	Std. Dev.	219.83	216.49	1697.75	1158.33	1354.38	2030.24	1335.25	1197.12	1749.73
Hardness-mg/l	Mean	89.5	71.4	66.70	78.44	68.89	67.38	111.9	95.03	71.80
	Std. Dev.	13.5	10.2	11.25	11.47	7.18	10.19	27.49	26.61	10.02
Nitrate- mg/l	Mean	0.24	0.22	0.25	0.20	9.53	0.20	4.31	5.40	0.31
	Std. Dev.	0.20	0.18	0.20	0.17	5.44	0.17	24.29	24.31	0.19
Nitrite- mg/l	Mean	0.05	0.05	0.05	0.05	0.19	0.05	0.05	0.10	0.10
	Std. Dev.	0.09	0.09	0.09	0.09	0.25	0.09	0.09	0.20	0.11
TDS- mg/l	Mean	159	130	120.7	148.4	228.5	134.8	204.8	198.0	134.4
	Std. Dev.	32.9	21.5	19.00	37.21	31.98	19.70	38.36	61.72	27.03
TSS- mg/l	Mean	3.31	3.67	9.86	5.14	4.06	7.97	2.06	2.89	4.86
	Std. Dev.	2.19	1.80	10.65	4.88	2.77	5.51	1.41	2.25	2.25
TKN- mg/l	Mean	0.39	0.44	0.43	0.50	28.24	0.53	0.44	14.38	0.76
	Std. Dev.	0.16	0.24	0.23	0.41	160.59	0.32	0.28	82.05	1.42
T. Phos- mg/l	Mean	0.04	0.04	0.04	0.05	0.45	0.06	0.05	0.14	0.05
	Std. Dev.	0.02	0.03	0.02	0.03	0.27	0.03	0.03	0.23	0.03
Turbidity-NTU	Mean	6.75	7.50	16.35	8.51	5.38	13.99	3.21	4.60	9.13
	Std. Dev.	2.95	5.73	19.62	4.98	1.98	11.00	1.31	2.24	5.44
Cond.-ohms/cm	Mean	253.83	207.36	179.42	230.75	358.44	199.42	331.97	302.25	210.94
	Std. Dev.	67.2	47.8	45.52	69.71	62.61	48.01	83.62	97.67	44.94

Table 4.23. Descriptive Statistics for 2009-2010 Water Quality Variables with Flow at the Reedy Fork-Buffalo Creek Watershed

Parameters	Description	BRR	FR	FCR	OORR	PRR	BA	AS	CR	FD
Flow-cms	Mean	1.40	1.69	44.8	2.23	6.92	5.98	5.11	7.73	12.16
	Std. Dev.	0.97	1.38	35.9	1.61	5.84	4.31	2.86	4.28	7.21
BOD-mg/l	Mean	2.67	3.52	2.04	2.22	2.01	2.24	2.75	2.63	2.95
	Std. Dev.	1.40	5.94	0.15	1.01	0.04	1.02	1.75	2.08	2.91
COD-mg/l	Mean	20.7	12.04	16.5	11.08	10.0	11.54	18.33	16.00	18.96
	Std. Dev.	21.5	8.97	12.8	6.68	6.50	6.37	13.61	11.94	14.43
F. Col-CFU/100ml	Mean	3447	958.7	347	655	261	813.8	1890	1517	4115
	Std. Dev.	7448	2063	648.1	973.9	261.5	1900	2637	1880	4135
Hardness-mg/l	Mean	37.1	40.19	36.6	57.85	37.0	47.77	63.44	70.22	82.03
	Std. Dev.	17.1	15.50	16.9	19.80	15.9	14.01	23.50	21.94	30.58
Nitrate-mg/l	Mean	0.22	0.17	0.12	0.32	0.24	0.23	0.30	0.39	0.37
	Std. Dev.	0.12	0.08	0.07	0.16	0.11	0.13	0.20	0.25	0.23
Nitrite-mg/l	Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	Std. Dev.	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01
TDS- mg/l	Mean	84.2	89.75	74.5	113.7	78.1	100.5	131.5	150.8	211.2
	Std. Dev.	13.7	19.58	15.30	26.72	18.19	17.67	42.78	40.19	76.19
TSS- mg/l	Mean	10.2	16.54	5.25	8.17	15.8	15.54	13.21	7.33	7.83
	Std. Dev.	14.0	20.80	5.94	7.99	16.77	20.54	22.01	8.08	10.38
TKN- mg/l	Mean	0.58	0.48	0.54	0.52	0.45	0.57	0.71	0.62	0.66
	Std. Dev.	0.42	0.24	0.27	0.29	0.32	0.29	0.43	0.34	0.52
T. Phos-mg/l	Mean	0.04	0.06	0.02	0.04	0.03	0.04	0.06	0.06	0.14
	Std. Dev.	0.04	0.13	0.01	0.04	0.04	0.04	0.08	0.08	0.14
Turbidity-NTU	Mean	12.5	49.27	11.1	20.95	29.7	23.11	19.73	14.30	20.06
	Std. Dev.	12.7	109.2	7.57	42.37	50.12	40.52	32.62	25.59	50.94
Cond.-ohms/cm	Mean	102	151.1	132.8	175.7	93.88	142.7	196.0	217.9	343.5
	Std. Dev.	36.6	155.2	171	63.27	28.0	41.25	62.27	85.14	152.7

Table 4.24. Descriptive Statistics for 2009-2010 Water Quality Variables with Flow at Reedy Fork-Buffalo Creek Watershed

Parameters	Description	MCCR	MD	16TH ST	RR	RMR	WJJD	WS	MCLR	SA
Flow-cms	Mean	16.39	3.30	2.89	7.75	18.04	2.01	2.23	40.59	2.94
	Std. Dev.	9.74	2.08	1.68	4.42	10.76	1.18	1.20	25.41	1.71
BOD-mg/l	Mean	2.58	2.74	3.04	2.53	2.36	2.75	5.82	2.52	2.67
	Std. Dev.	1.79	2.74	1.53	1.21	0.66	1.92	14.68	1.31	1.66
COD-mg/l	Mean	17.25	17.08	18.33	14.83	19.08	18.63	18.21	24.58	20.33
	Std. Dev.	11.51	10.56	8.26	9.19	9.22	12.57	14.32	13.34	18.03
F. Col-CFU/100 ml	Mean	1863.17	1475.29	2078.82	2165.17	1314.42	1389.96	4427.21	4684.38	2026.25
	Std. Dev.	2592.07	2425.82	2469.40	2241.26	2180.86	1877.83	8734.26	7097.14	2486.31
Hardness-mg/l	Mean	67.60	61.65	53.06	65.33	60.87	63.65	123.03	54.16	63.93
	Std. Dev.	25.94	21.76	20.33	24.60	19.46	28.28	214.0	20.64	22.15
Nitrate-mg/l	Mean	0.26	0.23	0.30	0.25	6.27	0.22	3.86	3.62	0.32
	Std. Dev.	0.17	0.12	0.38	0.14	3.88	0.13	16.92	3.46	0.20
Nitrite-mg/l	Mean	0.01	0.01	0.02	0.01	0.08	0.01	0.03	0.04	0.01
	Std. Dev.	0.01	0.00	0.03	0.00	0.11	0.01	0.02	0.05	0.00
TDS- mg/l	Mean	158.2	119.5	107.0	142.9	199.5	139.9	165.3	237.7	143.1
	Std. Dev.	52.17	26.06	28.02	48.13	54.76	74.54	50.77	137.04	35.74
TSS- mg/l	Mean	16.79	12.67	8.96	13.67	9.92	11.96	5.63	23.25	7.67
	Std. Dev.	23.61	16.59	9.75	15.89	12.04	12.29	6.05	29.27	8.56
TKN-mg/l	Mean	0.69	0.59	0.74	0.65	1.29	0.74	0.68	1.32	1.05
	Std. Dev.	0.46	0.28	0.50	0.31	0.43	0.47	0.46	0.60	1.63
T. Phos-mg/l	Mean	0.07	0.07	0.05	0.05	0.14	0.05	0.07	0.15	0.05
	Std. Dev.	0.06	0.12	0.06	0.07	0.10	0.06	0.09	0.14	0.03
Turbidity-NTU	Mean	25.19	26.49	20.86	18.48	17.54	17.79	12.51	29.08	16.86
	Std. Dev.	31.22	39.53	36.74	20.36	31.93	15.43	31.43	41.21	38.45
Cond.-ohms/cm	Mean	237.6	172.0	179.9	212.4	301.0	209.7	262.3	324.9	227.0
	Std. Dev.	100.6	56.09	139.3	85.97	98.38	141.2	102.7	165.7	70.27

Table 4.25. Descriptive Statistics for 2011-2013 Water Quality Variables with Flow at the Reedy Fork-Buffalo Creek Watershed

Parameters	Description	BRR	FR	FCR	OORR	PRR	BA	AS	CR	FD
Flow-cms	Mean	1.03	1.06	29.6	1.65	4.23	4.35	4.34	6.59	9.92
	Std. Dev.	0.71	1.00	25.5	1.32	4.23	3.44	2.54	3.81	6.10
BOD-mg/l	Mean	2.75	2.48	2.11	2.18	2.02	2.09	2.65	2.44	2.69
	Std. Dev.	3.71	1.18	0.41	0.68	0.15	0.36	1.69	1.04	1.86
COD-mg/l	Mean	14.68	12.1	12.7	13.42	9.67	12.00	18.92	17.00	18.58
	Std. Dev.	13.00	7.80	6.37	8.35	5.49	7.56	10.25	8.98	10.29
F. Col-CFU/100ml	Mean	951.31	452.69	160.22	504.50	440.58	851.78	913.81	1172.76	1928.00
	Std. Dev.	1215	646	164.3	539.3	519.2	1424	1806	1782.8	2001.5
Hardness-mg/l	Mean	37.18	36.2	34.7	64.38	32.8	50.53	62.79	73.10	110.1
	Std. Dev.	7.29	9.30	7.99	18.49	5.61	13.12	21.93	20.89	32.68
Nitrate-mg/l	Mean	0.21	0.19	0.10	0.29	0.26	0.22	0.25	0.48	0.35
	Std. Dev.	0.10	0.09	0.06	0.15	0.11	0.13	0.15	0.82	0.21
Nitrite-mg/l	Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	Std. Dev.	0.00	0.00	0.02	0.00	0.02	0.00	0.01	0.01	0.02
TDS- mg/l	Mean	89.47	86.7	78.1	127.4	80.6	105.4	137.9	164.3	225.2
	Std. Dev.	20.62	21.00	14.22	43.33	10.95	25.48	69.78	83.40	89.76
TSS- mg/l	Mean	8.36	12.2	5.92	14.56	17.3	11.97	8.44	7.68	15.42
	Std. Dev.	10.81	16.50	6.29	16.91	22.42	10.93	10.95	7.55	20.90
TKN- mg/l	Mean	0.60	0.79	0.93	0.78	0.50	0.63	0.79	0.73	0.75
	Std. Dev.	0.37	0.88	1.59	0.71	0.32	0.34	0.48	0.48	0.49
T. Phos-mg/l	Mean	0.06	0.03	0.02	0.06	0.03	0.05	0.13	0.09	0.15
	Std. Dev.	0.07	0.02	0.01	0.05	0.03	0.09	0.11	0.06	0.11
Turbidity-NTU	Mean	15.97	18.4	11.3	26.28	24.1	23.96	22.62	12.61	23.27
	Std. Dev.	18.62	12.72	10.92	28.32	27.36	24.83	45.38	9.85	27.64
Cond.-ohms/cm	Mean	122.9	102.8	100.8	158.3	87.28	128.8	200.8	221.30	296.47
	Std. Dev.	131.6	28.8	22.7	70.97	16.0	46.49	145.0	120.4	141.7

Table 4.26. Descriptive Statistics for 2011-2013 Water Quality Variables with Flow at Reedy Fork-Buffalo Creek Watershed

Parameters	Description	MCCR	MD	16^{TH} ST	RR	RMR	WJJD	WS	MCLR	SA
Flow-cms	Mean	13.37	2.67	2.35	6.45	14.74	1.63	1.92	32.35	2.39
	Std. Dev.	8.22	1.79	1.39	3.88	8.93	0.99	1.08	20.59	1.41
BOD-mg/l	Mean	2.19	2.49	2.54	2.38	2.68	2.30	2.32	2.96	2.41
	Std. Dev.	0.51	1.13	1.22	0.88	1.43	0.54	0.76	2.17	1.06
COD-mg/l	Mean	17.32	17.6	17.25	18.19	19.00	20.31	19.39	31.94	15.83
	Std. Dev.	8.65	8.16	7.59	9.09	7.58	9.49	10.78	9.31	8.08
F. Col-CFU/100 ml	Mean	338.22	425.67	841.31	2507.14	1250.42	1020.11	1070.97	1311.91	1552.31
	Std. Dev.	269.9	294	1482.5	4995	1981	1284	1468	2903	4300
Hardness-mg/l	Mean	74.68	60.4	51.51	67.65	64.46	65.69	88.79	62.66	71.66
	Std. Dev.	27.00	23.7	14.21	24.65	15.18	23.96	39.31	13.36	21.98
Nitrate-mg/l	Mean	0.22	0.19	0.22	0.22	6.06	0.16	0.31	5.46	0.28
	Std. Dev.	0.13	0.10	0.24	0.16	3.31	0.10	0.22	4.00	0.16
Nitrite-mg/l	Mean	0.01	0.01	0.01	0.02	0.06	0.01	0.01	0.03	0.01
	Std. Dev.	0.00	0.00	0.02	0.05	0.07	0.01	0.01	0.08	0.01
TDS- mg/l	Mean	158.2	125	106.4	147.1	208.2	168.2	183.0	358.8	149.1
	Std. Dev.	92.46	70.1	32.43	90.73	64.10	148.0	131.5	119.8	67.32
TSS- mg/l	Mean	9.41	11.0	9.42	14.17	7.67	16.25	4.03	14.82	7.17
	Std. Dev.	10.05	15.8	10.40	17.74	6.27	14.83	2.82	18.15	6.12
TKN- mg/l	Mean	0.86	0.77	0.71	0.86	1.55	0.84	0.83	1.67	0.80
	Std. Dev.	0.56	0.48	0.38	0.56	0.77	0.40	0.45	1.35	0.50
T. Phos-mg/l	Mean	0.06	0.07	0.03	0.06	0.13	0.06	0.05	0.22	0.08
	Std. Dev.	0.04	0.13	0.03	0.05	0.09	0.05	0.04	0.17	0.05
Turbidity-NTU	Mean	18.69	21.4	15.30	23.69	15.44	22.31	16.49	18.24	14.90
	Std. Dev.	17.09	28.3	12.80	29.51	16.91	20.47	25.10	25.93	15.73
Cond.-ohms/cm	Mean	223.3	160	159.36	204.9	291.1	169.5	228.8	505.8	204.5
	Std. Dev.	127.7	104.	141.3	138.8	138.5	67.05	148.5	202.9	108.2

Factor Analysis

FA analysis was performed on the normalized datasets (12 variables) for the18 sampling sites at the Reedy Fork Creek Buffalo Creek watersheds to compare the compositional pattern between analyzed water samples and identify the most influencing factors affecting water quality in the watershed. For all the water quality data analyzed, communalities larger than 0.6 were observed in each case at each site. Hence, it may be assumed that all the variables were within an acceptable limit. In general, component loadings or correlation coefficients greater than 0.6 may be taken into consideration in the interpretation (Mahloch, 1974). That is, the most significant variables in the components represented by high factor loadings were taken into consideration in evaluating the components.

Similarly, eigenvalue which gives a measure of the significance of the factors were considered. The factors with the highest eigenvalues are the most significant. Eigenvalues of 1.0 or greater are considered significant (Kim and Muller 1987). As presented in Table 4.27 to 4.30, between three and five-factor loadings with eigenvalues >1 were obtained at the various measurement sites. These are enough to give an adequate representation of the data for the study year periods. KMO and Bartlett's test values greater than 0.6 and less than 0.05 ($P < 0.05$) respectively were obtained for individual site parameters.

Factors loadings obtained for all variables through FA explained variance are presented in Tables 4.27 to 4.30. FA of the 12 water quality variables for the 1999 to 2002 period yielded four factors with eigenvalues greater than 1 (> 1), explaining 63.7%

of the total variance of the data. For 2003 to 2008 variables, five retained factors explained 66.8% of the total sampled variance with eigenvalues greater than 1 (> 1). Also, for 2009 to 20, FA yielded four factors with corresponding eigenvalues greater than 1 (> 1), explaining 72.6% of the total variance, whereas, that of 2011 to 2013 datasets yielded three factors with eigenvalues greater than 1 (> 1), explaining 58.4% of the total variance. Miller et al., (1997), and Puckett and Bricker, (1992) classified the factor loadings as ‘strong’, ‘moderate’ and ‘weak’, corresponding to absolute loading values of >0.75, 0.75–0.50 and <0.50, respectively. For clarity and presentation purpose, low loadings are not reported in Table 4.27 to 4.30.

Table 4.27. Variables Associated with Strong Factor Loadings, Eigenvalue, Communalities and Variance Explained in the Reedy Fork-Buffalo Creek Watershed from 1999-2002

	Factor 1	Factor 2	Factor 3	Factor 4	Communalities
Nitrate	**0.88**	-	-	-	0.81
Total Phosphorous	**0.88**	-	-	-	0.88
TKN	**0.87**	-	-	-	0.60
Conductivity	-	**0.78**	-	-	0.86
Hardness	-	**0.89**	-	-	0.83
TDS	-	0.72	-	-	0.68
Turbidity	-	-	**0.83**	-	0.72
TSS	-	-	**0.82**	-	0.73
Fecal Coliform	-	-	-	-	0.59
BOD	-	-	-	**0.78**	0.82
COD	-	-	-	0.64	0.63
Nitrite	-	-	-	-	0.61
Eigenvalue	2.36	2.10	1.62	1.56	
Variance Explained (%)	19.69	17.51	13.49	12.99	

Table 4.28. Variables Associated with Strong Factor Loadings, Eigenvalue, Communalities and Variance Explained in the Reedy Fork-Buffalo Creek Watershed from 2003-2008

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Communalities
TDS	**0.91**	-	-	-	-	0.86
Conductivity	**0.91**	-	-	-	-	0.89
Hardness	**0.90**	-	-	-	-	0.82
BOD	-	**0.90**	-	-	-	0.81
COD	-	**0.89**	-	-	-	0.81
Nitrite	-	-	0.73	-	-	0.61
Total Phosphorous	-	-	0.70	-	-	0.63
Fecal Coliform	-	-	0.62	-	-	0.60
Turbidity	-	-	-	**0.78**	-	0.62
TSS	-	-	-	0.74	-	0.61
TKN	-	-	-	-	**0.79**	0.64
Nitrate	-	-	-	-	**0.78**	0.58
Eigenvalue	2.54	1.68	1.48	1.25	1.05	
Variance Explained (%)	21.19	14.02	12.40	10.43	8.77	

Table 4.29. Variables Associated with Strong Factor Loadings, Eigenvalue, Communalities and Variance Explained in the Reedy Fork-Buffalo Creek Watershed from 2009-2010

	Factor 1	Factor 2	Factor 3	Factor 4	Communalities
Nitrate	**0.93**	-	-	-	0.90
Hardness	**0.92**	-	-	-	0.90
BOD	**0.87**	-	-	-	0.91
Turbidity	-	**0.88**	-	-	0.81
TSS	-	0.74	-	-	0.70
Total Phosphorous	-	0.73	-	-	0.68
COD	-	-	**0.79**	-	0.68
TKN	-	-	**0.79**	-	0.72
Fecal Coliform	-	-	0.62	-	0.63
Nitrite	-	-	-	-	0.61
TDS	-	-	-	**0.93**	0.87
Conductivity	-	-	-	**0.89**	0.81
Eigenvalue	2.57	2.216	1.968	1.954	
Variance Explained (%)	21.414	18.471	16.399	16.287	

Table 4.30. Variables Associated with Strong Factor Loadings, Eigenvalue, Communalities and Variance Explained in the Reedy Fork-Buffalo Creek Watershed from 2011-2013

	Factor 1	Factor 2	Factor 3	Communalities
Conductivity	**0.88**	-	-	0.79
TDS	**0.89**	-	-	0.82
Hardness	**0.77**	-	-	0.63
Nitrate	**0.76**	-	-	0.60
TSS	-	**0.76**	-	0.62
Turbidity	-	**0.75**	-	0.61
Fecal Coliform	-	0.69	-	0.59
COD	-	0.56	0.50	0.60
TKN	-	-	**0.75**	0.56
Nitrite	-	-	0.73	0.58
BOD	-	-	0.60	0.58
Total Phosphorous	-	-	-	0.60
Eigenvalue	2.63	2.25	2.13	
Variance Explained (%)	21.88	18.74	17.78	

Correlation and Regression Analysis

To examine the potential temporal variations in the water quality variable, as well as, the effects percent LULC and landscape metrics exert on water quality, similar water quality variables with strong factor loadings (>0.75), obtained from the FA for 1999-2002, 2003-2008, 2009-2010, and 2011-2013 were separately examined through Pearson correlation and regression analysis. The correlation coefficients and significance between only water quality variables, as well as, between water quality variables and landscape characteristics for each year are presented in Table 4.31 and Table 4.32 to 4.35 for each year group respectively.

The results from the regression analysis, the coefficient of determination or R-squared regression values, produced by these tests for each analyzed year is presented in Table 4.36 to 4.39. These results were obtained with water quality variable datasets input as dependent variables and LULC spatial patterns at the various spatial scales as independent variables for each test.

Spatial and Temporal Variation in River Flow and Water Quality

Most of the water quality variables measured in the study area increase during the 1999-2013 periods (Table 4.31). Significant changes were observed for conductivity, hardness, nitrate, and TKN between the 2003-2008 and 2009-2010; and the 2009 –2010 and 2011–2013 periods. Between 1999-2002 and 2003-2008 period, no significant differences in water quality measures were detected among flow, conductivity, TKN, and turbidity, suggesting that water quality was similar for this periods. The mean concentrations of conductivity, hardness, nitrate, TKN, and turbidity all showed considerable variations among the study periods from 1999–2013, with the highest conductivity and hardness mean values occurring in 2003-2008, the highest nitrate and turbidity in 2010-2013, and highest TKN in 2010-2013. In contrast, lowest nitrate occurred in 1999-2002, lowest TKN and turbidity in 2003-2008, and lowest conductivity and hardness occurred in 2009-2010 (Table 4.31).

As expected, flow varied along the rivers in the watershed, but the differences in flow at each site tends to increase during the four study time periods (Fig. 4.15). The mean concentration of nitrate and TKN were high at RMR and MCCR sites for all study periods than the rest of the sites (Fig. 4.16 and 4.17). The mean concentrations of hardness, conductivity all showed a considerable amount of variations among the sites for all years, with the highest conductivity and hardness values occurring in the WS site, Fig. 4.18, and 4.19. In contrast, the concentration of turbidity had an unsteady change. 1999-2002 and 2003-2008 recorded low turbidity while, 2009-2010 and 2011-2013 recorded high turbidity values with overall turbidity obtained for the 2009-2010-year group, Fig. 4.20. Sites in Fig. 4.15 to Fig. 4.20 refer to:

Site 1= BRR, **Site2**=FR, **Site3**=FCR, **Site4**=OORR, **Site5**=PRR, **Site6**=BA, **Site7**=AS, **Site8**=CR, **Site9**=FD, **Site10**=MCRR, **Site11**=MD, **Site12**=16th St., **Site13**=RR, **Site14**=RMR, Site15=WJJD, **Site16**=WS, **Site17**=MCRL, and **Site18**=SA

Table 4.31. Pearson Correlation Test between Study Period Water Quality Variables (Mean Values) at the 0.05 Level among Different Time Periods in the Study Area. Under the Significant (2-Tailed) Values, "BOLD" Numbers Indicate Positive Relationship, "UNBOLD" Numbers Indicate No Significant Relationships. (Whole Watershed)

	1999-2002	**2003-2008**	**Significance (2-tailed)**
Flow	6.537	9.247	0.054
Conductivity	230.932	242.313	0.063
Hardness	72.266	79.123	**0.025**
Nitrate	0.289	0.440	**0.005**
TKN	0.592	0.540	0.072
Turbidity	14.456	17.981	0.784
	2003-2008	**2009-2010**	**Significance (2-taled)**
Flow	9.247	10.232	0.070
Conductivity	242.313	111.656	**0.041**
Hardness	79.123	60.348	**0.016**
Nitrate	0.440	0.872	**0.003**
TKN	0.540	0.741	**0.030**
Turbidity	17.981	22.527	0.060
	2009-2010	**2010-2013**	**Significance (2-taled)**
Flow	10.232	12.818	0.121
Conductivity	111.656	197.846	**0.049**
Hardness	60.348	71.648	**0.025**
Nitrate	0.872	1.400	**0.001**
TKN	0.741	1.855	**0.005**
Turbidity	22.527	29.178	0.322

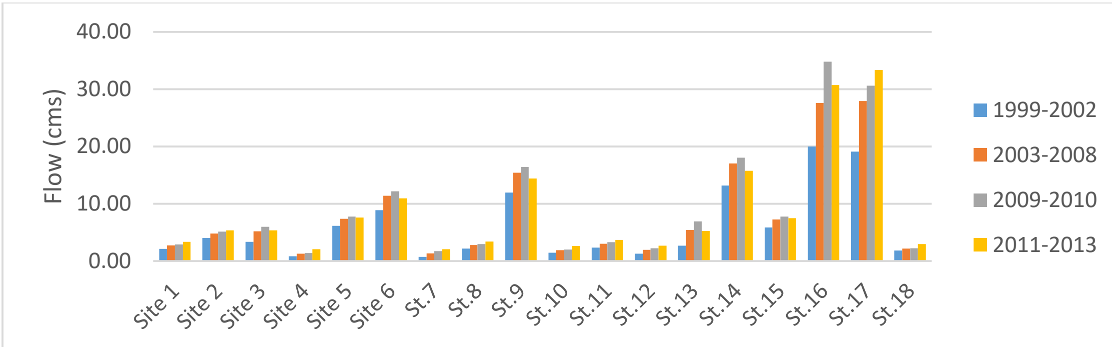


Figure 4.15. Differences in Flow Among the 18 Sites and the Study Period Means

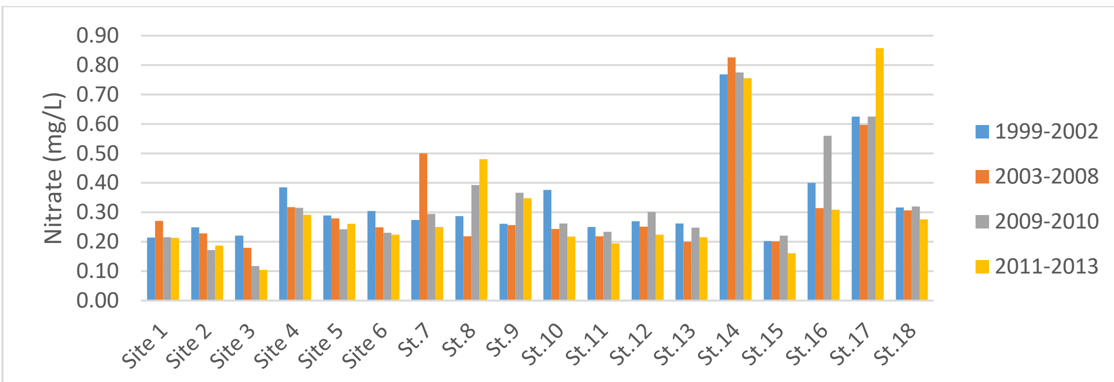


Figure 4.16. Differences in Nitrate Among the 18 Sites and the Study Period Means

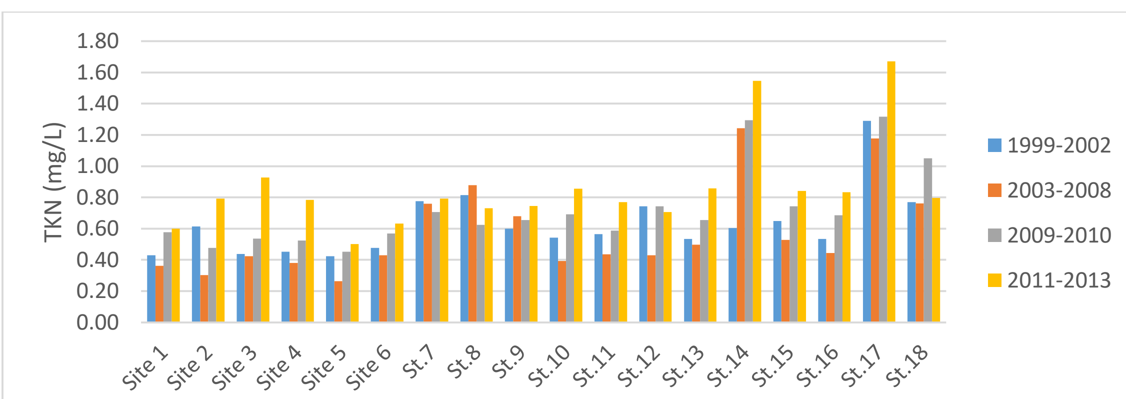


Figure 4.17. Differences in TKN Among the 18 Sites and the Study Period Means

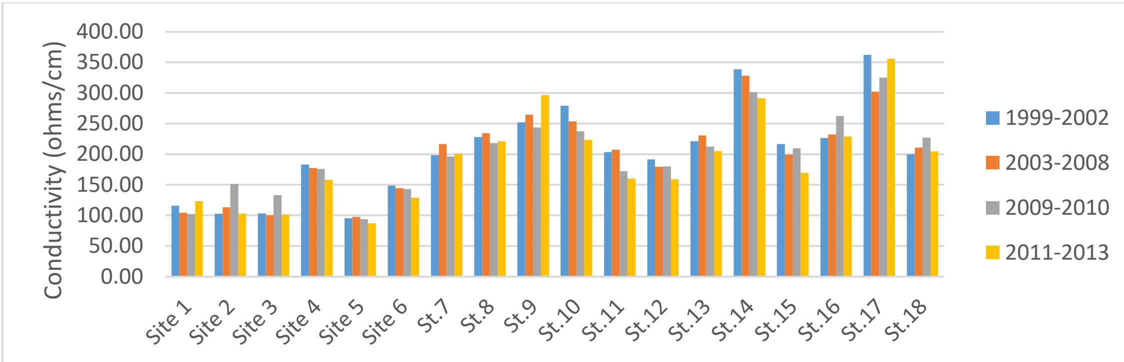


Figure 4.18. Differences in Conductivity Among the 18 Sites and the Study Period Means

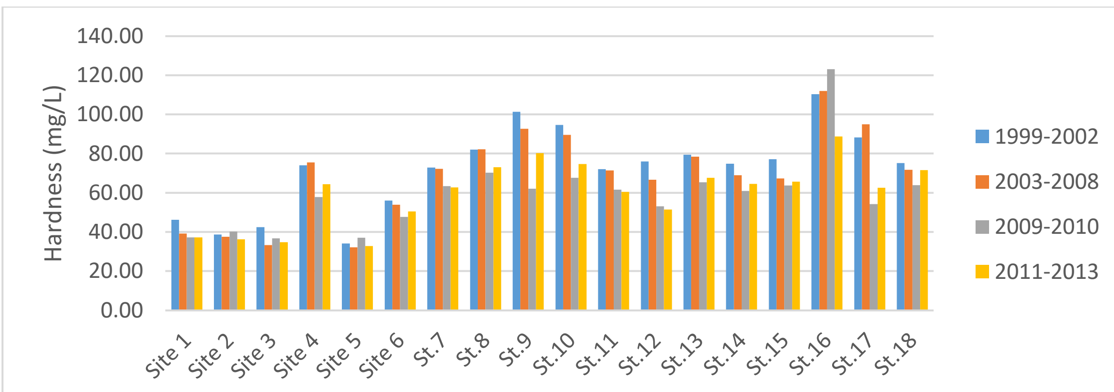


Figure 4.19. Differences in Hardness Among the 18 Sites and the Study Period Means

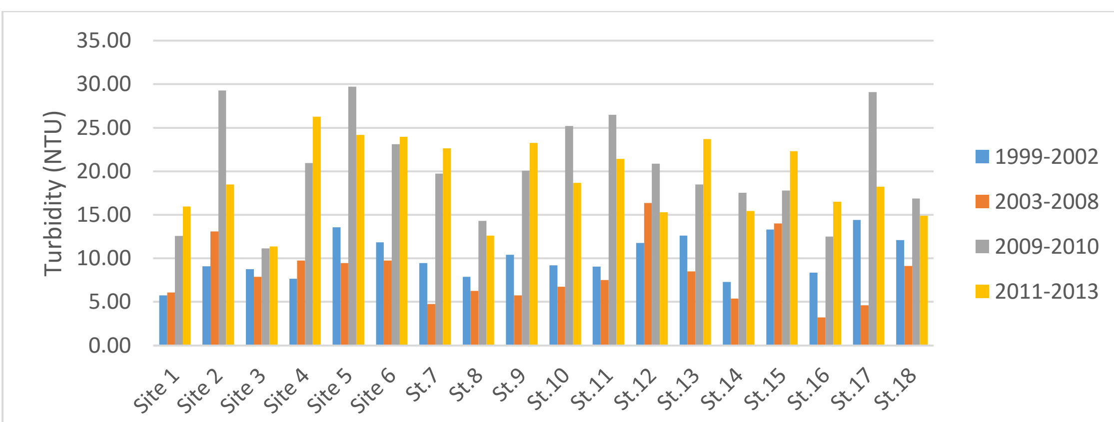


Figure 4.20. Differences in Turbidity Among the 18 Sites and the Study Period Means

Effect of LULC on River Flow and Water Quality with Scale

The results of correlation analysis between water quality variables and LULC patterns showed that the water quality variables of the Reedy Fork-Buffalo Creek watershed were correlated with certain land-use and landscape metrics at the different spatial scales, but not others (Table 4.32 to 4.35). Landscape metrics include the PLAND, NP, ED, and LPI of impervious, agricultural, grass, and forest LULC. Flow is measured in m^3/s, Turbidity is measured in NTU and conductivity is measured in ohms/cm, all the other variables are measured in mg/L. The correlation significance level is 0.05. At least one landscape metric was significant as an explanatory variable in each regression relationship. Specifically, for the 1999-2002, the PLAND occupied by impervious land-use was positively correlated with the mean concentrations of nitrate. In contrast with impervious land-use, the percentage of agricultural and forest land-use were negatively correlated with nitrate concentrations at the watershed and buffer scale (100 m and 150 m in buffer width). Impervious cover at watershed level was found to have the strong positive relationship with water quality contaminant level indicated by an r value of 0.673 for nitrate. The NP of impervious, agricultural, grass, and forest land-use were positively correlated with flow and conductivity with strong a flow (0.974) and conductivity (0.607) level recorded at the watershed and 100 m buffer scale respectively. The ED of impervious was positively correlated with nitrate and TKN, likewise grass and forest ED with TKN at the scales of watershed, and buffer (100-150 m buffer width). The landscape metrics of PLAND-grass, ED-agricultural, and LPI of agricultural, grass and forested LULC were not significantly correlated with water quality variables. None of the landscape metrics used in our analysis significantly correlated with Turbidity at all scales for the 1999-2002-year group (Table 4.32).

Nitrate, TKN, and Turbidity significantly correlated with the PLAND of landscape patterns for 2003 to 2008. Specifically, Nitrate positively correlated with PLAND of impervious and grass but negative with agricultural and PLAND of forest at all spatial scales. Conversely, Turbidity positively correlated with PLAND of agricultural and forest but negatively with PLAND of impervious and grass. TKN, on the other hand, correlated positively with impervious cover and negatively with grass cover at the 100m, 150m, and watershed scale. PLAND of forest at the watershed zone was found to have the strongest positive relationship with water quality contaminant levels, indicated by an r value of 0.794 for nitrate, forest at the 100 m zone had a strong positive relationship with Turbidity with an r-value of 0.686, and TKN a strong positive relationship with forest with an r value of 0.600 at the watershed scale. For NP, Flow positively correlated with impervious, agricultural, grass and forest at all the spatial scales. However, a strong relationship was observed between NP of grass and flow with an r value of 0.97 at the watershed scale. Conductivity, and TKN also showed a positive correlation with forest cover at all scales with conductivity having the strongest relationship with forest at the 100 m scale with an r value of 0.60. Regarding the ED, a positive correlation was observed between impervious, nitrate, and TKN; grass, nitrate, and TKN: and between agricultural and turbidity. However, nitrate and agricultural, as well as, turbidity with impervious and grass were negatively correlated at all spatial scales of analysis. Strongest positive correlation with an r value of 0.717 was obtained at the watershed level between grass and nitrate. LPI of agricultural and forest correlated positively with turbidity and negatively with nitrate at the 100 m, 150 m, and watershed scales with the correlation between turbidity and agricultural being the strongest with an r value of 0.751 at the 100 m spatial scale level. ED of forest and LPI of impervious cover did not correlate with any of the water quality variables at all scales for the 2003-2008-year group (Table 4.33).

For the 2009-2010 period of analysis, PLAND of impervious land-use exerted a positive relationship with nitrate, flow, and hardness. PLAND of forest negatively correlated with flow. These relationships were the same at all scales. The strongest positive correlation for the 2009-2010 was observed between PLAND of impervious land-use and nitrate at the watershed level with an r value of 0.799. NP of impervious, agricultural, grass, and forest cover has a positive correlation with the flow, NP of forest and grass positively correlated with TKN, and NP of forest correlated positively with conductivity, TDS, and TKN at all scales of analysis. Strongest NP relationship was obtained between flow and grass at the watershed scale having an r value of 0.982. ED of impervious cover correlated positively with nitrate and hardness, whereas LPI of impervious cover positively correlated with Conductivity, Nitrate, and Hardness at the 100 m, 150 m, and watershed levels. Hardness exhibited the strongest relationship with impervious ED and impervious LPI with r values of 0.672 and 0.791 respectively. ED and LPI of agricultural, grass and forest did not show correlation with any of the water quality variables. In the same manner, turbidity did not correlate with any of the land-use attributes (Table 4.34).

The correlation between water quality variables and landscape attributes for the 2011-2013 period exhibited the same trend at all scales of analysis. Flow positively correlated with percent agricultural, nitrate with PLAND impervious, and turbidity with PLAND grass. However, PLAND forest cover was negatively correlated with nitrate at the watershed level with an r value of –0.808. Flow positively correlated with NP of impervious, agricultural, grass, and forest. Conductivity with NP of grass and forest, TDS with that of NP forest and TKN positively correlated with NP of grass and forest with the strongest relationship observed between flow and NP of grass at the watershed level with an r value of 0.976. Positive correlation was observed between nitrate and impervious ED, as well as, impervious LPI. Conversely, negative correlation occurred between nitrate and forest ED and LPI at the 100 m, 150 m, and watershed scales with the strongest relationships observed at the watershed level between nitrate and impervious ED, and Nitrate and impervious LPI with r values of 0.585 and 0.782 respectively (Table 4.35). These results demonstrate the highly significant role that the various land-use percentage, landscape attributes, and spatial scales can play in analyzing the relationships between land-use and water quality.

Regression results also showed that the relationship between annual mean river water characteristics and landscape pattern varied with the spatial scale of analysis. The coefficient of determination, or *R*-squared, values at multiple spatial scales for each year group produced by these tests are presented in Table 4.36 to 4.39. The independent variables are the PLAND, NP, ED, and LPI of each land-use type (impervious, agriculture, grass, and forest). For the 1999-2002 period, river flow was strongly related to landscape indexes PLAND, NP, ED, and LPI (R^2 = 0.72, 0.96, 0.72, and 0.91, respectively) at the 100m buffers scale. For nitrate, the R^2 increased from 0.84 to 0.85 when buffer width increased from 100 m to 150 m for PLAND. The values of R^2 for nitrate were similarly high at the watershed (Table 4.36 to 4.39). Similar scale effects were also exhibited by the NP, ED, and LPI landscape patterns. Also, nitrate for 2003-2008, 2009-2010, and 2011-2013 exhibited similar incremental order as did 1999-2002 with the watershed scale having the highest explanatory values for all years.

Similar scale effects were also found with the other water quality variables for the various years. But generally, the effect is more pronounce at the watershed scale for most of the analyzed water quality variables in relation to the PLAND, NP, ED, and LPI. Annual variations in the explanatory power of PLAND, NP, ED, and LPI of the LULC for water quality at each spatial scale can be observed in Fig. 4.22 to 4.25.

Table 4.32. Correlation Result of 1999-2002 Water Quality Variables Against 2002 Landscape Metrics at Different Spatial Scales. “Bold” Numbers Indicate the Significant Positive Relationship, “Unbold” Numbers Indicate The Significant Negative Relationship and “Blank” No Correlation. The Significant Level is 0.05.

	PLAND_2002				**NP 2002**				**ED_2002**				**LPI_2002**			
100 m Buffer	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*
Flow					**0.926**	**0.717**	**0.911**	**0.796**								
Conductivity					**0.588**	**0.607**	**0.536**	**0.596**					0.526			
Nitrate	**0.637**	0.498		0.476					**0.503**							
Hardness																
TKN									**0.483**		**0.508**	**0.566**				
Turbidity																
150 m Buffer																
Flow					**0.925**	**0.73**	**0.917**	**0.806**								
Conductivity	**0.478**				**0.469**	**0.598**	**0.521**	**0.606**								
Nitrate	**0.65**	0.523		0.507					**0.518**							
Hardness																
TKN									**0.514**		**0.482**	**0.585**				
Turbidity																
Watershed																
Flow					**0.964**	**0.738**	**0.974**	**0.966**								
Conductivity	**0.502**	0.486			**0.589**	**0.555**	**0.527**	**0.506**					**0.534**			
Nitrate	**0.673**	0.588		0.516					**0.575**							
Hardness																
TKN									**0.619**		**0.569**	**0.644**				
Turbidity																

*IMP: Impervious, *AG: Agricultural, *GR: Grass, *FST: Forest

Table 4.33. Correlation Result of 2003-2008 Water Quality Variables Against 2008 Landscape Metrics At Different Spatial Scales. “Bold” Numbers Indicate the Significant Positive Relationship, “Unbold” Numbers Indicate the Significant Negative Relationship and “Blank” No Correlation. The Significant Level is 0.05.

	PLAND_2008				**NP 2008**				**ED_2008**				**LPI_2008**			
100 m Buffer	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*
Flow					**0.951**	**0.76**	**0.948**	**0.794**								
Conductivity								**0.596**								
Nitrate	**0.687**	0.567	**0.73**	0.72					**0.523**	0.531	**0.704**			0.513		0.588
Hardness																
TKN	**0.54**			0.514				**0.503**	**0.542**		**0.498**					
Turbidity	0.648	**0.652**	0.614	**0.686**					0.552	**0.648**	0.61			**0.751**		**0.598**
150 m Buffer																
Flow					**0.95**	**0.769**	**0.947**	**0.8**								
Conductivity								**0.593**								
Nitrate	**0.701**	0.576	**0.733**	0.735					**0.539**	0.544	**0.707**			0.528		0.593
Hardness																
TKN	**0.532**			0.534				**0.502**	**0.502**		**0.543**					
Turbidity	0.648	**0.646**	0.603	**0.678**					0.559	**0.649**	0.617			**0.731**		**0.578**
Watershed																
Flow					**0.932**	**0.758**	**0.97**	**0.962**								
Conductivity								**0.529**								
Nitrate	**0.765**	0.533	**0.771**	0.794					**0.604**	0.58	**0.717**			0.473		0.535
Hardness																
TKN	**0.537**			0.58				**0.503**	**0.592**		**0.626**					
Turbidity	0.61	**0.562**	0.617	0.619					0.518	**0.588**	0.588			**0.499**		**0.5**

*IMP: Impervious, *AG: Agricultural, *GR: Grass, *FST: Forest

Table 4.34. Correlation Result of 2009-2010 Water Quality Variables Against 2010 Landscape Metrics at Different Spatial Scales. “Bold” Numbers Indicate the Significant Positive Relationship, “Unbold” Numbers Indicate the Significant Negative Relationship and “Blank” No Correlation. The Significant Level is 0.05.

	PLAND_2010				**NP 2010**				**ED_2010**				**LPI_2010**			
100 m Buffer	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*
Flow	**0.516**			0.508	**0.974**	**0.841**	**0.939**	**0.798**								
Conductivity								**0.609**					**0.532**			
Nitrate	**0.711**			0.558					**0.625**				**0.569**			
Hardness	**0.513**								**0.526**				**0.521**			
TKN							**0.572**	**0.709**								
Turbidity																
150 m Buffer																
Flow	**0.544**			0.495	**0.972**	**0.832**	**0.935**	**0.802**								
Conductivity								**0.616**					**0.603**			
Nitrate	**0.719**			0.614					**0.655**				**0.644**			
Hardness	**0.516**								**0.537**				**0.586**			
TKN							**0.577**	**0.716**								
Turbidity																
Watershed																
Flow	**0.507**			0.586	**0.964**	**0.784**	**0.982**	**0.962**								
Conductivity								**0.569**	**0.502**				**0.496**			
Nitrate	**0.799**			0.741					**0.672**				**0.791**			
Hardness	**0.58**								**0.489**				**0.633**			
TKN							**0.55**	**0.655**								
Turbidity																

*IMP: Impervious, *AG: Agricultural, *GR: Grass, *FST: Forest

Table 4.35. Correlation Result of 2011-2013 Water Quality Variables Against 2013 Landscape Metrics at Different Spatial Scales. “Bold” Numbers Indicate the Significant Positive Relationship, “Unbold” Numbers Indicate the Significant Negative Relationship and “Blank” No Correlation. The Significant Level Is 0.05.

	PLAND_2013				**NP 2013**				**ED_2013**				**LPI_2013**			
100 m Buffer	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*	IMP.*	AG*	GR*	FST*
Flow		**0.513**			**0.938**	**0.733**	**0.938**	**0.818**								
Conductivity							**0.495**	**0.604**								
Nitrate	**0.749**			0.699					**0.484**			0.527	**0.694**			0.602
Hardness																
TKN							**0.674**	**0.711**								
Turbidity			**0.564**													
150 m Buffer																
Flow		**0.523**			**0.923**	**0.708**	**0.936**	**0.815**								
Conductivity							**0.495**	**0.634**								
Nitrate	**0.76**			0.748					**0.475**			0.522	**0.7**			0.516
Hardness																
TKN					**0.487**		**0.673**	**0.727**								
Turbidity			**0.585**													
Watershed																
Flow		**0.468**			**0.882**	**0.701**	**0.976**	**0.963**								
Conductivity							**0.472**	**0.641**								
Nitrate	**0.79**			0.808					**0.585**			0.581	**0.782**			0.611
Hardness																
TKN							**0.642**	**0.746**								
Turbidity			**0.506**													

*IMP: Impervious, *AG: Agricultural, *GR: Grass, *FST: Forest

Table 4.36. PLAND R-Squared Regression Results at Multiple Spatial Scales. The Independent Variables Are the PLAND of each LULC Type (Impervious, Agricultural, Grass, and Forest). The Numbers in Bold Indicate they are the Highest Value among Several Scales. The Significance Level is 0.05

	2002 PLAND			**2008 PLAND**			**2010 PLAND**			**2013 PLAND**		
	100 m	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**
Flow	**0.72**	0.71	0.61	0.52	0.54	**0.65**	0.70	**0.72**	0.65	**0.70**	0.69	0.62
Conductivity	0.72	0.72	**0.73**	0.50	0.52	**0.62**	0.60	0.57	**0.60**	0.58	0.57	**0.58**
Hardness	0.56	0.57	**0.62**	0.47	0.42	**0.48**	0.68	0.66	**0.76**	0.48	0.49	**0.52**
Nitrate	0.84	0.85	**0.89**	0.86	0.88	**0.95**	0.89	0.93	**0.97**	0.91	0.96	**0.97**
TKN	**0.66**	0.64	0.62	0.60	0.60	**0.66**	0.56	0.53	**0.57**	0.45	0.41	**0.46**
Turbidity	0.46	0.47	**0.48**	0.80	0.80	**0.87**	0.54	0.56	**0.68**	0.74	**0.76**	0.74

Table 4.37. NP R-Squared Regression Result at Multiple Spatial Scales. The Independent Variables are the NP of each LULC Type (Impervious, Agricultural, Grass, and Forest). The Numbers in Bold Indicate they are the Highest Value among Several Scales. The Significance Level is 0.05

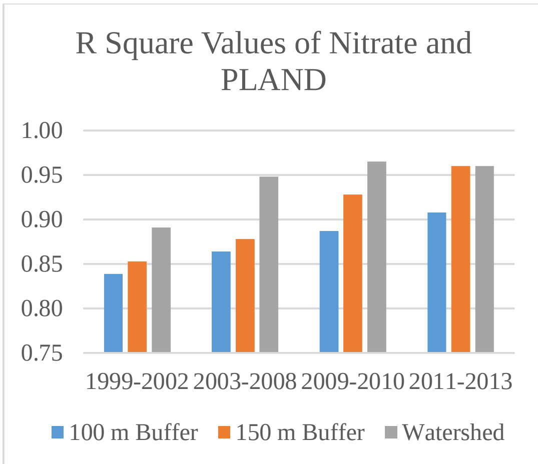
	2002 NP			**2008 NP**			**2010 NP**			**2013 NP**		
	100 m	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**
Flow	0.96	0.95	**0.96**	0.91	0.91	**0.98**	0.97	0.96	**0.99**	0.94	0.93	**0.97**
Conductivity	**0.73**	0.70	0.70	0.84	0.85	**0.93**	0.87	0.87	**0.98**	**0.99**	0.97	0.93
Hardness	**0.80**	0.77	0.64	0.62	0.66	**0.68**	0.53	0.54	**0.57**	**0.99**	0.96	0.94
Nitrate	0.76	0.80	**0.83**	0.60	0.61	**0.70**	0.97	**0.99**	0.97	0.91	0.92	**0.93**
TKN	0.75	0.74	**0.81**	**0.90**	0.81	0.80	0.98	0.90	**0.99**	0.89	0.87	**0.97**
Turbidity	0.47	0.51	**0.57**	**0.76**	0.75	0.75	**0.68**	0.72	0.64	0.61	0.67	**0.69**

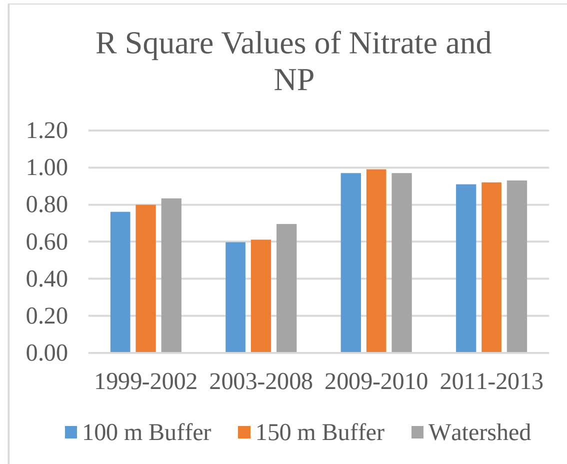
Table 4.38. ED R-Squared Regression Results at Multiple Spatial Scales. The Independent Variables are the ED of each LULC Type (Impervious, Agricultural, Grass, and Forest). The Numbers in Bold Indicate they are the Highest Value among Several Scales. The Significance Level is 0.05

	2002 ED			**2008 ED**			**2010 ED**			**2013 ED**		
	100 m	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**
Flow	**0.72**	0.72	0.68	**0.59**	0.59	0.53	**0.69**	0.68	0.59	**0.60**	0.63	0.56
Conductivity	0.64	0.69	**0.78**	0.58	0.60	**0.67**	0.64	0.66	**0.78**	0.42	0.47	**0.54**
Hardness	0.53	0.57	**0.62**	0.35	0.37	**0.44**	0.80	0.82	**0.84**	0.33	0.35	**0.44**
Nitrate	0.80	0.84	**0.92**	0.89	0.90	**0.91**	0.90	0.94	**0.99**	0.89	0.95	**0.99**
TKN	0.76	0.79	**0.92**	0.56	0.61	**0.76**	**0.60**	0.56	0.55	0.41	**0.43**	0.40
Turbidity	0.42	0.41	**0.46**	0.82	**0.83**	0.75	0.48	0.50	**0.56**	0.73	0.77	**0.84**

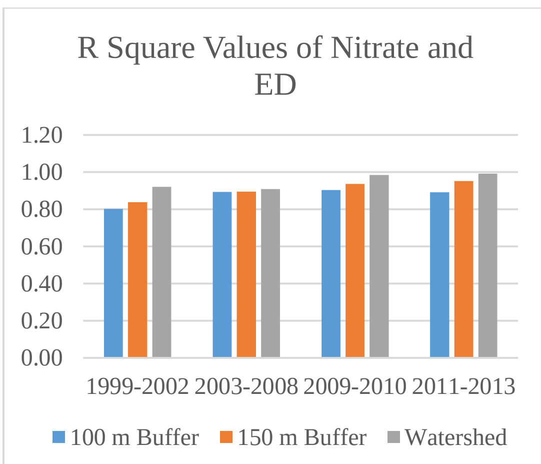
Table 4.39. LPI R-Squared Regression Results at Multiple Spatial Scales. The Independent Variables are the LPI of each LULC Type (Impervious, Agricultural, Grass, and Forest). The Numbers in Bold Indicate they are the Highest Value among Several Scales. The Significance Level is 0.05

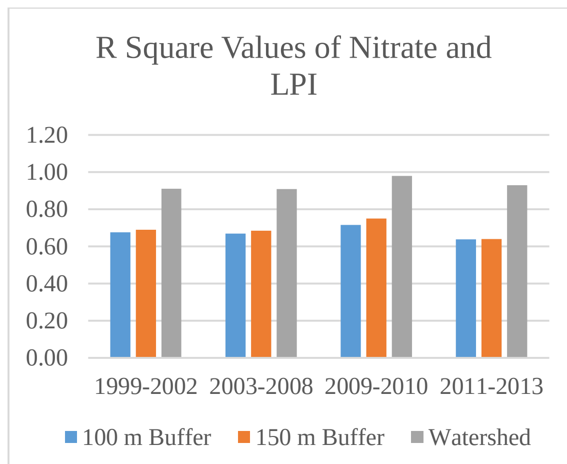
	2002 LPI			**2008 LPI**			**2010 LPI**			**2013 LPI**		
	100 m	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**	**100 m**	**150 m**	**Watershed**
Flow	**0.91**	0.90	0.80	**0.81**	0.78	0.78	**0.75**	0.65	0.61	**0.68**	0.65	0.63
Conductivity	0.63	0.63	**0.80**	0.54	0.53	**0.84**	0.52	0.50	**0.64**	0.49	0.49	**0.56**
Hardness	0.42	0.50	**0.59**	0.49	0.48	**0.60**	0.64	0.78	**0.82**	**0.59**	0.55	0.48
Nitrate	0.68	0.69	**0.91**	0.67	0.68	**0.91**	0.72	0.75	**0.98**	0.64	0.64	**0.93**
TKN	**0.68**	0.74	0.68	0.70	0.71	**0.80**	**0.60**	0.53	0.58	**0.55**	0.45	0.51
Turbidity	0.49	0.43	**0.50**	**0.90**	0.89	0.89	0.66	0.75	**0.73**	0.46	**0.59**	0.48





(a) (b)





(c) (d)

Figure 4.21. R-Squared Values from a Simple Regression of Mean Annual Nitrate Values and PLAND, NP, ED, and LPI at the Watershed and 100 m, 150 m, Riparian Buffer Distances

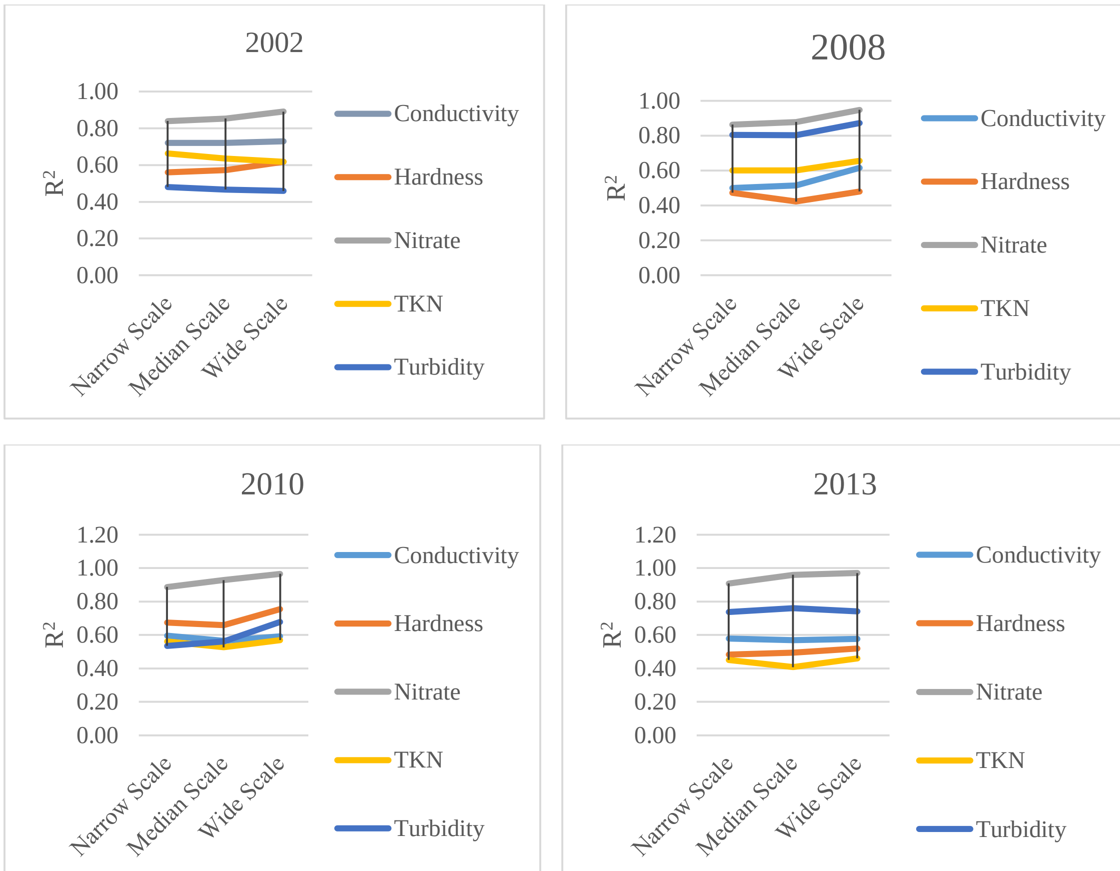


Figure 4.22. The Relationships between Water Quality Characteristics and Percent Land (PLAND) at Different Spatial Scales of Analysis. Narrow and Median Scales Represents the 100 m and 150 m Spatial Scales respectively. Wide Scale represents the Watershed Scale

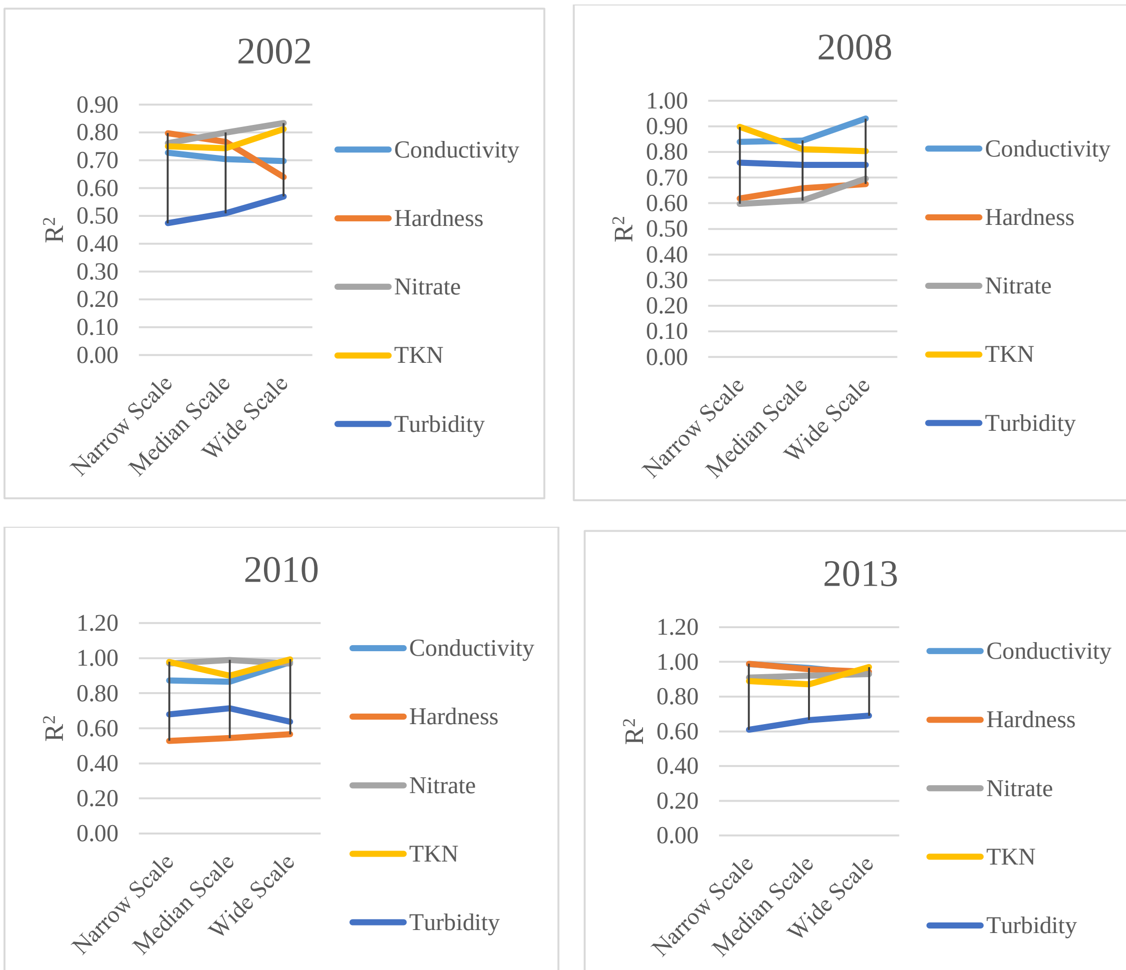


Figure 4.23. The Relationships between Water Quality Characteristics and Number of Patches (NP) at Different Spatial Scales of Analysis. Narrow and Median Scales Represents the 100 m and 150 m Spatial Scales respectively. Wide Scale represents the Watershed Scale

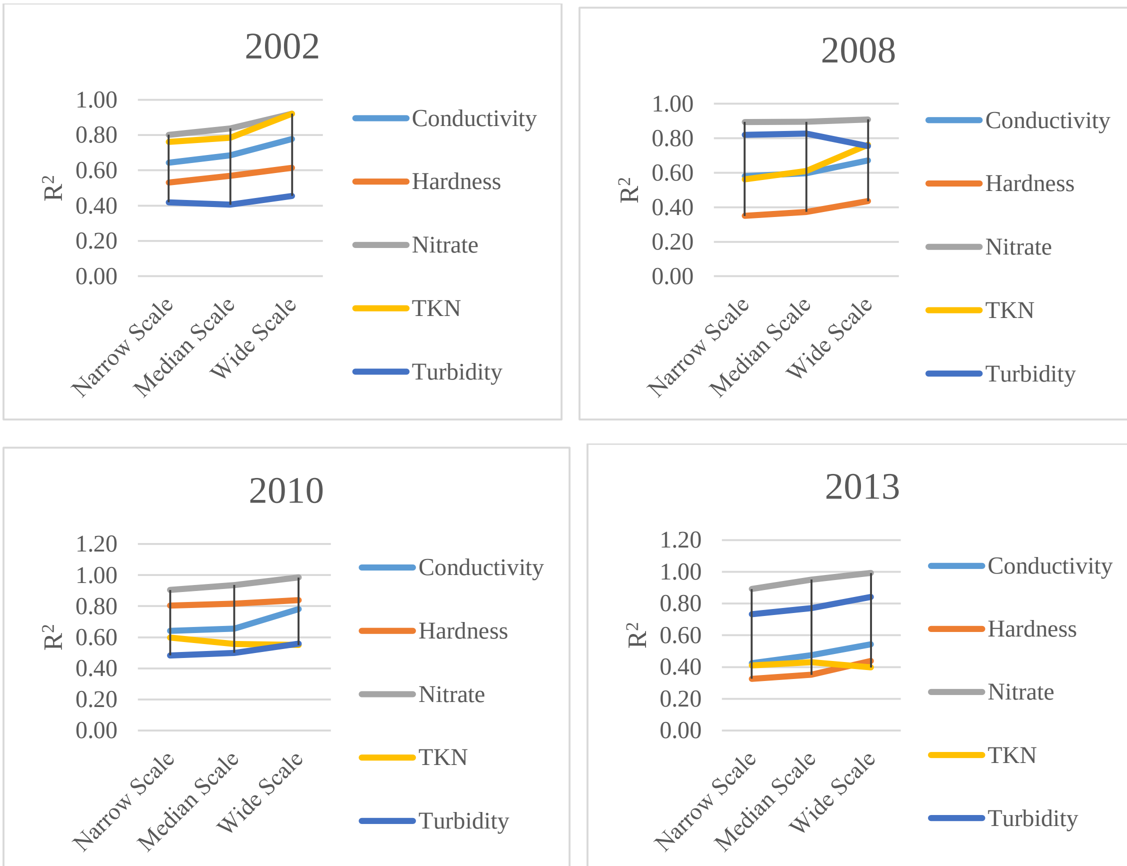


Figure 4.24. The Relationships between Water Quality Characteristics and Edge Density (ED) at Different Spatial Scales of Analysis. Narrow and Median Scales Represents the 100 m and 150 m Spatial Scales respectively, and Wide Scale represents the Watershed Scale

Figure 4.25. The Relationships between Water Quality Characteristics and Largest Patch Index (LPI) at Different Spatial Scales of Analysis. Narrow and Median Scales represents the 100 m and 150 m Spatial Scales respectively. Wide Scale represents the Watershed Scale

Modeled Relationship between LULC Change on Discharge and Water Quality-SWAT Model Calibration and Validation

The sensitivity analysis which followed the initial SWAT model run for discharge and nitrate at the Friendship Church Rd. and Mcleansville Road sampling sites resulted in nine and five “most sensitive” parameters for the discharge and nitrate respectively. The nine "most sensitive" parameters, their description, and their ranges used in the calibration and validation process are given in Table 4.40. The upper and lower bound of GWQMN, GW_REVAP, ESCO, GW_delay, were chosen considering the default values referred to by Van Liew et al., (2005). The scope of Alpha_BF, sol_K, CN2, and SOL_AWC were chosen on the premise of the after-effects of past SWAT adjustment (e.g. Eckhardt et al., 2005; Van Liew et al., 2005). The five “relatively sensitive” parameters for nitrate include: Rate coefficient for mineralization of the residue fresh organic nutrients (RSDCO), Nitrate percolation coefficient (NPERCO), Organic nitrogen enrichment ratio (ERORGN), amount of organic carbon in the soil layer (SOL-NO_3), and Initial NO_3 concentration in soil layer (SOL-ORGN).

Table 4.40. The Nine Most Sensitive Parameters and their Ranges for SWAT-CUP Calibration

				Friendship Church Road	**Mcleansville Road**
Discharge	**Parameter Name**	**Description**	**Min_Max**	**Fitted Value**	**Fitted Value**
	ALPHA_BF	Baseflow alpha factor (d-1)	0-1	0.05	0.02
	CN2	SCS runoff curve number for moisture condition II	-15%-15%	61	73
	ESCO	Soil evaporation compensation factor	0-1	0.9	0.95
	GW_DELAY	Groundwater delay (d)	0-1000	60	36
	GW_REVAP	Groundwater 'revap' coefficient	0-2	0.02	0.02
	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0-1000	850	725
	REVAPMN	Threshold depth of water in the shallow aquifer for revap to occur (mm)	0-1000	750	500
	SOL_AWC	Available water capacity of the soil layer (mm/mm soil)	-25%-25%	0.2	0.18
	SOL_K	Saturated hydraulic conductivity (mm h-1)	-25%-25%	21	30
Nitrate	BIOMIX	Biological mixing efficiency	0-1	0.45	0.15
	ERORGN	Organic nitrogen enrichment ratio	0-5	2.25	3.75
	NPERCO	Nitrogen percolation coefficient	0-1	0.85	0.85
	RSDCO	Residue decomposition factor	0.02-1	0.06	0.06
	SOL_ORGN	Initial organic nitrogen	0-100	32	15

After identifying the "most sensitive" parameters, model calibration was performed for the year 2002-2010 at both stations. The calibration was done with the monthly discharge and nitrate loads for study years. Graphical result of the model output compared with the observed discharge data recorded during these years were generated. It is observed that the modeled discharge and nitrate consistently matched the observed values of the calibrated years. Regression analysis was also performed between the observed and simulated values, and the best fit line is also shown for the calibrated discharge for years 2002 to 2010, Fig. 4.26. The statistical evaluation showed a strong correlation between the measured and simulated values, as indicated by the coefficient of determination (R^2) and Nash and Sutcliffe Efficiency (NSE) values for the calibration period, Tables 4.41 and 4.42. The R^2 and NSE values for discharge were 0.85 and 0.83, and 0.91 and 0.90 for the Friendship Church Rand and Mcleansville Road stations respectively. Consequently, R^2 and NSE values for nitrate were 0.78 and 0.75, 0.72 and 0.74 respectively, Table 4.43 and 4.44.

Furthermore, the efficiency of the model for simulating the discharge and nitrate was also tested using the mean and standard deviation. From Table 4.41 and 4.42, it is observed from the overall standard deviation and mean that the model slightly over-predict runoff during the years 2002 to 2010. Similarly, Table 4.43 and 4.44 also shows that mean and standard deviation for nitrate at both the Friendship Church Road and Mcleansville Road sampling outlets with satisfactory result.

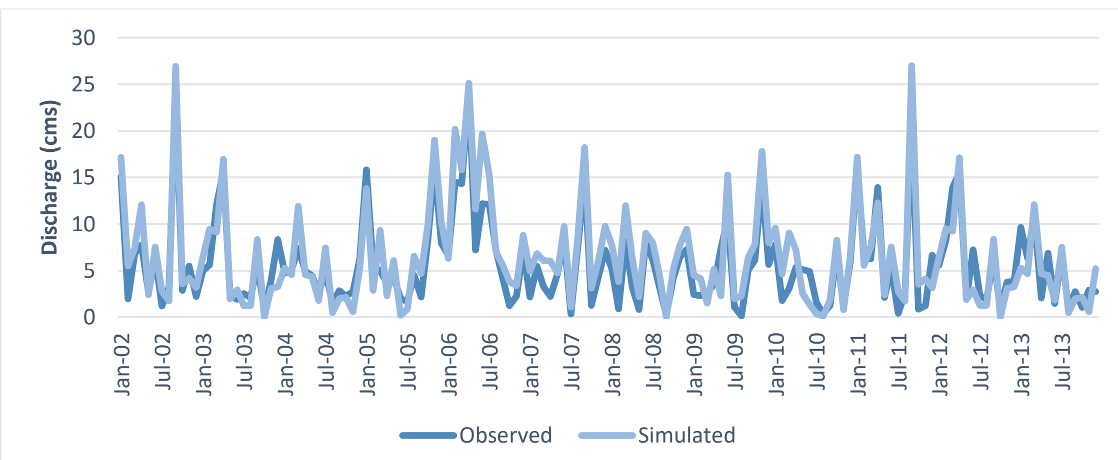


Figure 4.26. Monthly Discharge Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Friendship Church Road

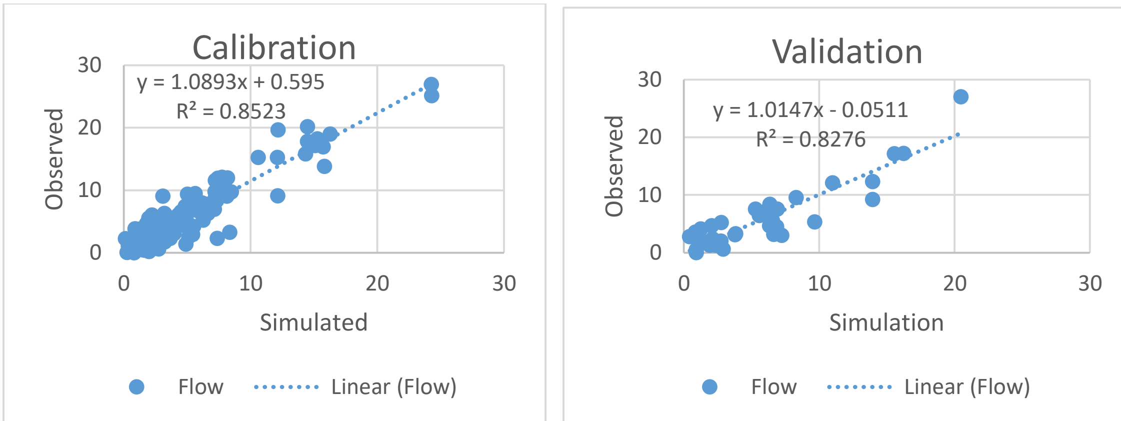


Figure 4.27. Monthly Discharge Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Friendship Church Road

Table 4.41. R^2 and NSE Values of SWAT Predicted Discharge versus Observed Discharge at the Friendship Church Road

	Calibration (2002-2010)		Validation (2011-2013)	
Parameters	Simulated	Observed	Simulated	Observed
Mean	6.73	5.64	2.07	1.85
SD	5.44	4.61	1.78	1.65
R^2	0.85		0.93	
NSE	0.83		0.92	

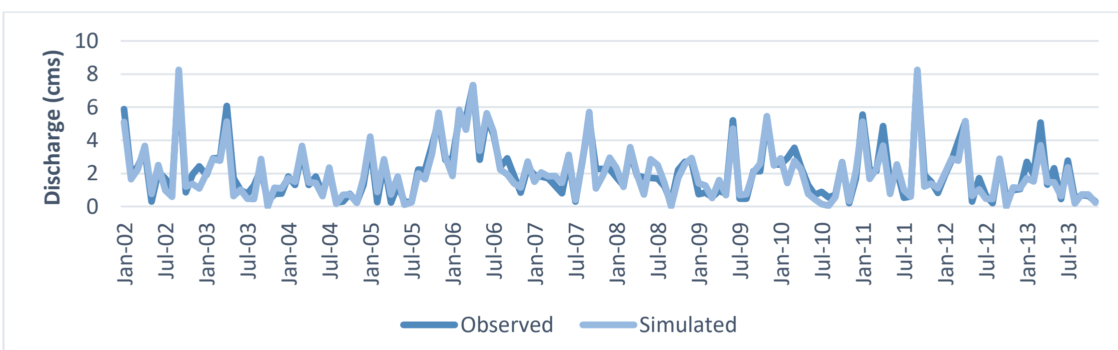


Figure 4.28. Monthly Discharge Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Mcleansville Road

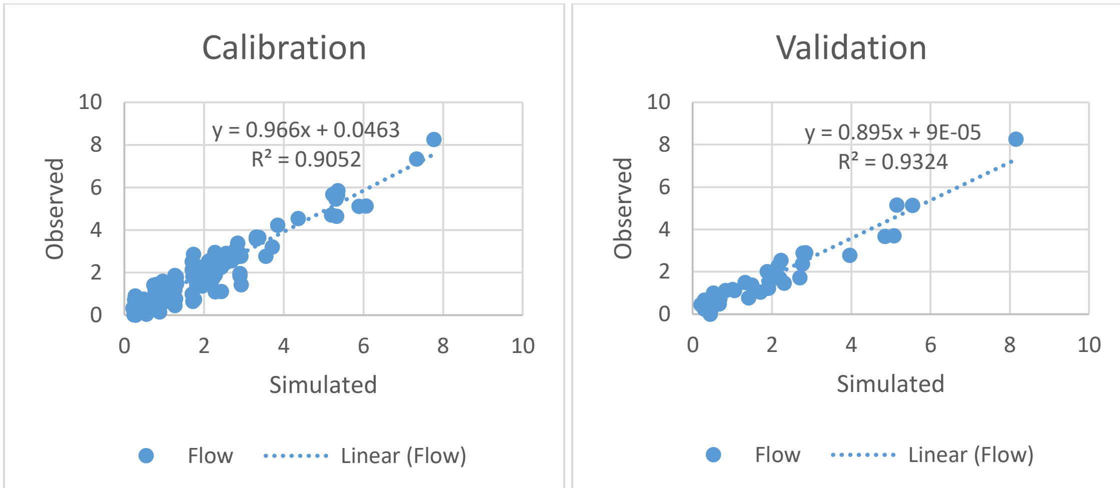


Figure 4.29. Monthly Discharge Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Mcleansville Road

Table 4.42. R^2 and NSE Values of SWAT Predicted Discharge versus Observed Discharge at the Mcleansville Road

	Calibration (2002-2010)		Validation (2011-2013)	
Parameters	**Simulated**	**Observed**	**Simulated**	**Observed**
Mean	2.09	2.12	2.07	1.85
SD	1.61	1.59	1.78	1.65
R^2	0.91		0.90	
NSE	0.9		0.91	

Model Validation for Discharge and Nitrate

The model validation is required to evaluate the performance of the model. This was achieved by running the model without changing any parameter and without adding a different set of input data from the one used for the calibration process. The was done using the discharge and nitrate data recorded at the Friendship Church Rand and Mcleansville Road stations from 2011 to 2013. The validation results were graphically compared with the observed discharge and nitrate data for the same periods. It was observed that the model discharge and nitrate closely matched the observed values. The output of the regression analysis performed between the observed and simulated discharge and nitrate best-fit line is also shown. The model slightly over predicted discharge (Fig. 4.28) which is quantitatively shown in the mean and standard deviation of the observed and predicted values. From Table 4.41 and 4.42, the R^2 and NSE discharge values were 0.93 and 0.92, and 0.90 and 0.91 for the Friendship Church Rand and Mcleansville Road stations respectively. The R^2 and NSE values for nitrate are also shown in Table 4.43 and 4.44.

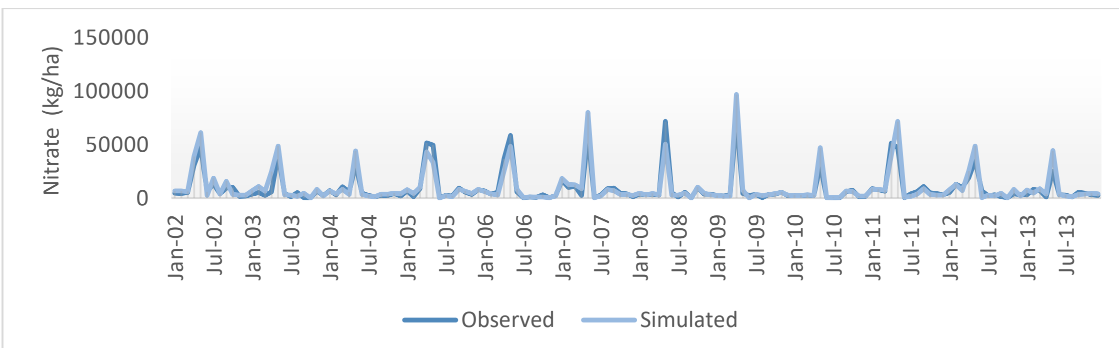


Figure 4.30. Monthly Nitrate Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Friendship Church Road

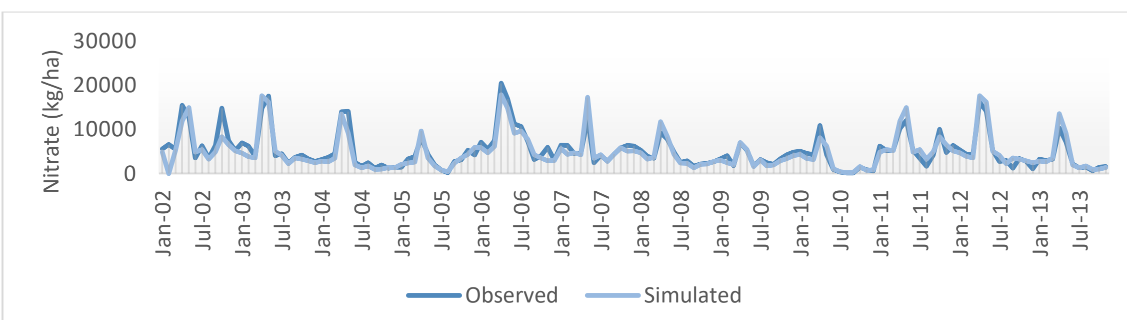


Figure 4.31. Monthly Nitrate Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Mcleansville Road

Table 4.43. Monthly Nitrate R^2 and NSE values of SWAT Predictions versus Observed at the Friendship Road

	Calibration (2002-2010)		**Validation (2011-2013)**	
Parameters	Simulated	Observed	Simulated	Observed
Mean	10308.78	8675.7	10340.65	9565.78
SD	18893.09	15006.94	15601.44	13080.88
R^2	0.91		0.90	
NSE	0.77		0.76	

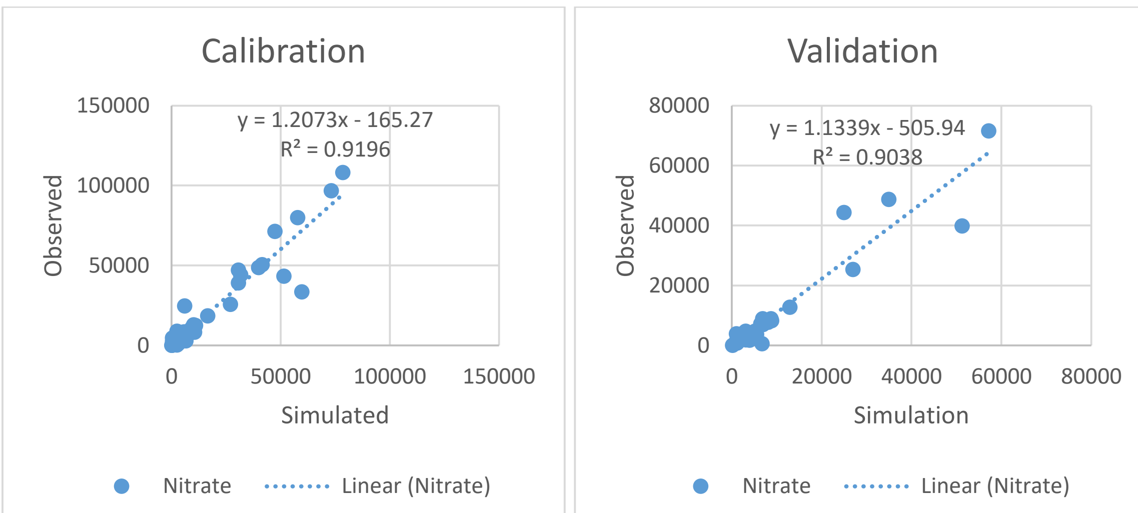


Figure 4.32. Monthly Nitrate Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Friendship Road.

Table 4.44. Monthly Nitrate R^2 and NSE Values of SWAT Predictions versus Observed at the Mcleansville Road

	Calibration (2002-2010)		Validation (2011-2013)	
Parameters	Simulated	Observed	Simulated	Observed
Mean	5680.13	5129.28	5322.15	4865.99
SD	4807.57	4002.56	4301.29	3762.41
R^2	0.89		0.93	
NSE	0.79		0.77	

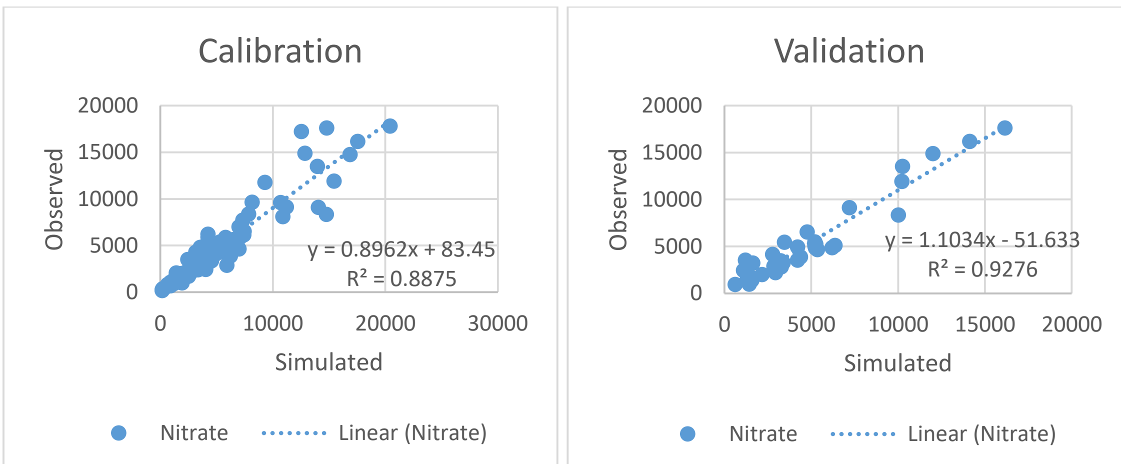


Figure 4.33. Monthly Nitrate Calibration and Validation for the Reedy Fork-Buffalo Creek Watershed at the Mcleansville Road

Water Balance Estimation

The SWAT model estimated other important water balance components in addition to the monthly discharge of the watershed. Average annual watershed values for the different water balance components during the base simulation periods, 2002-2013, shows average annual watershed gain and losses with a change in soil water storage capacity, Table 4.45. From these components, evapotranspiration (ET) contributed a larger amount of water loss from the watershed. Fig. 4.34 shows the average ET for the sub-basins for the 2002-2013 periods. It was noted that sub-basin 18 has the highest contribution ET of about 960 mm. Further analysis also shows that the northern part of the watershed, which is mostly vegetative, has contributed a large percentage of ET in the area. The lowest contributor of ET came from the southern area which has limited vegetation with a vast impervious presence. Total water yield, which is the amount of streamflow leaving the outlet of watershed during the time step, was predicted to be about 313.16 mm. The total water yield is made up of; surface runoff (131.87 mm), groundwater flow (185.71 mm), and transmission losses (4.43 mm). The water yield is also one of the important parameters for efficient water management and planning.

Table 4.45. 1999-2013 Average Annual Water Balance Components for the Entire Reedy Fork-Buffalo Creek Watershed

Water Balance Component	**Depth (mm)**
Precipitation	1036
Surface runoff	131.87
Groundwater (shallow aquifer) flow	185.71
Evapotranspiration	677.7
Transmission loss	4.43
Total water yield[a]	313.16

[a] Total water yield = surface runoff + groundwater flow − transmission loss.

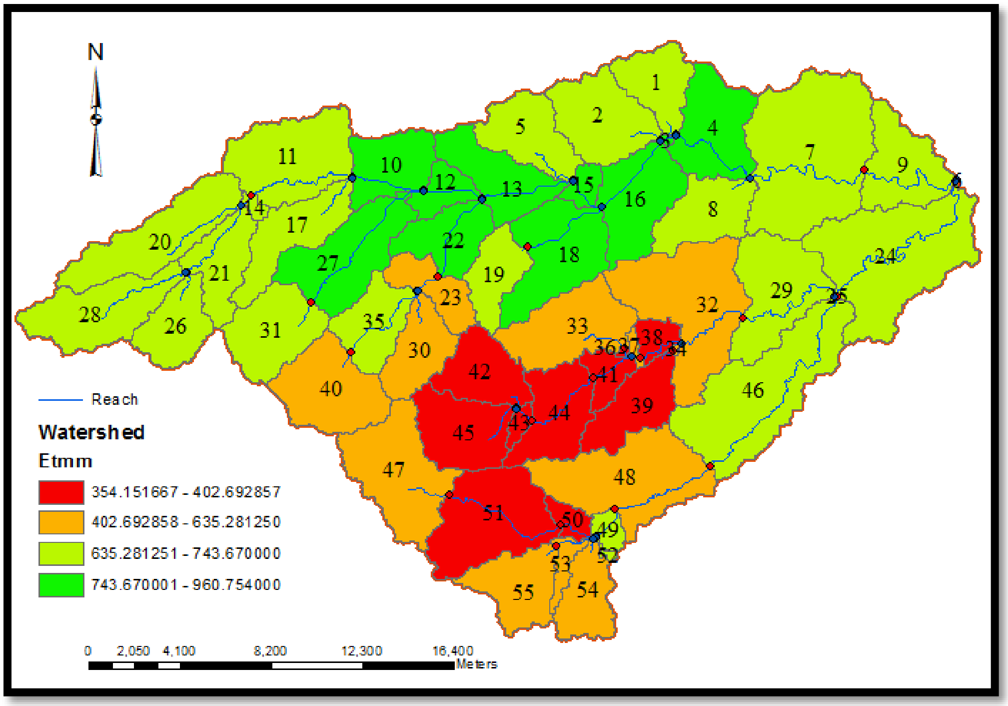


Figure 4.34. Predicted Evapotranspiration for the Reedy Fork-Buffalo Creek Watershed for the 2002-2013 Study Years

The hydrological process for each year was also quantified for the study area. Results showed ET has the highest share of the water balance with values between 58.4% (2003) to 83.6% (2012). Lateral flow has the lowest percentage values ranging from 1.0% in 2012 to 2.5% in 2003. The component with low percentages in all cases is deep aquifer with percentage variation of 2.9%-15.5%. This implies that the water-yielding potential of deep aquifers in the watershed will be quite small. Fig. 4.35 and 4.36 show the model predicted water balance over the years.

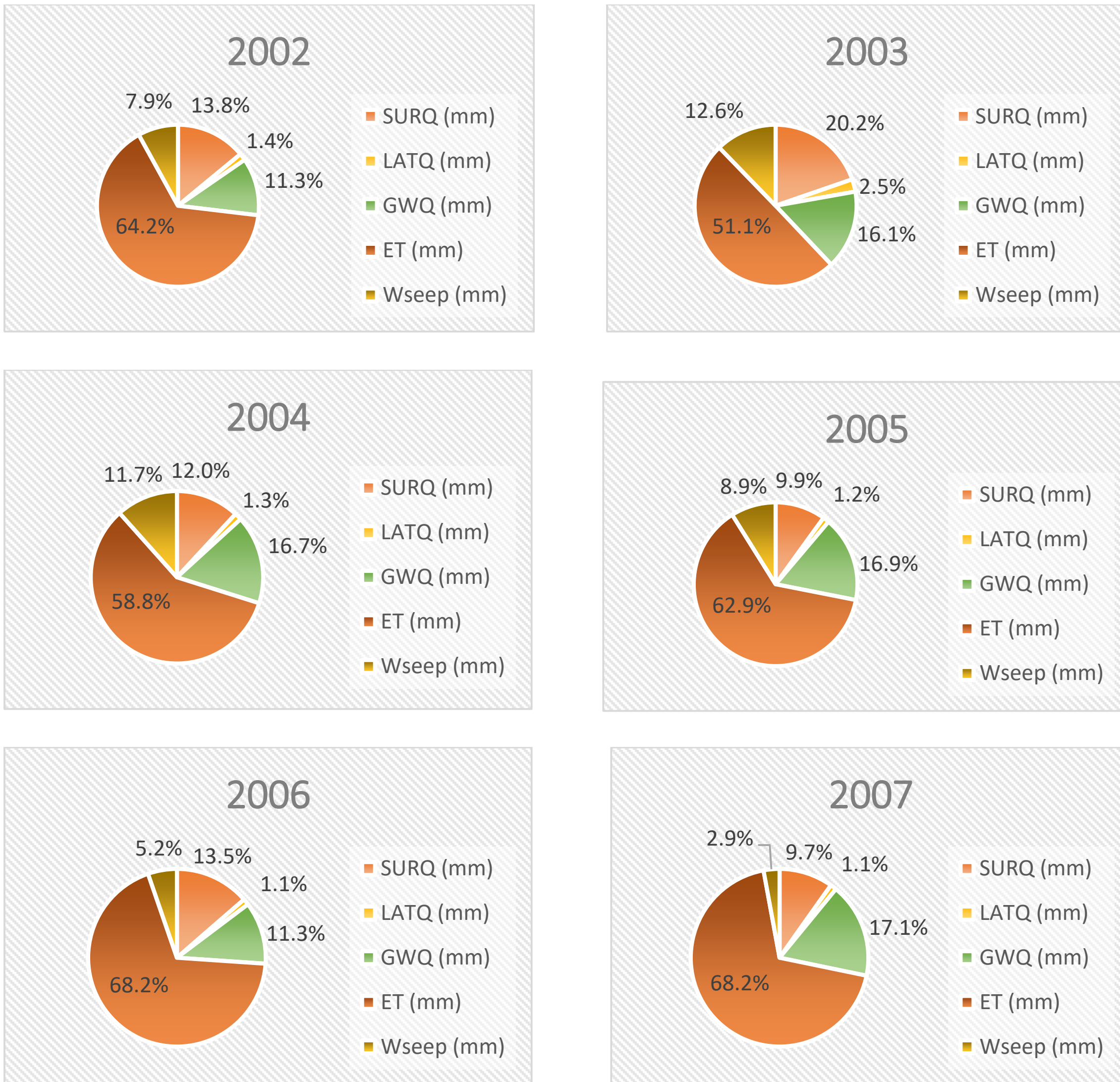


Figure 4.35. Predicted Water Balance of the Individual Years in the Reedy Fork-Buffalo Creek Watershed.

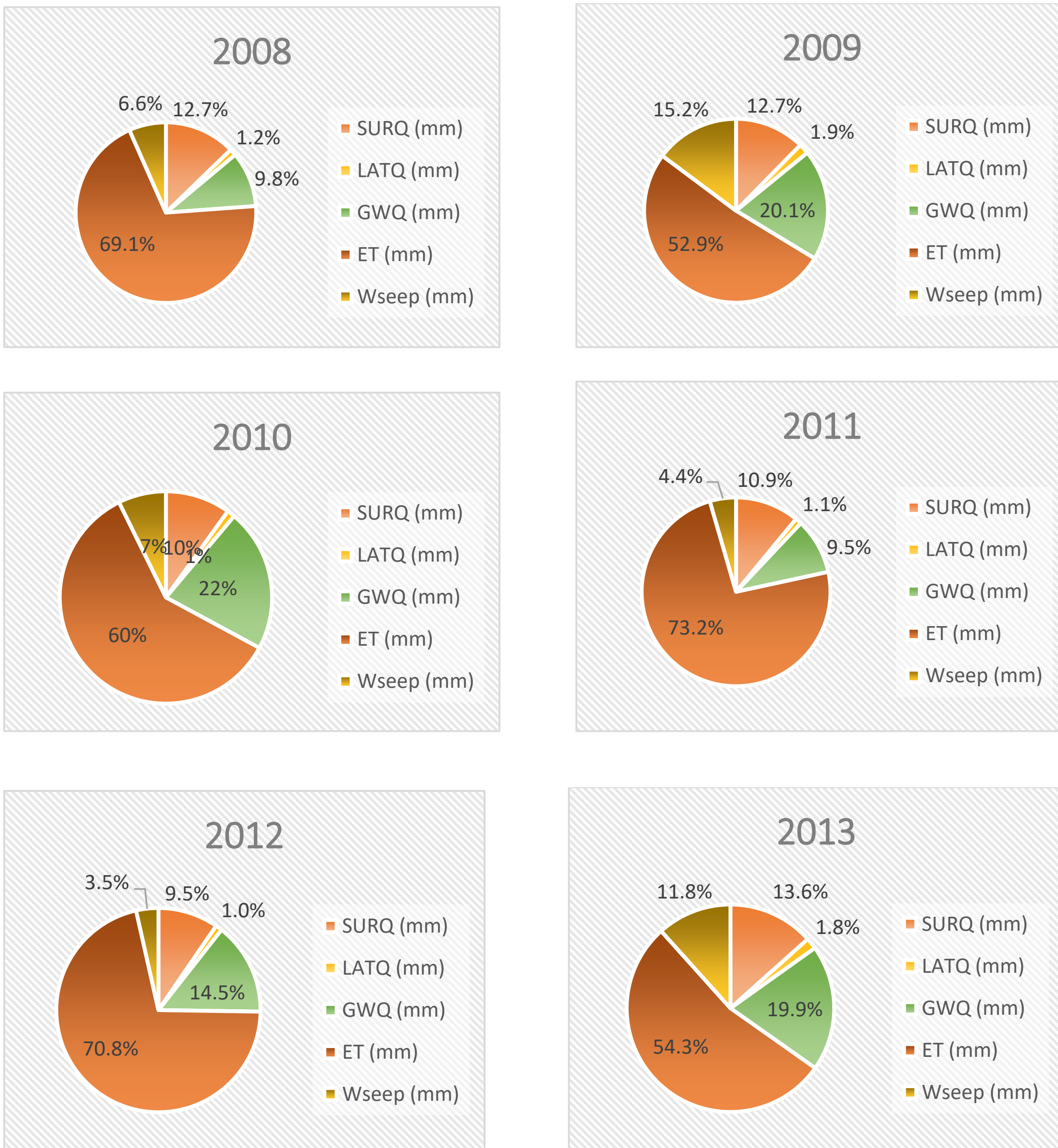


Figure 4.36. Predicted Water Balance of the Individual Years in the Reedy Fork-Buffalo Creek Watershed.

Land-Use Scenario – Increased Imperviousness

The result of the simulated LULC is presented in Fig. 4.37 and Table 4.46. The result shows that land-use changes in the Reedy Fork-Buffalo Creek watershed area are mainly the conversion of forest, grass, and water to impervious developed land-use. In 2030 LULC scenario, the impervious land cover is predicted to be 36.5% of the entire Reedy Fork-Buffalo Creek watershed. This is an increase of 12.9% from the 2010 impervious surface land-use. Forest land cover decreased slightly by 4% in 2030 from 42.7% in 2010. The greatest contributor to the increase in the future impervious surface in the watershed is grass. Grass decreased by 7.6% from 24.6% in 2010 to 17.0% in 2030. Water and agricultural decreased slightly by 1.2% from 2.7% to 0.9%, and 0.1% from 5.8% to 5.1% respectively from 2010 to 2030.

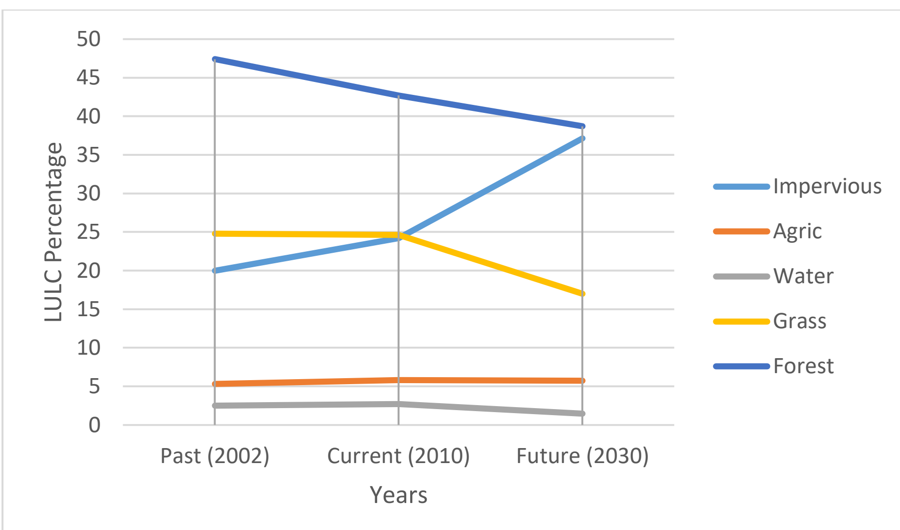


Figure 4.37. Forecasted LULC for 2030 Scenario.

Table 4.46. Composition of the Past, Current, and Future LULC at the Reedy Fork-Buffalo Creek Watershed.

LULC Type	2002		2010		2030	
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%
Impervious	120.3	20	145.9	24.2	223.5	37.1
Agricultural	32	5.3	35.0	5.8	34.33	5.7
Water	15.2	2.5	16.1	2.7	9.0	1.5
Grass	149.6	24.8	148.1	24.6	102.4	17.0
Forest	285.3	47.4	257.2	42.7	223.9	38.7

Table 4.47. Comparison of Water Quality and Water Quantity Parameters under Current Land-Use and Future Land-Use Scenarios. The number in parentheses indicates Percent Change in Runoff and Nitrate from the Current to Future Land-Use Scenario

	Past Scenario (2002)	Current Scenario (2010)	Future Scenario (2030)	Pass to Current Change (%)	Current to Future Change (%)	Units
Surface Runoff	115.07	131.87	152.34	+16.8 (+12.7%)	+20.47 (+13.5%)	mm
Water Yield	328.75	342.96	377.97	+14.21 (+4.15%)	+53.01 (+9.26%)	mm
NO_3 Yield in Surface Runoff	0.751	0.995	1.46	+0.24 (+24.5%)	+0.46 (+31.85%)	kg/ha
NO_3 Yield in Subsurface/Lateral Flow	0.11	0.123	0.18	+0.013 (+10.57%)	+0.06 (+31.7%)	kg/ha

In Table 4.47, the watershed runoff, water yield and nitrate loads for the past (2002), current (2010), and future (2030) LULC scenarios under present climatic conditions are presented. The modeling results indicate that the annual runoff, water yield, nitrate yield from runoff, and nitrate yield in lateral flow increases from 2002 to 2010 to 2030. From Table 4.47, the model predicted a 13.5% increase in the watershed runoff from 131.87 mm in 2010 to 152.3 mm in 2030. Water yield also increased by 4.15% from 328.75 mm in 2002 to 342.96 mm in 2010 and 9.26% from 342.96 mm in 2010 to 377.97 mm in2030. Nitrate loading to stream in surface runoff and nitrate loading to stream in lateral flow in the watershed for the simulation also increased by 0.46 and 0.06 representing 31.85% and 31.8% respectively from 2010 to 2030. The increase in imperviousness results in a lack of infiltration, hence, increase in runoff and water yield in the study area for the predicted year. Increase in surface runoff by urbanization is reported by other researchers (Rafiei-Emam et al., 2015). Subsequently, increase in nitrate yield may be due to increased fertilizer application on lawns, pet droppings, as well as industrial waste and septic waste leakages as the area moves towards extreme urbanization.

CHAPTER V

DISCUSSION

Classified LULC Map

The LULC classification maps of the Reedy Fork-Buffalo Creek watershed for 2002, 2008, 2010, and 2013 produced are shown in Fig. 4.5 to 4.8. The accuracy of the classification results assessed using error matrix reveals that the total accuracies of the LULC classification were 95%, 93%, 95%, and 94% for 2002, 20088, 2010, and 2013, respectively. The Kappa coefficients for these years were 0.93, 0.90, 0.93, and 0.92, respectively. According to Lea and Curtis (2010), for accuracy assessment, it is required that the overall accuracy of the classified image should be above 90% and kappa coefficient above 0.9. These were successfully achieved in this research. Hence it can be stated that the classification technique used demonstrated that, it is an accurate and reliable method and as such, the accuracy obtained was deemed sufficient to meet the needs of the LULC classification in the studied watershed.

Naturally, the Reedy Fork-Buffalo Creek is surrounded by agricultural lands in the north, east, and southeast with urban LULC located in the middle and southwest area of the watershed. There are also dispersed impervious areas in different fields of the watershed. Forests and grasslands are principally situated in and around the agricultural areas around the plains. However, some are within the urban environment. Clearly, the LULC pattern is related to the geographical conditions of the watershed. In the time series, Table 4.5 and 4.6, the LULC classes from 2002 to 2013 were particularly portrayed by the development of the urban zone of Greensboro and changes in the forest and grassland pattern. The impervious region ventured into a great part of the forest, and the grassland expanded into the north and east, outward of the existing urban areas of the watershed. Other LULC types did not display such natural and distinct changes and appeared to be occupied by forest and grassland.

The comparison of each LULC class from 2002 to 2013 showed that there had been a marked LULC change during the periods of the study. During the 2002 to 2013 period, the percentage area covered by impervious class in the watershed increased from 20% to 28% with a relative change of 40.7%. The changes in LULC in the Reedy Fork-Buffalo Creek watershed are related to the fast urbanization process in Greensboro area of the watershed. Urbanization became one of the important themes in the early 2000s. The urbanization process was accompanied by increased population due to the movement of a countless number of people from rural to urban areas. The fast increment in the urban populace was likewise joined by quick development of the real estate industry, and the expansion of transportation system, including a 44mile “urban loop” that will allow traffic to bypass Greensboro and improve congestion on existing I-40 and other urban infrastructure (Transportation update report, 2015). At the same time, quick development in the interest for sustenance (vegetables and foods) are grown from farming activities, lodging, and drinking water (Madjd-Sadjadi et al., 2014) in the Reedy Fork-Buffalo Creek watershed. This instinctively represents the rapid urbanization process in the LULC pattern. The expansion of impervious areas within the watershed is characterized by a mode of urban sprawl into the surrounding forest and grassland. The slight increment in water area from 0.7% in 2002 to 1.8% in 2013 may be closely related to the improvement in the study area water system to cater for the growing number of people. However, the utilization of land areas for agricultural purposes did not diminish during the 2002 to 2013 study period, inferring that the vital part of the agricultural area was not reduced, and food security was given high priority to guarantee the manageability of human life in the watershed.

The dynamics of development and expansion of impervious areas in the three-time intervals of 2002 to 2008, 2008 to 2010, and 2010 to 2013 were calculated. The dynamics of the developed (impervious surface) areas in the watershed are influenced by the urban sprawl, unique to the City Greensboro. The urban sprawl assumes the typical urban expansion method of structures and outward movement patterns of development. That is the irregularity and emergence of existing developed impervious areas and newly built areas expanded outward while constantly and gradually filling the vacant land areas adjacent to the existing impervious areas. In general, spaces for expansion were not very limited for impervious cover development because there is boundless plain topography of grass and forest land in the watershed. This was especially true for the spatial development; as natural conditions have not restricted the room for impervious surface expansion. Notwithstanding, the new developed (impervious) areas occupy the forest land surrounding the urban area of Greensboro and its neighboring cities, which has led to a large decrease in forest land. With numerous studies proving that, water quality and stream habitats are sensitive to degradation with 10% impervious cover (Schueler, 1994;

CWP, 2003; and Brabec et al., 2002), it is believed that the rapid expansion of the impervious area in and around Greensboro may bring about more household and industrial waste to the water bodies in the watershed, with serious consequences for water quality and environmental pollution and degradation.

Landscape Metrics

Fig. 4.10 to 4.13 shows the landscape metrics fragmentation of all LULC classes in the Reedy Fork-Buffalo Creek watershed landscape from 2002 to 2013. Specifically, Fig. 4.10 illustrates the dynamics of the landscape metrics spatial distribution of impervious area from 2002 to 2013. The NP value increased incredibly from 2002 to 2010 and leveled off to a slower, enduring growth level in 2013. Correspondingly, the persistent increase in the ED value was also observed from 2002 to 2013. As per the dynamic index of the impervious surface area displayed in Fig. 4.10, the increases in the NP and ED values illustrate an increase in the number of developed impervious land-use patches and an improvement of the edge complexity of impervious cover. The increase in LPI affirms this finding since a large number of patches of newly developed area emerged amid the rapid urban sprawl.

Compared to impervious surfaces, there was no much change in agricultural land-use during the 2002 to 2013 study period (Table 4.5). However, with the huge expansion in newly developed impervious land-use, it is deduced that the shape and spatial pattern of agricultural land changed accordingly. LULC maps of the four-time intervals shown in Fig. 4.10 to 4.13 gives a natural representation of this impact. The transition matrix of

LULC in Table 4.6 shows that some portion of the agricultural land cover (about 3.8%) was used fundamentally for transformation into developed impervious areas.

In the Reedy Fork-Buffalo Creek watershed, expansions of developed areas, mainly tend to occupy forest lands surrounding urban areas. However, these occupied forest land covers were supplemented in other regions of the watershed by the implementation of the dynamic equilibrium of other LULCs (e.g. grass). This practice is probably the essential reason behind why there has been no obvious change in the structure of agricultural land in the watershed.

The NP value of the agricultural land decreased from 2002 to 2008, increased slightly from 2008 to 2010 and again decreased slightly between 2010 and 2013 (Fig. 4.11). This phenomenon demonstrates a decrease in the number of agricultural land patches during 2002 to 2013 as well as the increase in the number of agricultural patches. The subsequent decline and increase of the LPI also confirm this finding. The increase and decrease in ED value from 2002 to 2008 are an indicating of enhancement and downgrading of the edge regularity of agricultural land-use patches.

The forest land cover is very dynamic in patch type, and it is the largest natural land-cover class in the study area (Table 4.5). However, the forest cover area percentage decreased slightly with a relative change of -12% during the study period while the NP increased from 15566 to 20470 (Fig. 4.13), indicating more fragmented forest area. The decrease in the LPI of forest cover shows that forest patches have changed over into various little fixes and segregated in recent times.

The changes in the various spatial metrics of grassland demonstrate its general decreasing propensity compared to other land-use class aside NP values. The NP for grass increased from 15557 in 2008 to 33483 in 2010 after an initial decrease from 21325 in 2002. Such increase and decrease the NP of grassland areas is as a result of changes in other land-uses and the natural vegetation. The general decrease in the grassland edges indicates the simplicity of its edge density.

Exploratory Analysis of Key LULC Patterns on Water Quality at Multiple Scales

The relationship between LULC spatial pattern and water quality performed in this research gave a clear insight as to how the LULC characteristic plays a major role in the deterioration of water in the Reedy Fork-Buffalo Creek watershed. The results of the descriptive statistics, FA, correlation, and regression analyses in this research demonstrated that this relationship is a strong one. The relationship is more pronounce, with particularly robust results observed in the r values obtained from correlation analyses with the annual mean water quality datasets, and the R-squared values obtained from the simple regression analyses. Among the 12 original parameters used in the FA, the most influential variables common among all year groups (1999-2002, 2003-2008, 2009-2010, and 2011-2013) were used in the correlation and regression analysis. These groupings were made totally with the classified maps (2002, 2008, 2010, and 2013) for ease and consistency of analysis, as well as, clarity of result presentation. The results of the common and most influential water quality variables (conductivity, hardness, nitrate, TKN, and turbidity), in the study area based on the year groups area presented in Table 4.27 to 4.30. Correlation coefficients of water quality variables together with flow, as well as, that of water quality and landscape patterns are presented in Table 4.31 and Table 4-32 to 4.35 respectively. Regression results of landscape patterns and nitrate (the most dominant water quality) variable at all spatial scales of analysis are depicted graphically in Fig. 4.21.

Water Quality Deterioration in Reedy Fork-Buffalo Creek Watershed

The spatiotemporal pattern of water quality in the Reedy Fork-Buffalo Creek watersheds displays a trend of river deterioration. The present study result suggests that; a large portion of the pollution sources was related to anthropogenic activities. From Table 4.30 – 4.33, it is clearly seen that conductivity, hardness, nitrate, TKN, and turbidity, are the five most common and dominant parameter with the strongest factor loadings in all the study period year groups.

In Table 4.34, hardness changed significantly for all year groups indicating high levels of calcium, magnesium, and other mineral salts such as iron. This may be due to lack of rainfall leading to a reduction in discharge in within the watershed. As the stream discharge slows, metals are allowed to dissolve in the water, which increases hardness levels (Elmhurst University 2008). Similarly, nitrate changed significantly. Nitrate can get into the water directly due to runoff of fertilizers containing nitrate. Nitrate can also be formed in water bodies through the oxidation of other, more reduced forms of nitrogen, including ammonia, and organic nitrogen compounds such as amino acids. Ammonia and organic nitrogen can enter water through sewage effluent and runoff from the land where manure has been applied or stored. Some nitrate enters the water from the atmosphere, which carries nitrogen-containing compounds derived from automobiles and other sources. Urban streams tend to have higher reduction rates most likely due to high nitrate concentration (Mulholland et al., 2008; Silva et al., 2011). High input of nitrogen into the river from wastewater in urban areas and lawn and farmland fertilizers affects water quality (Broussard and Turner, 2009; Zhang et al., 2010). In the study area, most of the pollution may have come from fertilizer application to lawn and agricultural environment which are washed off into the creek or river (Greensboro Water Resources Dept., 2012) leading to poor water quality.

Correlation between LULC Pattern and Water Quality

Results from the correlation analysis suggest that LULC pattern has major impacts on the flow and water quality in the Reedy Fork-Buffalo Creek watershed at the selected spatial scales (watershed, and riparian buffer zone of 100 m and 150 m) of analysis during the study time frame. Specifically, impervious land-use exerted a disproportionately large influence both at the watershed level and over buffer distance (100 m and 150 m). Degraded streams and rivers that channel impervious landscapes often have higher nitrate loads and other contaminant concentrations, as well as changes the morphology of streams, subsequently, decreasing biodiversity (Meyer et al., 2005). The outcome from the Reedy Fork-Buffalo Creek watershed bolsters this general perception.

At the watershed and riparian buffers scales of 100 m, 150 m, the NP of impervious, agriculture, grass, and forest positively correlated with flow for all study periods. Indicating that, the number of LULC patches is significant enough to induce flow. There were no significant effects of agricultural LULC pattern on most water quality measures at all analyzed scales, except for a negative correlation between nitrate and agricultural PLAND of 2002 and 2008; and a positive correlation between conductivity and agricultural NP of 2002. A positive correlation between agricultural ED of 2008 and turbidity at the all three spatial scale was also obtained. Despite the fact that agriculture land-use did not have much significance with the majority of the water quality variables, it does not imply that agricultural has a positive impact on water quality. In the study area, top crops like forage land for Hays, soybeans, and top livestock like poultry were the primary form of agricultural land-use (CDL, 2002; CDL, 2008; CDL, 2010; and CDL, 2013). It is possible that the reduction in fertilizer application due to a reduction in agricultural land-use for this crops and reduction in poultry production might have influenced agricultural land not having a significant impact on water. The positive correlation between NP of agricultural and conductivity can be as a result of an increase in the mineral component of the river from dissolved nitrate and phosphate (Phosphorus) within the watershed. Turbidity is related to sediments and can be attributed to construction activities, with the most noticeable one being the building of the Greensboro "Urban Loop" which began in 1995 and is estimated to be completed in 2018. The study years 1999 to 2013 fell within this range.

Furthermore, Snyder et al., (2003) observed a positive relationship between the extent of agriculture and biological integrity scores in their study area watersheds. This may also be part of the explanation for the relationship between agricultural land and nitrate found in the study. Notwithstanding, various studies have observed that water quality, natural surroundings, and biological diversity decrease as the extent of agricultural land increases (Allan, 2004). The absence of huge impacts of agriculture on water quality measures in our study may also have to do with the particular farming practices, interactions among numerous elements, and impacts of point sources of pollution that were not identified.

Regression Analysis of the Relationship between Landscape Pattern Scale Variation and Water Quality

Further results demonstrated that the influence of LULC on water quality is scale dependent (Table 4.36 to 4.39), as reported in other studies (Hunsaker and Levine, 1995; Sliva and Williams, 2001; Sponseller et al., 2001). The results suggest that key topographical and anthropogenic factors interact with water quality in this region mainly at the watershed scale. The effects of LULC patterns on water quality were much weaker on the 100 m and 150 m buffer scales. Recent studies have suggested that the distance over which LULC pattern affects water quality depends on the size of the streams and stream buffers within the watershed area (Tran et al., 2010). For example, Buck et al., (2004), reported that LULC upstream had stronger influences on large river buffers, whereas local LULC and other factors were more important to small stream buffers. Dodds and Oakes (2008) found out that, riparian buffer scales and LULC close to streams were more important to water quality than the landscape pattern of the entire catchment area. However, other studies showed that LULC pattern close to the river was not a better predictor of water chemistry than LULC pattern away from the river (Houlahan and Findlay, 2004; Meynendonckx et al., 2006). The main advantage of multi-scale LULC and water quality analysis is to identify the appropriate scales at which relationships between different kinds of variables ought to be examined (Wu, 2004; Wu et al., 2006). Though different years of LULC and water quality variables were used in this study, taking the most current parameters into consideration, regression results suggests that the most appropriate scale for assessing the effects of LULC on river water quality in the Reedy Fork-Buffalo Creek should include: PLAND 2013 (100 m scale for river flow and TKN, the 150 m buffer scale for turbidity and the watershed scale for conductivity, nitrate, and hardness), NP 2013 (100 m scale for river conductivity and hardness, and the watershed scale for flow, nitrate, TKN and turbidity), ED 2013 (100 m scale for river flow, the 150 m buffer scale for TKN, and the watershed scale for conductivity, nitrate, and hardness), and LPI 2013 (100 m scale for conductivity, and the watershed scale for flow, nitrate, hardness, TKN, and turbidity). With regards to the PLAND 2013, flow and TKN were influenced mostly by direct factors in surrounding landscape, so the proper scale is relatively small. Higher TKN concentrations may be due to factors such as higher fertilizer, livestock facilities or sewage disposal areas within the study area. In general, the study results indicate that the water quality variables are better assessed at the watershed scales taking into consideration the R-squared values at all the scales of analysis.

Impervious Surfaces Thresholds and Water Quality

In this research, the relationship between impervious surface and LULC were also examined. An impervious surfaces threshold pattern similar to the ones discussed by Brabec et al., (2002), Schuler (1994), Arnold and Gibbons (1996), and others becomes discernable upon examination of the conductivity and LULC at the 100 m, 150 m, and sub-watershed scales for the study period, Table 5.1, 5.2, 5.3 and 5.4. These researchers had suggested that if the impervious surface in makes up 10% of the total watershed, the water quality is impaired. With impervious surfaces between 10% and 20%, the stream is impacted. They further stated that water quality becomes much more impacted beyond a threshold of 20% impervious surfaces within a watershed, with severe degradation occurring to water quality and stream system health beyond imperviousness of 30% within a watershed. Studies in water quality have shown that a limited number of water quality parameters can be used to determine the health of a stream than had been previously used (e.g. Dow and Zampella, 2000). Hence, this threshold pattern can be observed in the results of this research with the study period annual mean conductivity water quality data. The conductivity and impervious surface data are also presented graphically in Fig. 5.1 to 5.4. This clearly displays the rapid rise in the Pollutant level for conductivity water quality variable beyond the impervious level of approximately 10% at the sub-watershed and 100 m and 150 m riparian buffer scales. With data for all variables sorted in ascending value based on annual average conductivity values, several observations can be made:

1) At all spatial scales in all 18 the sub-watersheds, there was no impervious surface less than 10% indicating that the stream in the study area is not in good health.
2) For 2002, FCR, PRR, and FR at the 100 m, level and FCR, PRR, at the 150 m and watershed scale exhibited impervious surfaces greater than 10% but less than 20%. Similar levels of imperviousness were observed for the following;

a) FCR, PRR, and FR at the 100 m, and 150 m and PRR, and FR. at the sub-watershed scale levels for 2008.

b) FCR, PRR and BRR at the 100 m level and FCR and PRR at the 150 m and sub-watershed scale for 2010 and

c) PRR at the 100 m and 150 m scales for 2013.

All these exhibited much greater specific conductivity values than the original condition of the stream systems.

3) At the 100 m, 150 m, and sub-watershed for all years, impervious surfaces exhibited the greatest specific conductivity levels between 20.23% and 63.22%, with the overall highs for each year group obtained at the MCCR. sub-watershed.

Table 5.1. 1999-2002 Conductivity Annual Mean Values Sorted in Ascending Order with 2002 Impervious Land-Use at Composite Scales

Sub-watershed Name	Conductivity	100 m	150 m	Sub-Watershed Scale
Friendship Church Rd.	95.38	10.36	10.39	14.58
Pleasant Ridge Rd.	102.52	12.06	13.07	16.81
Fleming Rd.	103.00	18.90	20.23	24.04
Bluff Run Rd.	115.62	25.28	26.13	24.46
Battleground Ave.	148.57	21.88	23.71	27.83
Old Oak Ridge Rd.	183.14	25.50	27.47	32.56
16th St.	191.58	26.86	28.97	33.28
Aycock St.	198.10	35.58	36.81	39.24
Merritt Dr.	203.40	36.97	39.72	42.14
W. JJ Dr.	216.57	26.38	26.90	31.64
Randleman Rd.	221.43	31.70	34.47	40.23
Summit Ave	227.00	35.72	37.32	40.52
Church St.	228.00	37.71	39.03	42.71
McConnell Rd.	278.95	29.84	31.60	35.62
White St.	326.43	24.10	26.00	30.38
Fieldcrest Dr.	422.05	31.64	34.01	36.93
Rankin Mill Rd.	438.81	29.98	31.62	35.07
McLeansville Rd	456.22	42.52	44.59	50.93

Table 5.2. 2003-2008 Conductivity Annual Mean Values Sorted in Ascending Order with 2008 Impervious Land-Use at Composite Scales

Sub-watershed Name	Conductivity	100 m	150 m	Sub-Watershed Scale
Pleasant Ridge Rd.	91.75	11.98	12.63	15.54
Friendship Church Rd.	94.31	11.06	11.86	16.12
Fleming Rd.	104.15	14.21	14.75	29.47
Bluff Run Rd.	110.50	34.43	27.39	20.42
Battleground Ave.	144.50	24.10	25.48	28.89
Old Oak Ridge Rd.	177.17	24.94	26.37	30.36
16th St.	179.42	28.94	31.17	35.99
W. JJ Dr.	192.47	27.10	31.40	33.22
Merritt Dr.	204.58	34.56	36.78	39.88
Summit Ave	204.58	34.58	36.11	39.63
Aycock St.	213.56	30.39	35.60	38.50
Church St.	226.47	35.87	37.16	40.80
Randleman Rd.	227.97	30.75	33.13	38.83
McConnell Rd.	251.06	29.80	31.29	34.98
White St.	329.19	24.08	25.88	30.58
Rankin Mill Rd.	355.67	29.29	30.91	34.66
Fieldcrest Dr.	388.42	30.65	32.58	36.41
McLeansville Rd	482.88	35.49	37.64	43.92

Table 5.3. 2009-2010 Conductivity Annual Mean Values Sorted in Ascending Order with 2010 Impervious Land-Use at Composite Scales

Sub-watershed Name	Conductivity	100 m	150 m	Sub-Watershed Scale
Pleasant Ridge Rd.	93.88	12.00	12.87	15.80
Friendship Church Rd.	101.96	12.02	13.00	18.13
Bluff Run Rd.	132.75	19.94	29.49	27.56
Battleground Ave.	142.67	24.67	26.38	30.08
Fleming Rd.	151.13	28.44	20.61	24.50
Merritt Dr.	167.88	33.99	36.69	38.21
Old Oak Ridge Rd.	175.71	26.80	28.29	32.59
16th St.	179.93	32.03	34.50	39.35
Aycock St.	196.04	37.49	39.06	41.74
W. JJ Dr.	209.75	29.46	30.22	36.12
Randleman Rd.	212.46	31.42	34.11	38.70
Church St.	217.92	39.68	41.25	44.86
Summit Ave	227.00	38.20	40.04	43.50
McConnell Rd.	237.67	34.29	35.87	39.33
White St.	262.33	28.73	30.40	34.58
Rankin Mill Rd.	301.00	32.68	34.41	38.08
Fieldcrest Dr.	343.54	32.53	34.93	38.23
McLeansville Rd	495.22	39.75	42.05	49.25

Table 5.4. 2011-2013 Conductivity Annual Mean Values Sorted in Ascending Order with 2013 Impervious Land-Use at Composite Scales

Sub-watershed Name	Conductivity	100 m	150 m	Sub-Watershed Scale
Pleasant Ridge Rd.	87.28	18.45	18.65	20.31
Friendship Church Rd.	100.89	23.51	22.98	20.99
Fleming Rd.	102.83	28.04	27.99	31.17
Bluff Run Rd.	122.94	39.41	39.75	36.50
Battleground Ave.	126.78	29.89	31.69	35.80
Old Oak Ridge Rd.	156.69	33.83	35.65	40.92
16th St.	159.36	40.20	42.24	46.16
Merritt Dr.	160.25	45.17	47.81	49.75
W. JJ Dr.	166.78	44.99	45.03	49.24
Aycock St.	200.89	48.66	50.12	52.27
Summit Ave	204.58	49.73	51.36	54.12
Randleman Rd.	204.94	45.87	48.04	52.43
Church St.	221.30	52.05	53.49	56.64
McConnell Rd.	223.32	44.22	45.66	48.74
White St.	228.86	35.89	37.51	41.28
Rankin Mill Rd.	291.17	41.98	43.50	46.44
Fieldcrest Dr.	296.47	46.10	47.88	50.01
McLeansville Rd	505.88	55.24	57.06	63.22

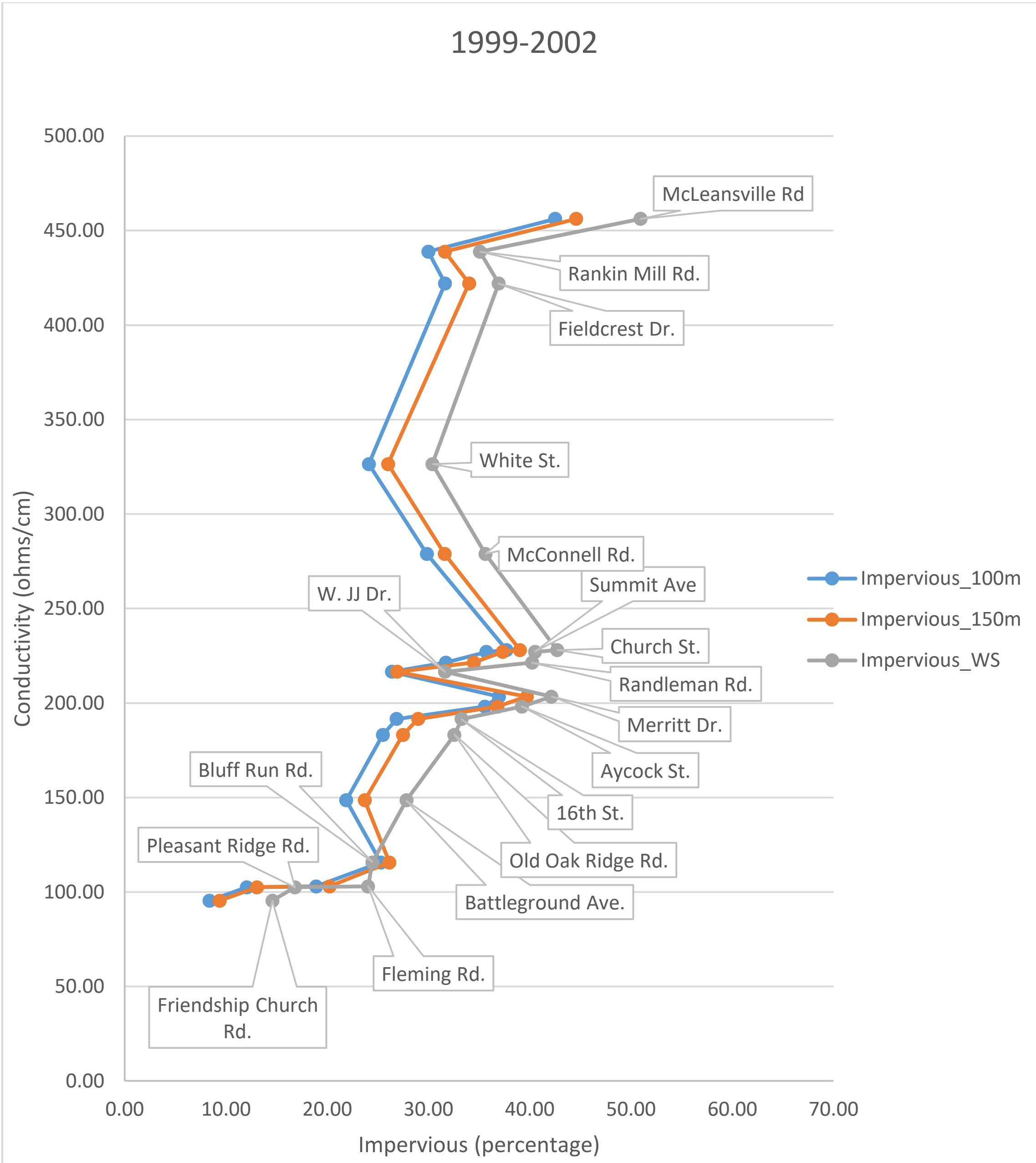


Figure 5.1. Scatterplots of 1999-2002 Conductivity and 2002 Impervious Land-Use at the 100 m, 150 m, and Sub-Watershed Spatial Scales

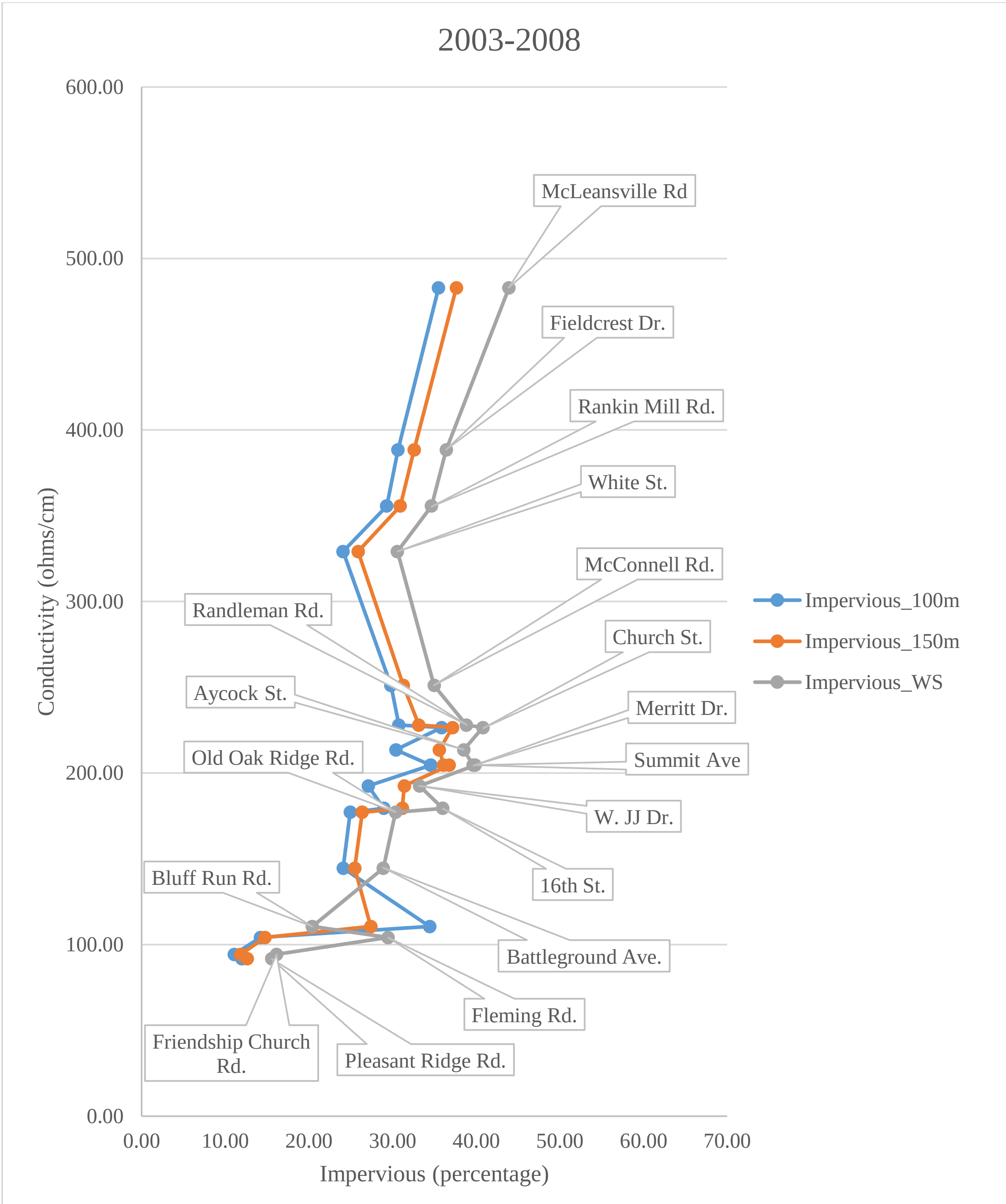


Figure 5.2. Scatterplots of 2003-2008 Conductivity and 2008 Impervious Land-Use at the 100 m, 150 m, and Sub-Watershed Spatial Scales

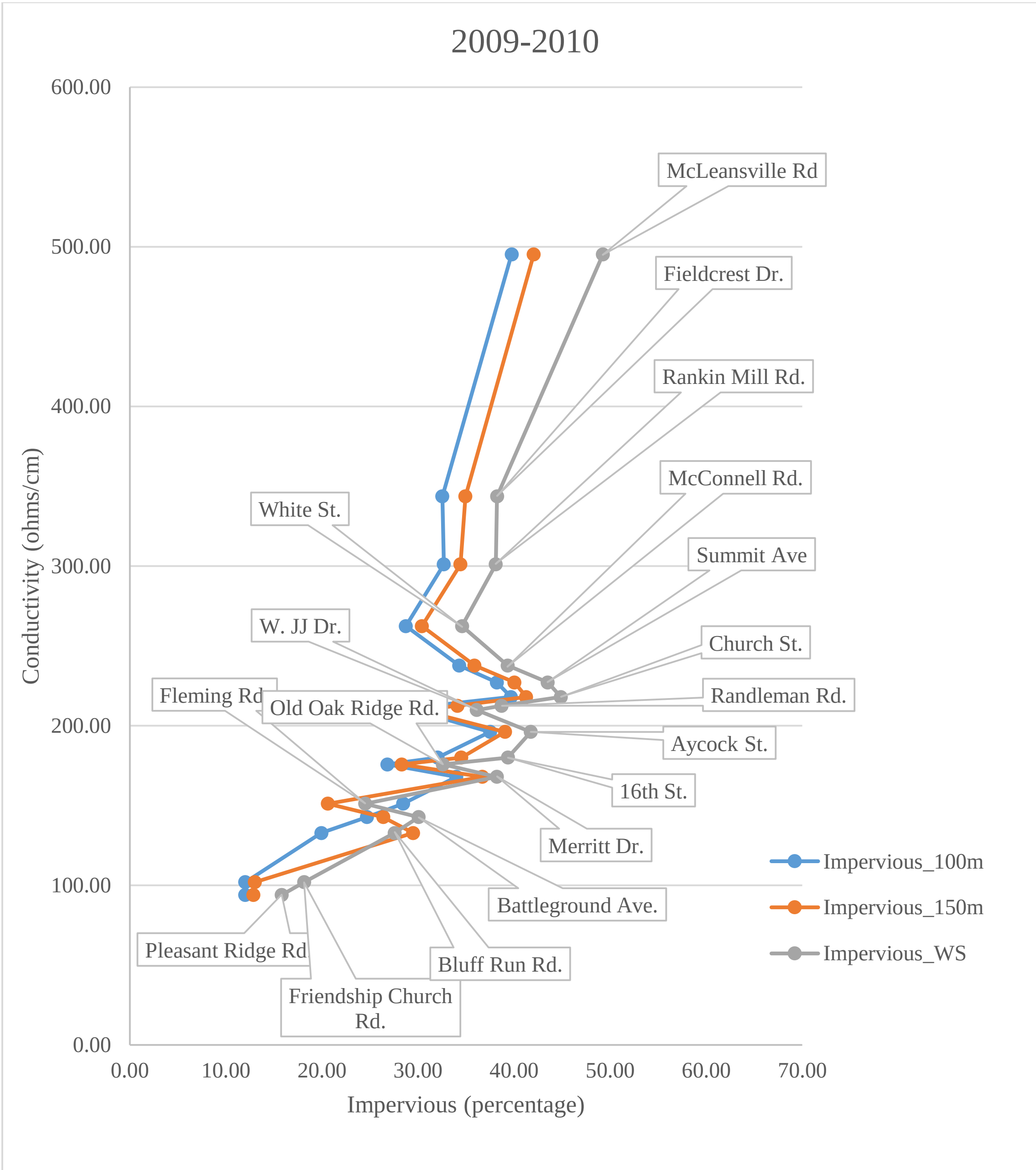


Figure 5.3. Scatterplots of 2009-2010 Conductivity and 2010 Impervious Land-Use at the 100 m, 150 m, and Sub-Watershed Spatial Scales

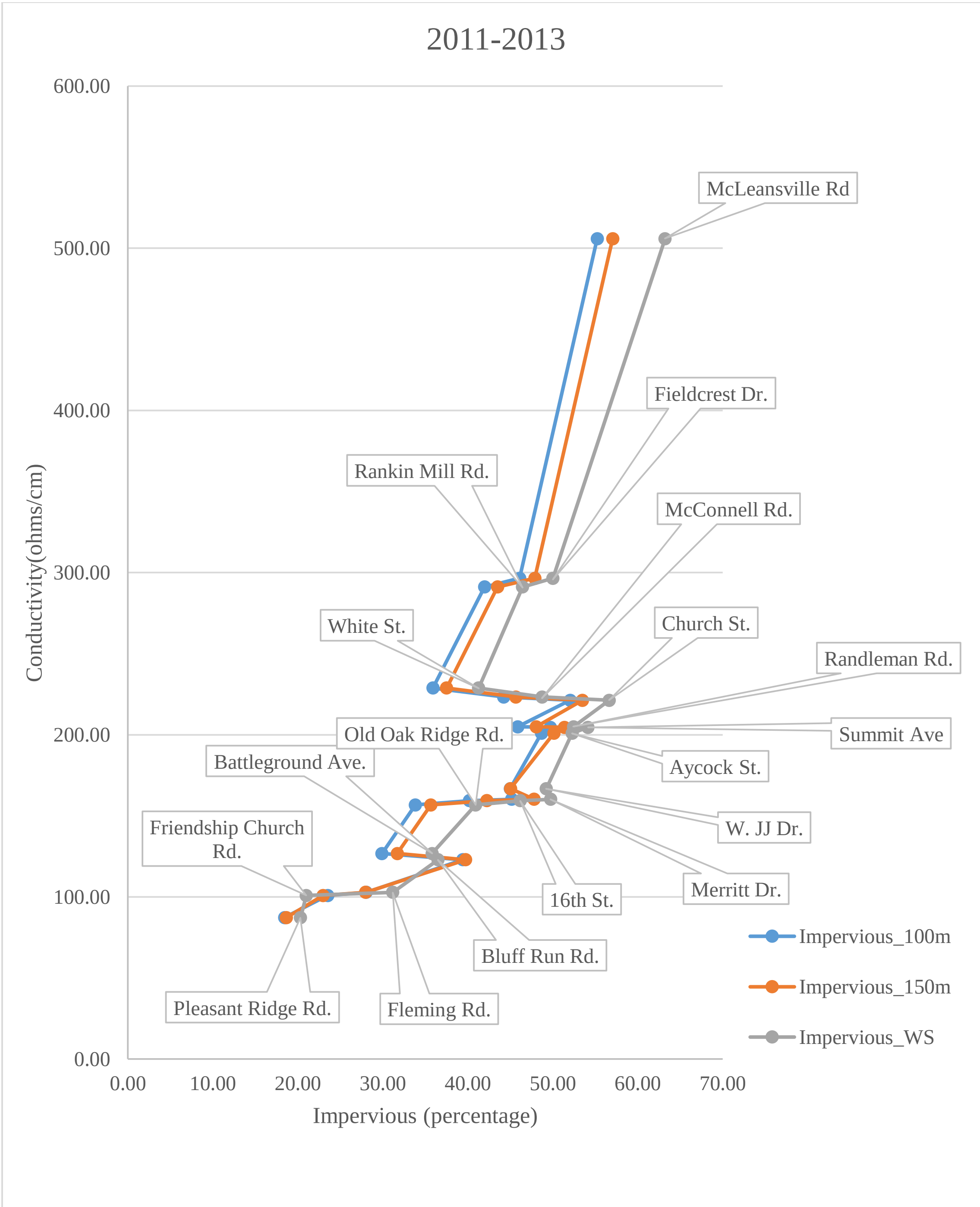


Figure 5.4. Scatterplots of 2011-2013 Conductivity and 2013 Impervious Land-Use at the 100 m, 150 m, and Sub-Watershed Spatial Scales

Modeling Study

The aim of the SWAT modeling study was to estimate the runoff and nitrate yield (the most dominate water quality variable from the exploratory analysis) in the Reedy Fork-Buffalo Creek watershed. To model the runoff and nitrate, the SWAT model was calibration and validation at two sampling sites, Friendship and Mcleansville Road, on monthly time steps by using measured climate `data. Utilizing guidelines given in Moriasi et al., (2007), the general performance of the SWAT model regarding NSE and R^2 can be judged as great, particularly considering limited data conditions in the studied area. On a monthly basis, values obtained at the Friendship Road and Mcleansville Road outlet for R^2 and NSE were 0.85 and 0.83, and 0.91 and 0.90 for the calibration period. Whereas for the validation period, the values were 0.93 and 0.92, and 0.90 and 0.91 respectively.

To deal with water management issues, it is perfect to analyze and quantify the diverse components of hydrological processes occurring within the study area. The SWAT model estimated other pertinent water balance components in addition to the monthly flow or discharge. Reference Sathian and Syamala (2009), stated that the most imperative components of the water balance of a watershed are; precipitation, surface runoff, lateral flow, base flow, and evapotranspiration. Among these, every one of the variables, except precipitation, needs forecast for quantifying as their estimation is difficult. The average annual basin values for the different water balance components during the calibration and the validation periods simulated by the model are reported in Table 4.45 and calculated as a relative percentage of average annual rainfall in Fig. 4.35

and 4.36. From these components, evapotranspiration (ET) contributed a larger amount of water loss from the watershed. High evapotranspiration rate anticipated could be ascribed to the kind of vegetation spread and high temperature connected with the area. North Carolina positions 6th in the Nation in average annual precipitation (50 inches) and has a mild, humid climate. About 72 percent of the precipitation that occur in North Carolina is returned to the atmosphere using evapotranspiration (ET), and about 20 percent recharges the ground-water system (Winner and Simmons, 1977). The overall 2002-2013 water balance component results from Table 4.45 shows that the value of the annual ET as a relative percentage of average annual rainfall for the study period was 65.4%. This is in line with that of Winner and Simmons (1977). Total water yield (WYLD) is the amount of streamflow leaving the watershed outlet amid the time step. Based on Table 4.45 values, it can be seen that a significant part of the precipitation received by the watershed is lost as stream flow. The total annual water yield for 2002-2013 was predicted to be about 313.16 mm, which is made up of 131.87 mm of surface runoff, 185.7 mm of baseflow (groundwater flow), and transmission losses of 4.43 mm. According to Santhi et al., (2007), the baseflow volume for Guilford County, North Carolina, and its surroundings is estimated to be between 101mm to 220mm with precipitation and baseflow percentage between 20 to 40% or lower. The baseflow volume simulated by the SWAT model was within this range. Hence it can be it can be asserted that the model performed well in estimating the water balance in the study area watershed.

The impacts of urbanization on runoff and nitrate losses for the entire watershed were assessed based on the predicted impervious development. The impact of land-use change on stream runoff modeling results indicates that the annual flow under the future land-use scenario is about 152mm. This is a 13.5% increase from the current land-use scenario (Table 4.47). A possible reason for the increase in surface runoff may be due to the conversion of forest and grasslands to impervious land uses. Currently, the predominant land use in the watershed is forest cover and grasslands. It makes up over 42.7% and 24.6% of the watershed respectively. In the future, land-use scenario, forest land over decreased marginally making up 39.9% of the watershed, whereas the areas of grassland use and impervious land-use have changed dramatically, with grasslands comprising 16.4% of the watershed, and impervious developments comprising nearly 38% of the watershed. In the SCS equation, the curve number is reliant on the combination of land-use and soil types. A lower curve number means a reduction in surface runoff as the land-use and soil type combination is less resistant to infiltration. As the curve number increases, the land-use and soil type combination present is more resistant to infiltration, resulting in the increase in the amount of surface runoff. Since the typical curve numbers for watershed areas with more than 12% impervious surfaces (such as low-density residential developments) are higher than most agricultural lands (USDA 1986), the volume of surface runoff in the watershed areas is higher.

Table 4.47 also shows the comparison of the annual load nitrate modeled in SWAT under the past, current and future land-use scenarios. In most cases, there was an increase in the annual nitrate load to nearly 31%. The increase in nitrate under the future land-use scenario is probably attributed to the increase in impervious land-use. The reduction in forested lands in the future land-use scenario may also be responsible for such increase. In spite of the fact that the current land-use configuration is made up of 5.8% agricultural land and 24.2% impervious area, over 42.7% of the land is forested. The vegetation cover on forested land helps in the uptake of nitrate (a very soluble nitrogen species), which in one way or another leach off into the surface runoff. In the future land-use scenario, the forested land was reduced to 38.7% of the watershed area from 42.7% in 2010. With the amount of agricultural land reduced to 5.7% from 5.8% in 2010 and a projected 37.1% impervious area from 24.2% in 2010, there is probably an insufficient vegetation cover present to retain the nitrate from the surface runoff, bringing about an increased nitrate load. Another conceivable reason may be due to the utilization of nitrate fertilizer in lawns and gardens in the urban and suburban areas. Since nitrate is all the more promptly consumed by grass and ornamental species, numerous homeowners in addition to landscaping and real estate managers prefer to use fertilizer enriched with nitrate instead of other nitrogen species.

CHAPTER VI

CONCLUSION

With the number of people in the Reedy Fork-Buffalo Creek watershed constantly on the rise, the quality of the water bodies in the watershed cannot be overlooked. Although numerous researches has identified the existence of relationships between LULC and the quality of surface water, study within the study region with regards to the spatial pattern fragmentation of LULC in relations to water quality is non-existence. The main purpose of this dissertation research was to investigate, the relationship between the change in the LULC pattern distribution and stream water quality, both spatially and temporally, in the Reedy Fork-Buffalo Creek watershed located in the headwaters of the Cape Fear River Basin from 2002 to 2013 at multiple spatial scales. The questions addressed includes: at what spatial scale does heterogeneity in the landscape act to influence water quality and what components of the urban watershed landscape fragmentation are mostly related to changes in water quality at those scales, and will an increase in impervious surface (<10%) cause a significant increase in water quality concentrations in the studied watershed.

Detailed LULC classification of the study area was perfumed by integrating HR orthophotos and ancillary data. The classes of the LULC include: impervious, agricultural, water, grass, and forest LULC maps with the dominant land-use type being forest cover for all the analyzed years. The LULC class that experienced the most change from 2002 to 2013 was impervious surface. Landscape metrics derived using FRAGSTATS revealed four main class level metrics of the classified maps; PLAND, NP, ED, and LPI. This was used to determine the existence of relationships with water quality. Descriptive statistics were used to give a general overview of the LULC types and water quality trends of the entire and individual watersheds over the study period.

The findings from the landscape metrics disturbance indicators suggested that the individual watersheds: Sixteenth St (16th St), Aycock St. (AS), Church Rd. (CR), Fieldcrest Dr. (FD), McConnell Rd. (MCCR), Meritt Dr. (MD), Randleman Rd. (RR), Rankin Mills Rd. (RMR), Summit Ave.(SA), West JJ Dr.(WJJD), and White St. (WS) were relatively stable and dominated by complex patches that corresponded to a greater degree of human intensity in the southern part of the watershed. Lee et al., (2009) determined that in areas where urban land-uses represent the largest patch, water quality declines. Water quality issues in the southern portion of the Reedy Fork-Buffalo Creek watershed, where the urban sub-watershed are located, include sewage discharges, high nutrient loads, turbidity, and heavy metals (Alleman et al., 1995). These issues are unlikely to be altered by land-use changes that do not fundamentally shift the overall urban landscape characteristics. Unlike the Southern part, critical issues in the Northern part of the watershed mostly made up of forest and agricultural lands, where the was changes in the composition and spatial distribution of residential and agricultural land-use classes. The individual watersheds within the region include; Battleground Ave. (BA), Bluff Run Rd. (BRR), Fleming Rd. (FR), Friendship Church Rd. (FCR), Mcleansville Rd. (MCLR), Old Oak Ridge Rd. (OORR), and Pleasant Ridge Rd (PRR).

Impervious land-use classes in this area extended further inland into the forest and agricultural lands and this has led to changes in the landscape structure of that region. The increased development intensity associated with PLAND, NP, ED, and LPI of the various land-use classes, especially, forest and agricultural lands can affect the type of possible pollutants. It should be noted that the issues of PLAND, NP, ED, and LPI have linked land use with water quality in a majority of the literature (Schueler, 1994; Brabec et al., 2002; Osborne and Wiley 1988; Harman-Fetcho et al., 2005, Roth et al., 1996; and Johnson et al., 2001), as the proportion and spatial fragmentation of LULC within watersheds can have significant influences on water resources (Roth et al., 1996; Johnson et al., 2001).

FA results show that, among the 12 water quality variables analyzed, 5 variables: conductivity, hardness, nitrate, TKN, and turbidity with strong factor loadings (>7.5) and common to all analyzed years were influential in determining the water quality of the study area. These variables can be individually linked to specific pollutant sources and can lead to a more comprehensive understanding of the sources of pollutants across the watershed.

In addition to FA, regression analysis was used to demonstrate the impact of specific LULC type pattern on water quality at selected spatial scales. Across the watershed, the correlation and regression results indicate that impervious surfaces relating to PLAND, NP, ED, and LPI at the watershed scale exert the strongest effect on water quality. However, greater variation in correlations and explanatory value of the PLAND, NP, ED, and LPI of agricultural, grass, and forest composition for water quality were observable at the various spatial scales. These observations have not only been linked through statistical analysis in this research but also through the intensive review of the literature on the relationships between LULC and water quality. This finding is very significant, in that, the studied watershed is not only highly urbanized and populated, but it also serves as the headwaters of the Cape Fear River basin. Hence activities in the Reedy for Buffalo Creek watershed may end up affecting downstream water quality.

Also, one of the goals is to determine if the increase in impervious surface (<10%) will cause a statistically significant increase in water quality concentrations. The Reedy Fork-Buffalo Creek watershed of the Cape Fear River Basin is an excellent example of the potential for damage to water quality as a consequence of unrestricted growth and urban development. The highly urbanized Reedy Fork-Buffalo Creek watershed, with a large amount impervious surface, provides substantial evidence of the negative effects of urban growth on water quality in headwater streams. The impervious surface in all the individual watersheds were more than 10% for all the years. The mean conductivity which was used to represent impairment with regards to imperviousness in the watershed over the study period was 235 μhos/cm for 1999-2002, 390 μhos/cm for 2003-2008, 415 μhos/cm for 2009-2010, and 432 μhos/cm for 2011-2013. Each far exceeded the normal conductance range of natural North Carolina freshwater streams of 17- 65 μhos/cm as described by the North Carolina Division of Water Quality (2009). This result demonstrates that the effects of impervious surfaces on stream water quality are clearly identifiable and significant.

Generally, LULC composition pattern within the watershed scale appears to be of particular importance for all water quality variables. Hence, consideration should be given to the LULC composition at the watershed scale with respect to any type of development (infrastructure, planning, commercial, or other projects) to ensure that water quality is not compromised by depletion of forests within the watershed and the introduction of impervious surfaces. The results of this research demonstrate that the effects of impervious surfaces on stream water quality are clearly identifiable and significant. Limiting the area of impervious surfaces that occur within the Reedy Fork-Buffalo Creek watershed would serve to protect stream water quality from the effects of non-point source pollution. Prohibiting impervious surfaces from being introduced within the watershed scale, 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. Hence, it would be in the best public interests for water quality managers, zoning and planning measures, and other public-policy administration organizations to use this information to help inform future public-policy decisions.

The importance of continued emphasis on water quality analysis and watershed monitoring programs in Guilford County, North Carolina is of paramount significance, particularly in light of increasing population growth, LULC conversion and changing climatic conditions. The findings of the modeling exercise assisted in determining the runoff and nitrate yield with regards to current and future LULC scenarios. The present climatic condition was assumed and used for the future land-use scenario simulations.

The results from the modeled LULC scenario demonstrate that the future (2030) LULC would bring about a 13.5% increase in surface runoff and its associated 31.85% increase in nitrate level concerning current LULC (2010). An examination of the forecasted LULC distribution graph shows that the predominant land-use change that occurred amongst present and future conditions are the transformation of grass and forest land to impervious development. These outcomes bolster the findings of a previous study (Liu et al., 2000), which indicates that reduces impervious development results in decreased levels of runoff and nutrient loading and vice versa. This suggests that land-use type must be taken into account when calculating runoff volume. Previous model studies have shown that when the land-use changes from forest to agriculture or from forest to impervious development, there is usually a corresponding increase in the in-stream loads and concentrations of total nitrogen and total phosphorus (Tufford et al., 1998, Karvonen et al., 1999). Undeniably, with increases in greenhouse gasses, our future climate and weather patterns may change, which may induce significant hydrologic impacts. A similar study examining the plausible hydrologic impacts of climate change had already been conducted, and the results were presented in a separate paper (Tong et al., 2007). Furthermore, the concerted effects of climate and land-use changes in water resources had also been examined using the Lower Great Miami River, as a case study (Tong and Liu, 2006). The results from these two studies revealed that although climate change might contribute to the deterioration of water resources, a reduction in agricultural and impervious land in the watershed indeed could reduce the nutrient loadings. Nonetheless, one needs to be reminded that although this suggestion may be a good remedial measure in controlling nutrient (i.e., nitrate) pollution, it may not be effective in curbing conservative solutes, such as sodium and chlorides which bring about hardness in water, and other pollutants from roadways or urban impervious surfaces. Hence, further research into these contaminants is required to ascertain the overall hydrologic effects of land-use change in impervious development.

One possible source of excess nitrate in the Reedy Fork-Buffalo Creek watershed include tributaries that receive runoff from urbanized impervious developments and farmlands. Nitrate is one of the basic components of agricultural and lawn fertilizer, and surface runoff can easily transport it from the fields to streams that eventually flow into the Reedy Fork-Buffalo Creek. If, however, terrestrial sources of nitrates can be identified, water resource managers can implement cost-effective best management practices (BMPs) to curtail its presence in urban runoffs.

Overall, this dissertation has provided robust evidence to support the fact LULC patterns affects water quality in the Reedy Fork-Buffalo Creek watershed at the selected spatial scales with the watershed scale exhibiting the greatest effect. Whether examined at the watershed scale or the riparian buffer scale, impervious cover serves to degrade water quality, whereas, vegetative land-covers serve to protect and enhance the water quality of rivers and streams. The exploratory and environmental modeling results produced by this dissertation represents a great beginning for what will, hopefully, remain a continuous study in the Reedy Fork-Buffalo Creek watershed. This type of water quality research provides invaluable insight 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 anytime soon in the Reedy Fork-Buffalo Creek 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 Reedy Fork-Buffalo Creek watershed can be preserved through protection of its stream systems.

Future Research

1. Streamflow and nutrient data are very important in knowing the degree to which changing climatic condition and LULC influence and water quality in the watershed. With more effective and comprehensive data, in-depth research could be carried out to incorporate the effect of seasonal variation.
2. Since anthropogenic activities have been realized as an important factor in research along this line, more data is needed to determine the extent of some of the activities carried out by humans in the watershed such as lawn and agricultural fertilizer application, and development to determine how they affect water quality.
3. In general, human from WWTPs tend to impact water quality. Including the location of these facilities will aid in establishing the role they play in water degradation.

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