IMPERVIOUS AREAS: EXAMINING THE UNDERMINING EFFECTS ON SURFACE WATER QUALITY

A Dissertation

by

DE'ETRA JENRA YOUNG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Forestry

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ABSTRACT

Impervious Areas: Examining the Undermining Effects on Surface Water Quality.

(December 2010)

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Co-Chairs of Advisory Committee: Dr. Raghavan Srinivasan
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This study explored the relationship between increased proportions of imperviousness in a watershed on surface water quality and examined the effectiveness of using remote sensing to systematically and accurately determine impervious surfaces. A supervised maximum likelihood algorithm was used to classify the 2008 high resolution National Agriculture Imagery Program (NAIP) imagery into six classifications. A stratified random sampling scheme was conducted to complete an accuracy assessment of the classification. The overall accuracy was 85%, and the kappa coefficient was 0.80. Additionally, field sampling and chemical analysis techniques were used to examine the relationship between impervious surfaces and water quality in a rainfall simulation parking lot study. Results indicated that day since last rain event had the most significant effect on surface water quality. Furthermore, concrete produced higher dissolved organic carbon (DOC), dissolved organic nitrogen (DON), potassium and calcium in runoff concentrations than did asphalt. Finally, a pollutant loading application model was used to estimate pollutant loadings for three watersheds using two scenarios. Results indicated that national data may overestimate annual pollutant loads by approximately 700%. This study employed original techniques and methodology to combine the extraction of impervious surfaces, utilization of local rainfall runoff data and hydrological modeling to increase planners' and scientists' awareness of using local data and remote sensing data to employ predictive hydrological modeling.

DEDICATION

I would like to dedicate this dissertation to: my loving parents, Terry and Lorraine Turner, little sister, Zandrea, niece, Zaria and Aunt Joyce. Thank you for your continuous support and encouragement in all my endeavors.

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"For today and its blessings, I owe the world an attitude of gratitude" -Clarence E. Hodges. I would like to acknowledge my mentor and major professor, Dr. Raghavan Srinivasan, for his immeasurable guidance, assistance and continuous support for the past six years at Texas A&M University. Thank you for welcoming me into the Spatial Sciences Laboratory. I will also like to thank my Co-Chair, Dr. Jacqueline Aitkenhead-Peterson for her consistent push for academic excellence. Your little words of advice and encouragement helped me push forward finishing the task at hand. Thanks for not only being an extremely intelligent mentor, but a great friend. I'm grateful for my committee member, Dr. Sam Brody for his guidance and keen knowledge over the past five years. Additionally, I would like to thank Dr. Astrid Volder for words of wisdom and technical writing support. I would like to thank all the members of the Spatial Sciences and Nutrient and Water Analysis Research Laboratories, in particular, Lesli Gomez, Jared Stukey and Nina Stanley for your unwavering technical assistance. I would like to thank Adrian and countless friends and family for their support and love. Finally, I would like to thank my loving heavenly Father, Jehovah God, for allowing me the faith and determination to complete this research.

NOMENCLATURE

BASINS	Better Assessment Science Integrating Point & Non point Sources
CWP	Center for Watershed Protection
DOC	Dissolved Organic Carbon
EMC	Event Mean Concentration
EPA	Environmental Protection Agency
GIS	Geographic Information System
NAIP	National Agriculture Imagery Program
NPS	Non point Source
PAHs	Polycyclic Aromatic Hydrocarbons
PLOAD	Pollutant Loading Application
TN	Total Nitrogen
TP	Total Phosphorus
TDS	Total Dissolved Solids
TDN	Total Dissolved Nitrogen
TMDL	Total Maximum Daily Loads
TSS	Total Suspended Solids
US	United States

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CHAPTER I

INTRODUCTION AND

LITERATURE REVIEW

Background of Study

Population growth with its concomitant urban sprawl has been occurring since the late nineteenth century. Between 1800 and 1950 the U.S. population increased by 1650% (Hall 1984). Since the 1950s, cities transitioned from a largely agricultural focused society resulting in rapid urban development. This increase in population has yielded a greater demand for water and has led to the urbanization of our nation's watersheds (U.S. EPA 2006). Bhaduri et al. (2000) asserted that land use change by humans has played a significant role in changing the hydrologic system. During this change, land was transformed to several uses such as agriculture, mining, industrial and residential uses and these transformations have changed the hydrologic characteristics of the landscape. Thus, increased building and population density has a noticeable strong influence on urban hydrological processes (Hall 1984) and natural hydrological processes (Niemczynowicz 1999).

Impervious surfaces have been noted as indicators of urbanization for many years. As land is covered with impervious surfaces such as roofs, roads, parking lots, buildings and sidewalks, the natural hydrologic cycle is disrupted.

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This dissertation follows the style of *Urban Water Journal*.

In natural environments rainfall is managed through the hydrological cycle and a large portion of the rainfall is filtered through the soil layer before reaching surface water such as rivers, streams and lakes or alternatively, infiltrates the soil to deeper layers to become groundwater (Echols 2008).

That precipitation which falls onto impervious surfaces quickly runs off directly into stormwater systems to local surface water altering the hydrologic cycle. Thus, instead of infiltrating into the soil, precipitation in urban areas is quickly transported out of the system (Lazaro 1990). Urbanization has transformed the characteristics of watersheds (Schiff and Benoit 2007, U.S. Soil Conversation Service 1986). For example, new impervious structures reduce the water storage capability of the watershed and the result is unfavorable physical and ecological impacts on the environment, leading to unstable stream channel morphology and increasing the hydraulic efficiency of a catchment (Schiff and Benoit 2007, Pappas et al. 2008). As a result of this shift in the natural landscape, runoff volume and peak flow increases (Pappas et al. 2008).

When there is an increase in the impervious to pervious surface ratio, stream systems display base flow is decreased and pollutant load carried by stormwater is increased (Brabec et al. 2002). There is a direct negative correlation between water quality and urbanization (Gnecco et al. 2005, Arnold and Gibson 1996, Stoel 1999). For example, Brett et al. (2005) noted that urbanization marked a decrease in water quality in 17 urban streams in Seattle. They reported that stream phosphorous concentrations were correlated ($r^2 = 0.58$) with catchment land cover, yet nitrogen concentrations were only weakly correlated with land cover type. Furthermore, urban streams were attributed with having higher total phosphorous, higher soluble reactive phosphorous and higher turbidity than forested streams.

The United States (US) Environmental Protection Agency (EPA), in 1984, reported to congress that nonpoint source (NPS) pollution was one of the leading causes of water quality problems in the US. Nonpoint source pollutants can be grouped into several categories. These categories include pathogens, nutrients, metals, pesticides, toxic containments and debris (Arnold and Gibson 1996).When there is a large concentration of nutrients in surface waters, this can lead to algal blooms, which can lead eventually to eutrophication with anoxic conditions resulting in low dissolved oxygen and fish kills. Heavy metals and pesticides affect many aquatic organisms and can also pose an aesthetic concern because they increase water turbidity, often discoloring water. Additionally, odors may be indicative that contaminants are from municipal or industrial waste sources.

The EPA has estimated that it will have to increase its spending by $263 billion dollars over the next 20 years to maintain its water services because of concerns over water quality (Young 2006). Because of the relationship between pollution loading and urban land use, there is potential to improve our nations' water quality by adopting land use management practices aimed at reducing pollution (Basnyat et al. 2000). Beneficial practices to ameliorate urban surface waters might include incorporation of low impact development techniques such as pervious pavements, grass swales, bioretention areas, constructed wetlands and rain gardens in urban planning (Li et al. 2010)

Geographic Information Systems (GIS) and Modeling

As technology advances, the growth of cities and transitioning land uses are commonly examined using aerial photography that incorporates spectral data. The use of multi-spectral data allows planners and scientists the ability to measure and foresee land use and land cover changes (Carlson and Arthur 2000). The use of aerial photography is often expensive and flights are only flown occasionally. As anthropogenic development is causing rapid land use change, satellite imagery becomes a more practical alternative for planners and managers. Multi-spectral imagery utilizes a scale that can easily detect land use changes and allows the user to foresee and predict future surface land use change. Complex computer models are cost-effective, resourceful tools in urban planning and management used to measure water quality and control (Chen and Adams 2007).

Combining GIS and water quality run-off data fosters a better understanding for planners in establishing management practices while examining impervious surfaces and their potential effects on surface runoff quality and quantity (Goldshleger et al. 2009). The joining of remote sensing data such as land use and land cover with runoff data is generally helpful in determining the relationship between runoff and fundamental land changes (Goldshleger et al. 2009).

Significance of Study

Urban hydrology is concentrated in areas with high levels of human interaction with nature’s processes and has gained a significant amount of attention during the last couple of decades, (Niemcynowicz 1999). Johnson (2001) asserted that "increased run-off of stormwater and increased rise of flooding incidences" was a significant environmental impact of urban sprawl. Even though these impacts are easily observed, they are often difficult to measure. It is important then that we gain a better understanding of the complex concepts associated with urbanization, impervious surfaces and urban runoff (Goldshelger et al. 2009).

Impervious surface area in relationship to urbanization is relatively simple to calculate and has been noted as an effective indicator of declines in stream quality and quantity (Brabec 2002). Recently there has been a push for research that examines the correlation between urban sprawl and surface runoff quality. In addition to conducting research, models for predictive/preventative, and management measures are also emerging (Brabec 2002). Models are currently being used as a supporting tool to determine real time data. Advanced modeling tools and techniques to be applied in stormwater management are now considered to be a priority (Chen and Adams 2007).

Definition of Terms

There is a need to distinguish differences among terms to avoid confusion in research. Throughout this study, impervious surfaces will be defined or identified as a feature that disallows water from naturally infiltrating watershed soil. Concrete, pavement and other impermeable surfaces, such as rooftops and swimming pools, are all features of urban landscapes and are considered impervious surfaces. As a result, this study identifies two types of impervious surfaces: effective and non-effective areas

(Alley and Veenhuis 1983). Effective impervious areas are those areas that are hydraulically connected to the channel drainage system, whereas, non-effective impervious surfaces drain to nearby pervious areas (Alley and Veenhuis 1983).

Research Purpose and Objectives

The overall aim of this dissertation research was to better understand the linkage between impervious surfaces and urban water quality. As a result, the overall research question for this study was "*what is the relationship between increased proportions of imperviousness in a watershed on surface water quality?"* I employed a research strategy that used both field experimental data and hydrological modeling to answer this question.

The primary objectives of this study were threefold:

(1) to effectively use remote sensing and GIS data to systematically and accurately determine impervious surfaces for urban water quality modeling;

(2) to establish the common relationship between impervious surfaces and water quality across an urban setting while focusing on surface material characteristics, i.e. asphalt vs. concrete, parking intensity and days since significant rainfall; and

(3) to spatially explore a correlation between impervious surface area and the effects on water quality utilizing BASINS Pollutant Loading Application (PLOAD), Geographic Information Systems (GIS) and remote sensing

Dissertation Structure

This dissertation has five chapters that examine the relationship between impervious surfaces and urban hydrology. Specific topics for each chapter are summarized as follows:

(1) Chapter I introduces a brief background of the research, presents its significance and research objectives. It also reviews urban hydrology and hydrological modeling literature to effectively expand on the importance of linking urbanization to water quality. This chapter presents the history of urbanization, impervious surfaces and degrading water quality. The second part of this literature review pertain a review of hydrological predictive modeling and water quality. Lastly, this chapter contains a conceptual framework to present the linkage and theoretical components along with research hypotheses. This chapter builds the foundation for later chapters;

(2) Chapter II aims to use remote sensing data, high resolution imagery, to accurately extract impervious surface classifications;

(3) Chapter III attempts to utilize a rainfall simulation field sampling technique to the examine the first flush of nutrients in storm runoff;

(4) Chapter IV evaluates and compares the effectiveness of using predictive hydrological models and data accuracy; and,

(5) Chapter V summarizes key findings, provides concluding remarks and addresses research limitations and suggests future research.

Literature Review

This section will outline key areas of research literature to effectively expand on the importance and understanding of linking urbanization and impervious surface area to their effects on nonpoint source pollution. In particular, it will cover the history of urbanization and runoff and its associated pollutants. This review will also explain the "first flush" phenomena and its linkage to nutrient concentration. Lastly, this review will cover the critical use of models to assist planners, researchers and managers in spatially correlating the significance of impervious surfaces in urban watersheds.

Impervious Surfaces and Urban Water Quality

Urbanization often results in an influx of impervious surfaces, which contributes to negative environmental impacts. An increase in manmade surfaces replacing natural native ground cover has altered the hydrological cycle, resulting in decreasing water infiltration and increasing runoff (Leopold 1968, Pappas et al. 2008). With this expansion of impervious surface area, pollutants attached to these impervious surfaces, which can include pollen, dusts and soil particles from construction activities, domestic and wildlife feces, and novel carbon compounds and metals from vehicles are transported to water bodies via runoff.

Rainfall frequency, volume, and intensity are important characteristics in estimating runoff volume and water quality. These characteristics are useful in associating precipitation with runoff pollution and erosion problems. Rainfall events are generally characterized by size, duration and intensity. This affects runoff rates and pollutant concentration levels which drive pollutant concentrations and loading (Shaver et al. 2007).

The Center for Watershed Protection (CWP) compiled a database of national stormwater runoff water quality (CWP 2007). CWP noted that the western U.S. has a very distinct wet season, whereas the eastern and Midwestern U.S. has more dispersed precipitation patterns. Factors such as long or short duration and low or high intensity storms control Event Mean Concentration (EMC) levels for nutrients, sediments and metals. Arid and semi-arid zones often have prolonged wet or dry rain events, therefore impairing the hydrological balance in urban regions for longer periods (Pilgrim et al. 1988). The majority of pollutant loading for some chemical constituents is correlated with smaller flow volumes. Driver and Tasker (1988) reported that the highest nutrient EMCs in stormwater were from arid or semi-arid regions.

Rainfall duration plays a key role in stormwater models. Time influences the gravitational, thermodynamic, and other natural forces that create runoff (Shaver et al. 2007). There are two fundamental measures of time that affect stormwater runoff. Runoff response time of the drainage to the rainfall input measures how quickly the rates of runoff will change as the runoff rates change. Secondly, the effective event time describes how much time an area takes to respond to rainfall.

Rainwater produces ions such as sulfates (SO_4^{2-}), chloride (Cl^-), ammonium (NH_4^+), nitrates (NO_3^-), and orthophosphates (PO_4^{3-}) as wet atmospheric deposition in quantifiable concentrations. The pH and electrical conductivity of rainfall typically increases during the first 2mm of a rainfall event and then decreases (Göbel et al. 2007).

For example, the pH value for rainwater in Germany has increased by 16% over a 10 year period (Göbel et al. 2007). Pollutants are also carried to ground surfaces through dry-fall or dry deposition. Dry-fall is contributed by industrial, construction and agriculture activities which deposit dust, aerosols and gas from the atmosphere to ground and plant surfaces. A residue is formed on the land surface from higher water density particles and washed into waterways as concentrated pollutants in the initial runoff caused by a rainfall event. This is known as the "first flush". First flush is the initial period of stormwater runoff and it produces higher pollutant concentrations (Lee et al. 2002, Goonetilleke et al. 2005). Researchers have frequently examined several contributors to urban stream runoff (e.g. Deletic 1998, Aitkenhead-Peterson et al. 2009, 2010b, Steele et al. 2010). For example, Lee et al. (2002) examined 13 urban watersheds and 38 storm events to investigate the first flush phenomenon, describing the magnitude of the first flush and other applicable ways to examine its effects, i.e., not just concentration but quantity or mass export. They also reported the higher the magnitude of the first flush the greater effect on suspended solids and lesser effect on chemical oxygen demand. Other researchers have commented that the significance of the first flush is overrated and that not all storms will exhibit this phenomenon (e.g. Hall and Ellis 1985, Sonzongni et al. 1980).

Pappas et al. (2008) used laboratory rainfall simulations to evaluate hydrological and sheet erosion of impervious surfaces on a small spatial scale. From this laboratory controlled study, they concluded that plots containing at least 50% impervious area initially produced significant higher runoff rates. Hope et al. (2004) measured the concentrations of soluble nutrients on four plots in Phoenix, Arizona and concluded that parking lots are important sites to examine nutrient accumulation, dissolved organic carbon (DOC) in particular. By utilizing a rainfall simulator on 38 asphalt sites with increasing vehicular usage, the Hope et al. (2004) study concluded that NO_3^-N runoff concentrations were significantly higher on asphalt surfaces, than similar data collected on developed soil surfaces. Also, the highest concentrations of DOC (26 to 296 mg C L^{-1}) were found in commercial sites from sources such as leaking vehicles, leaching surface particulates from the breakdown of asphalt surfaces, and atmospheric deposition. Surface and subsurface soils located in the watershed also play a direct role in estimating runoff volume and rate from a rain event. Soil texture, structure and thickness determine how much rain can be infiltrated and retained in a soil. Silt and clays have a smaller saturated storage capacity than granular soils such as sand. Hard-packed soils lack permeability and affect the rate at which rainfall can enter and move through the soil which can lead to throughflow. Thus soils can play a vital role in producing storm runoff. Soil properties in urban areas that generate runoff are often hard to describe (Berthier et al. 2004) because for the most part they are constructed soils designed for strength for buildings and moisture retention for landscaping.

One of the most common urban land uses are residential areas or sub-divisions that contribute to the ‘urban sprawl’ outside of the commercial regions of the city. Residential areas also produce driveway runoff. Driveway concrete produces a moderate concentration of solids, nutrients, metals and polycylic aromatic hydrocarbon (PAH) in urban areas. Mahler et al. (2004) sampled runoff and scrapings from 4 test plots and 13 urban parking lots to investigate PAH from seal-coated parking lots. PAH concentrations in the particulates in runoff coal-tar-sealed parking lots were 3,500,00 mg kg^{-1} were significantly higher compared to those of asphalt sealed (620,000 mg kg^{-1}) and unsealed parking lots (54,000 m kg^{-1}). In an urban study conducted by Bannerman et al. (1993), residential driveways produced 21% of total runoff relative to 7% from lawns. Driveways in the Bannerman et al. (1993) study represented 5% of their study area. Furthermore, they reported that driveways contributed large phosphorous concentrations (1.16 mg L^{-1}) while galvanized roof tops produced significant zinc concentrations (149 μg L^{-1}).

Research has identified stormwater runoff as a major contributor to degrading and compromising water quality (Field 1985, Sickman et al. 2007, Sansalone and Kim 2008). Water quality data is often used by State and Federal agencies to guide decision making (Trench and Kiesman 1998). Toxic compounds, bacteria, oxygen-demanding and suspended solids are often significantly higher in urban stormwater (Field 1985). Sickman et al. (2007) reported total organic carbon (TOC) (4 to 49 mg L^{-1}) from urban runoff in Sacramento were 4 to 20 % greater than downstream. Classified as point or non point source pollutants, the impact of stormwater runoff pollutants on the receiving water bodies depends on a number of factors. The EPA has identified nonpoint source pollutants as one of the major causes of water impairment (U.S. EPA 1994). Pollutants are generally quantified by concentrations and loadings. Pollutant concentration is defined as the mass of pollutant per unit volume of water sample and expressed as mg L^{-1}l or μg L^{-1} and loading is defined as the mass over time and typically expressed as mg d^{-}

^{1} or kg yr^{-1}. To normalize values and aid to comparison among urban watersheds, exports defined as mg m^{-2} yr^{-1} or kg km^{-1} yr^{-1} can be used.

Urban water runoff pollutant loads contain a mixture of the following constituents: sediments, nutrients, heavy metals, biological oxygen demand (BOD) and organic chemicals (e.g. Zhao et al. 2007, Adams and Papa 2000, Shaver et al. 2007, Steele et al. 2010). Section 303(d) of the Clean Water Act and the EPA Water Quality Planning and Management Regulations require states to identify water bodies that have impaired water quality and develop total maximum daily loads (TMDLs) for pollutants of concern. To appropriately address water quality concerns, it is important to understand the type of pollutants present, as pollutants impact water bodies differently. Pollutants affect aquatic life, but can also directly impact human recreation uses and activities. The Nationwide Urban Runoff Program (NURP) compiled a data report examining national mean concentrations of pollutants between 1979 and 1983 which resulted in a plethora of EPA handbooks for the management of stormwater and best management practices (e.g. U.S. EPA 1993, Burton and Pitt 2002, EPA 2005).

Eight percent of impaired water bodies in the U.S. are due to sediments (Borah et al. 2006) and are either eroded from exposed soil construction sites, washed off from impervious surfaces in urban areas or are due to erosion of the stream channel. Maniquiz et al. (2009) reported that active construction contributed the majority of sediment from several urban development sites. Parking lots, streets, rooftops, driveways and lawns receive dry deposited such as windblown sediments. Finally, due to altered hydrology in urban watersheds resulting in extremely high discharge, increased erosion of the stream channel is often observed which will too contribute to sediment in the water column (Nelson and Booth 2002). Sediments have been reported as Total Suspended Solids (TSS), Total Dissolved Solids (TDS) and/or Turbidity (Adams and Papa 2000). TSS measures the total mass of suspended particles in a sample of water and is used to estimate sediment load transported to downstream receiving waters. TDS measures the dissolved solids and minerals present in stormwater runoff and TDS amount is used for assessing the purity of drinking water. Suspended particles such as dust and eroded sediments increase turbidity, which measures scattering of light by the suspended sediments in a water sample making it cloudy (Tsihrintzis and Hamid 1997). A high turbidity reduces the penetration of light and thus decreases the activity and growth of photosynthetic organisms but may protect other aquatic organisms. Turbidity aesthetically detracts from the water body and high levels of suspended solids may clog and damage fish gills (CWP 2003). Davies-Colley and Smith (2001) associated suspended solids in increasing turbidity in waterbodies and irritating fish gills. Sediments also slightly increase stream temperatures and serves as a major carrier of nutrients and metals (CWP 2003). Nelson and Booth (2002) reported urbanization increased Issaquah Creek watershed sediment production through channel erosion and accounted for 20% of the total watershed sediment budget.

Nutrients are another cause of water quality impairment (Borah et al. 2006). Nitrate-N and orthophosphate-P in urban streams not impacted with waste water treatment plants averaged 0.51 and 0.07 mg L^{-1} over a large range of reported urban streams (e.g. Steele et al. 2010). Nitrate (NO_3), ammonium (NH_4) and total nitrogen (TN) are commonly found in chemical fertilizers that are applied to lawns and gardens in residential areas. Nitrogen can also originate from failed septic tanks. For example, the Illinois Department of Natural Resources has been concerned about the long-term impact of urbanization on NPS pollutant loads in St. Louis metropolitan area (Wang et al. 2005). In St. Louis, nutrients from fertilizers are main causes of water quality problems. Lee and Olsen (1985) combined aerial photographs and nitrogen loading concentrations from septic and lawn fertilization from the Long Island area to examine pollutant loadings to area salt ponds. In the Ninigret salt pond, septic tanks produced 2844 kg N per year more than lawns. Nitrate is of high concern because as a conservative ion with a single negative charge, it is not readily absorbed by mineral soil and moves with infiltrating or runoff water (Shaver et al. 2007). Phosphates found in runoff are reported as soluble reactive phosphorous (SRP) or orthophosphate which is available for plant uptake. Total Phosphorous (TP) is also measured. Phosphates are typically linked to sewage, fertilizer and soil erosion. Nitrogen and phosphorus are essential plant nutrients, necessary to promote healthy growth of plants. However, when nutrients appear in excessive concentrations they contribute to the eutrophication of water bodies (CWP 2003, Steele et al. 2010). Excessive nitrogen and phosphorous increased the growth of flagellates and nuisance blooms were formed in the Mississippi River (Rabalais et al. 1996). Dissolved oxygen can also be depleted when the blooms are encouraged by phytoplankton raiding dissolved oxygen during the daylight and significantly reducing dissolved oxygen saturation during the night.

Urban areas also contribute a significant amount of metals in urban water surfaces (Steele 2010, Göbel 1997). Non-point source pollution from motor vehicles is one of the major contributions of metals to the environment. Metals such as lead, zinc, copper, chromium, arsenic, cadmium, nickel can all be found in urban waters (Tsihrintzis and Hamid 1997). Heavy metals sources include lead leaking from leaded fuel vehicles, lead, oxide, copper from tire wear, copper, chromium and nickel from brake linings and engine parts (Tsihrintzis and Hamid 1997).

Hydrological Modeling

Models are critical tools used to gain understanding of the fate and transport of runoff to a watershed. Problem areas are easy to identify, but nonpoint sources and causes are not (Engel et al. 1993). Hydrological models have the potential to assist land use managers and planners, to help mitigate and predict future conditions for a watershed. Chen and Adams (2007) successfully demonstrated that closed-form analytical models could be used to estimate stormwater runoff through two case studies. These case studies verified and evaluated rainfall-runoff transformations. In the type I and II analytical models used by Chen and Adams (2007) comparable results to the Stormwater Management Model (SWMM) were provided. The Type I analytical model estimated annual runoff to be 138 mm yr^{-1} compared to 149 mm yr^{-1} estimated by the SWW for the Upper East Don watershed in the city of Toronto, Ontario, Canada. Brun and Band (2000) used the Hydrological Simulation Program- FORTRAN (HSPF) with GIS to investigate the runoff ration and base flow and runoff relationship to percentage impervious cover and soil saturation. Results from this simulation developed an impervious surface threshold for the Upper Gwynn's Falls watershed in Baltimore, Maryland. A percent impervious cover of 20-25% was the lower threshold for runoff concentration levels to remain constant. As models become popular, it is important to understand what steps, techniques and methodology should be taken to develop and parameterize an accurate model.

Satellite derived data to predict changes associated with development in climatic and land surface parameters, such as runoff and evapotranspiration was used in Chester County, PA, by Carlson and Arthur (2000) to assist planners in management and development. In this study, AVHRR and Landsat TM data was used to predict that the region's scaled surface temperature will increase by 58% and the evapotranspiration net radiation ration will decrease by approximately 10% , Schiff and Benoit (2007) explored water and habitat water quality in relationship to total impervious area over four spatial scales in New England, USA. Using GIS and water chemistry tests, their watershed study, determined that bicarbonate, calcium, and chloride were dominant ions found in streams relative to concentrations of nutrients and particular matter, which were relatively low. They reported a correlation between stream variables and impervious cover at the smaller, more local scale. As a result of their study, a critical level of 5% impervious cover was established as a condition where stream health declined.

Conceptual Framework

This section provides a conceptual framework that will be used to further present the linkage and theoretical components of linking land use change to the degradation of urban water quality and the advantageous uses of applying GIS and computer modeling to predict future stormwater runoff outcomes. Conceptual models are essential to identify key factors, such as independent and dependant variables, and assist in developing hypothesis based literature reviews. The framework links literature to core concepts and essentially answers the research question.

This study will focus on three essential factors that will serves as the key elements in examining the effects of urbanization on water quality. As a result, the primary factors include:

(1) Site specification and land use, specifically, impervious surfaces that are defined as areas that disallow water from penetrating the ground naturally. This particular factor will examine impervious surfaces such as asphalt and concrete, high and low traffic areas, and residential and recreational areas;
(2) spatial data factors, primarily, remote sensing and GIS data layers such as: 2008 NAIP, zoning, roads, hydrology and re-classification data layers; and,
(3) environmental data factors, mainly, event mean concentrations, pollutant concentrations, rainfall simulation analysis.

The conceptual framework provides the foundation of how each factor or component is internally related and establishes the ground basis for formulating research hypotheses (Figure 1).

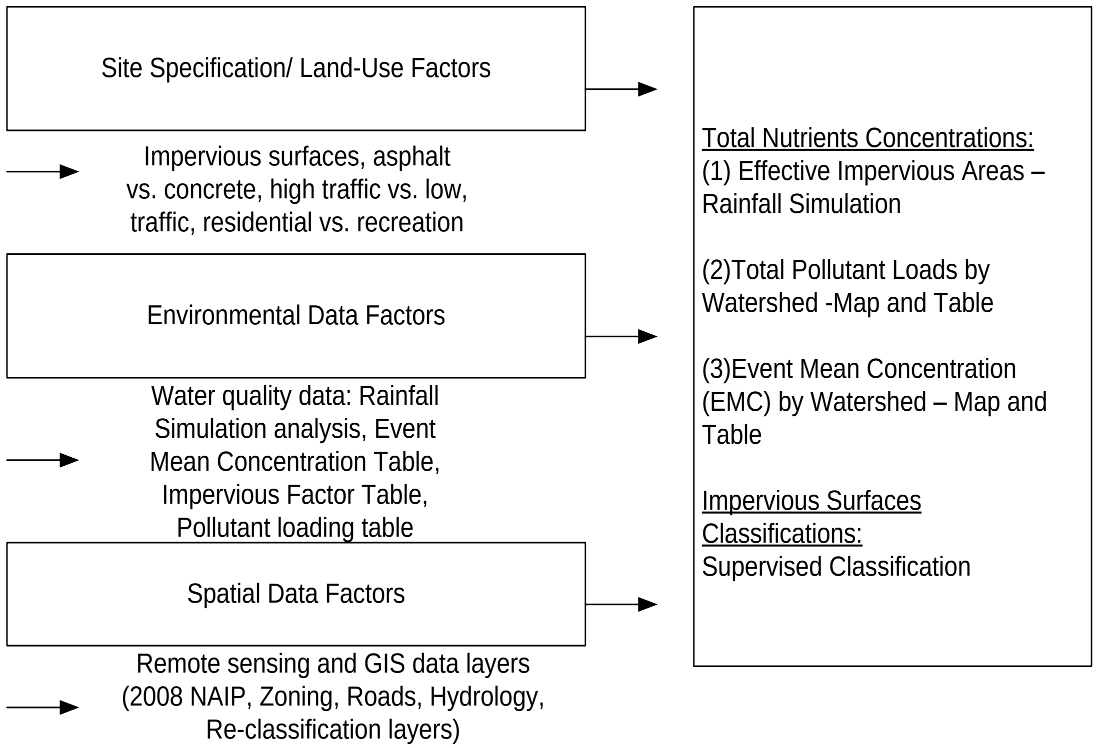

Figure 1. Conceptual framework used to determine research direction

Dependent Variables

The dependent variables of this study provides information on the total nutrients from effective impervious areas, predicted total pollutant loads by watershed, and predicted event mean concentration levels by watershed. As stated in the literature review, land use and water quality typically have a positive correlation. As land use changes with an increase of impervious areas, there is a significant increase in runoff pollution.

Nutrient concentrations will be quantified after collection by rainfall simulation and surface runoff chemistry concentrations will be estimated. Predictability concentration numbers will be estimated utilizing BASINS PLOAD and the simple calculation method.

Independent Variables

Site Specifications, Land Use, and Environmental Factors

Planners and researchers are interested in finding ways to mitigate or reduce nonpoint source pollution in the urban environment. A number of studies have related water quality to impervious surface, or the percent of land use (Scheuler 1994, Rogers 1994, Deletic et al. 1997, Pappas et al. 2008, Hope et al. 2004, Spångberg and Niemczynowicz 1992). Also water quality data provides essential information in assisting planners and mangers in watershed management, development and restoration.

> ***Hypothesis 1****: Parking lot substrate will have a significant effect on nutrient concentration.*
>
> ***Hypothesis 2:*** *An increase in parking lot intensity will have a significant impact on nutrient concentration.*

Spatial Data Factors

Multi-spectral satellite data can be used as a resource to detect land use and land cover change on a spatial scale. Using GIS and remote sensing data integration and spatial analysis tools can be used to examine the relationship between land use and water quality over different spatial scales (Tong and Chen 2002). GIS models provide tools to handle large amounts of spatial data for modeling and assessing the contributions of non point source pollution. These models provide tools to obtain predicted annual values, monitoring and visualization of pollutant loads and transport.

Hypothesis 3: *An increase in satellite imagery resolution will have a significant effect on impervious surface classification accuracy.*

CHAPTER II

A SYSTEMATIC APPROACH FOR DETERMINING IMPERVIOUS SURFACES FOR URBAN WATER QUALITY MODELING

Impervious surfaces are utilized to link urbanization to non point source pollution (NPS) and are identified as a critical indicator in evaluating urban ecosystems. The extraction of total area covered with an impervious surface from land use data serves as an important component in water quality and quantity models. This study aims to accurately quantify impervious surfaces using 2008 National Agriculture Imagery Program (NAIP) 1m high resolution imagery. This study area quantified the amount of impervious surfaces in Brazos County, Texas and developed six impervious classes using supervised classification. An accuracy assessment indicated an overall accuracy of 85%. As a result, a unique way of classifying impervious surface type, i.e., asphalt, concrete, building surface tops, was employed to be used in enhancing hydrological models.

Introduction

Impervious surfaces influence the hydrologic cycle by increasing runoff, deteriorating stormwater quality, transporting non point source pollutants and reducing ground water recharge (Arnold and Gibbons 1996, Scheuler 1994, Brabec et al. 2002).

Impervious surface area is a key indicator to measure the effect of land use change on surface water quality (Scheuler 1994). Commonly, an impervious surface, which constitutes two major components, can be categorized as: a) rooftops (i.e., residential and commercial buildings) and b) transportation system (i.e., parking lots, road networks, sidewalks, driveways, etc.). These components can be quantified and used to establish the health of a watershed (Scheuler 1994). In general, the transportation system is the largest contributor of total impervious area (Scheuler 1994).

Impervious surface area quantification has emerged as a tool to assist planners and managers in water protection plans and future development. Determination of where impervious surfaces are concentrated and distributed throughout the watershed landscape (Arnold and Gibbons 1996) coupled with current and precise spatial data allows for effective land use decision making (Yang et al. 2003).

Arnold and Gibbons (1996) established four key environmental indicator properties for impervious surface area and the urban environment quality: (1) impervious surfaces can be classified as altering the hydrological cycle and degrading waterways; (2) impervious surfaces are linked to urbanization and produces multiple pollutants; (3) impervious surfaces devoid the natural pollutant removal process by preventing percolation; and (4) impervious surfaces serves as a main transportation mechanism for pollutants to waterways. Yuan and Bauer (2007) compared the normalized difference vegetation index (NDVI) and percent impervious surface as an indicator of urban heat island effects. Results indicated a strong linear relationship ($r^2 > 0.97$) between impervious surface area and land surface temperature.

There is a need to enhance land use classification accuracy. Various approaches utilizing the incorporation of geographic data, census data, structural types, have been applied to classify urban land use. However, shadows, mixed pixels and spectral confusion cause a decrease in extraction and accuracy. Efforts began in the 1970s to class impervious surfaces from remote sensing data (Lu and Weng 2006). Classifications provide essential measurements for water quality and quantity models such as: Soil and Water Assessment Tool (SWAT), Better Assessment Science Integrating Point and Nonpoint Sources (BASINS), Agriculture Non point Source (AGNPS), Source Loading and Management Model (SLAMM), Stormwater Management Model (SWMM) (Lenzi and Di Luzio 1997, Tong and Chen 2002, Abbaspour et al. 2007, Jat et al. 2009).

In the past, methods and techniques used in estimating and mapping impervious surfaces were initially evaluated in three basic ways: (1) using photographic interpretation and a planimeter to estimate impervious surfaces (Draper and Rao 1986, Graham et al. 1974) and (2) employing detailed map and grid overlays (Avery and Berlin 1992). More recently classification of remotely sensed data has been utilized (Lu and Weng 2006). The most identified and accurate method of classification are ground based surveys, however, these surveys are costly and time-consuming (Bird et al. 2000).

High spatial resolution data, in addition to spaceborne and airborne sensors have become a primary source in environmental modeling (e.g. Benz et al. 2004, Martin et al. 2008). Smith et al. (2003) used Hyperion and Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data to estimate nitrogen concentrations levels in the Bartlett Experimental Forest in New Hampshire, USA. Accuracy of Hyperion and AVIRIS were within 0.25% and 0.19%, respectively, of field measurements. Deriving information from a land or water surface, multi-spectral imagery is obtained from the reflection of varied wavelengths of the electromagnetic spectrum. This reflection allows for features to be automatically identified and quantified.

Wu and Murray (2003) estimated impervious surface fraction by analyzing low and high albedo end members. In their model, impervious surface distribution, vegetation and soil cover had an overall root mean square (RMS) error of 10.6%. Yang et al. (2003) examined an approach to quantify impervious surfaces as a continuous variable by using Landsat ETM+ and high resolution imagery at a 30 meter sub-pixel area. Impervious surfaces were mapped using a regression tree model and average error values ranged from 8.8 to 11.4%. Deguchi and Sugio (1994) evaluated the use of satellite imagery to estimate percentage impervious areas using satellite imagery to construct a simple high-medium-low classification. Data interpreted from their study noted pixels in urbanized area are mixtures of various surfaces; and therefore classes not identified as impervious may, in reality, have impervious surfaces. Monday et al. (1994) used the Normalized Difference Vegetation Index (NDVI) transformation to assist in classifying impervious surfaces for utility fee applications from a four-band multi-spectral image.

Objectives

Extraction of impervious surface area from images is a challenge, due to the limitations associated with the mixing of urban land types and the selection of training sites, which leads to misclassification. As a result, the goal of this research is to apply a supervised classification of impervious surfaces, with accurate, up-to-date high resolution (1 meter) satellite imagery.

The goal and objective of this research is to effectively and accurately develop an improved impervious surface classification scheme using high resolution satellite imagery (NAIP 2008b) for hydrological modeling. This study aims to convert spectral data into six land cover classes using a supervised classification algorithm- maximum likelihood.

Study Area and Data

The study area is located within the cities of Bryan and College Station, Texas, USA (Figure 2). This study area possesses several components that make it an appropriate choice for a study and it was selected due to its rapid population growth. Currently agricultural and native rangeland land use is undergoing significant transitional changes due to population growth. Condominiums, apartments, single family homes and strip mall developments are continually being built to house the increasing population. Carter Creek located in Brazos County has been identified as a third-order stream contributing to the Brazos River drainage basin (TWRI 2010). Carter Creek in particular has been chosen as the study area of choice because its headwaters originate in Bryan/College Station. Carter Creek watershed has been placed on the EPA 303(d) listing for impaired water by *E. coli (Esherichia coli)* since 1999 and high nutrient concentrations since 2006. The state of Texas requires that water quality in Carter Creek (Segment 1209C) be suitable for contact recreation, aquatic life, and fish consumption uses, as designated in the Texas Surface Water Quality Standards.

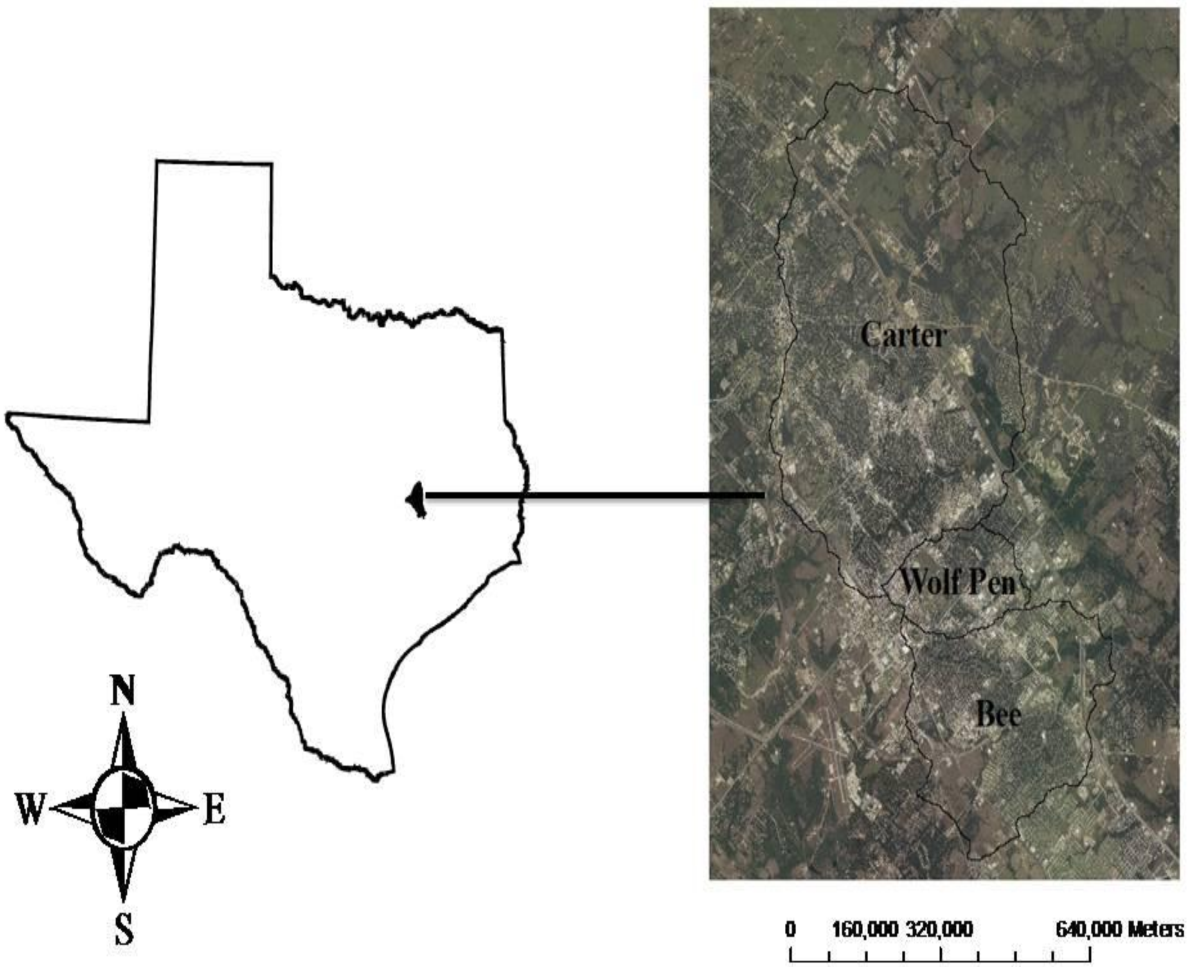

Figure 2. Study area for the impervious surface extraction study (NAIP 2008a).

Data Sets

The United States Department of Agriculture NAIP image of Bryan and College Station, Texas, which was acquired on June 1, 2010, was used for this research. The NAIP image has a 1 meter ground sampling distance (GSD) resolution with 5 meters of reference ortho imagery. The image is in natural color. The NAIP contract states that *"95% of well-defined points tested shall fall within 6 meters of true ground."* In 2008, Texas was contracted with meeting 95% accuracy specifications for this image at absolute ground control specification. Received as a Digital Ortho Quarter Quad (DOQQ), this image tile covers a 3.75 x 3.75 minute quarter quadrangle in addition to a 300 meter buffer on all four sides. DOQQs have high resolution and are capable in producing high accuracy levels in determining impervious surfaces (Bird 2000). The image was downloaded in GeoTiff format and cast to the Universal Transverse Mercator (UTM) projection, and referenced to the North American Datum of 1983 (NAD83).

The National Hydrography Dataset (NHD) was also used in this study. The NHD is a surface-water component of the United States Geological Survey National Map. This spatial dataset comprises of waterbodies, i.e., lakes, ponds, streams, rivers, canals, and dams, within this study area. Designed to be used hydrological mapping and modeling, this seamless dataset was acquired on June 1, 2010 as a high-resolution 1:24,000 – scale topographic mapping. The data set was cast to the Universal Transverse Mercator (UTM) projection, and referenced to the North American Datum of 1983 (NAD83).

Extraction of Impervious Surfaces and Results

ITT Visual Information Solutions (ITT VIS) Environment for Visualizing Images (ENVI) v4.5 was used as a platform to deliver results for this study. ENVI was used for the visualization, analysis and presentation of all types of imagery data. ENVI was written in Interactive Data Language (IDL) and allows integrative image processing. Collectively, the components make ENVI the best software choice for this study.

A NDVI layer was created from the NAIP imagery using the expression (NIR-R)/(NIR+R) and then stacked with the original NAIP image.

A supervised classification algorithm was used to classify the image. Regions of Interests (ROI) were selected for 9 classes: Natural Grass, Irrigated Grass, Bare Soil, Tree, Shrub, Concrete, Light/Old Asphalt, Dark/New Asphalt, and Painted/Metal Surfaces. Although the final classification had fewer classes, these classes allowed for more separation between classes than fewer, more generalized classes would have. The ROI were selected based on ground-truth knowledge of the area which included driving around the study area and using Google Maps, especially the street view feature.

After the ROI were selected, a Maximum Likelihood (ML) classification algorithm was employed. The ML classifier assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold, the pixel remains unclassified (Richards 1999). The discriminant functions for each pixel in the image are implemented in the ML classification (Equation 1):

$$g_i(x) - \ln \rho(\omega_i) - {}^{1}/_{2} \ln|\Sigma_i \quad | - {}^{1}/_{2} \, (x - m_i)^t \, \Sigma_i^{-1}(x - \, m_i) \qquad (1)$$

where:

i = class

x= n-dimensional data (where n is the number of bands)

$\rho(\omega_i)$ = probability that class ω_i occurs in the image and is assumed the same for all classes

$|\Sigma i|$ = determinant of the covariance matrix of the data in class ω_i

Σ_i^{-1} = its inverse matrix

m_i = mean vector.

Classes were then combined to form 6 Classes:

1) Grass (Natural Grass and Irrigated Grass)
2) Tree/Shrub (Tree and Shrub)
3) Bare Soil
4) Painted/Metal Surfaces
5) Concrete or Light/Old Asphalt (Concrete and Light/Old Asphalt)
6) Dark/New Asphalt

Natural Grass and Irrigated Grass were combined because the separation of the two is not required for this study. Tree and Shrub were combined to reduce the occurrence of shrubs appearing at the edge of forest stands. Shrubs were also a nominal portion of the study area. After the classification was performed, areas of Concrete and Light/Old Asphalt were significantly mixed. Concrete and Light/Old Asphalt were nearly inseparable. Asphalt grays as it loses it ages because the oil in it evaporates. As the asphalt grays it becomes spectrally similar to concrete. The Painted/Metal Surfaces class was used to separate buildings and water towers from concrete as much as possible. After combining the classes, a majority filter with a 3x3 window was passed over the image to remove some of the salt and pepper effects of the classification. The Bare Soil class was eliminated by the majority filter because it was a very small class and often put in areas of Painted/Metal Surfaces and Concrete or Light/Old Asphalt. National Hydrology Dataset data was downloaded at the High Resolution level. The Waterbody layer was overlaid onto the classification to create the water class. The final class list (Figure 3 and Table 1) is:

1) Grass (Natural Grass and Irrigated Grass)
2) Tree/Shrub (Tree and Shrub)
3) Painted/Metal Surfaces
4) Concrete or Light/Old Asphalt (Concrete and Light/Old Asphalt)
5) Dark/New Asphalt
6) Water

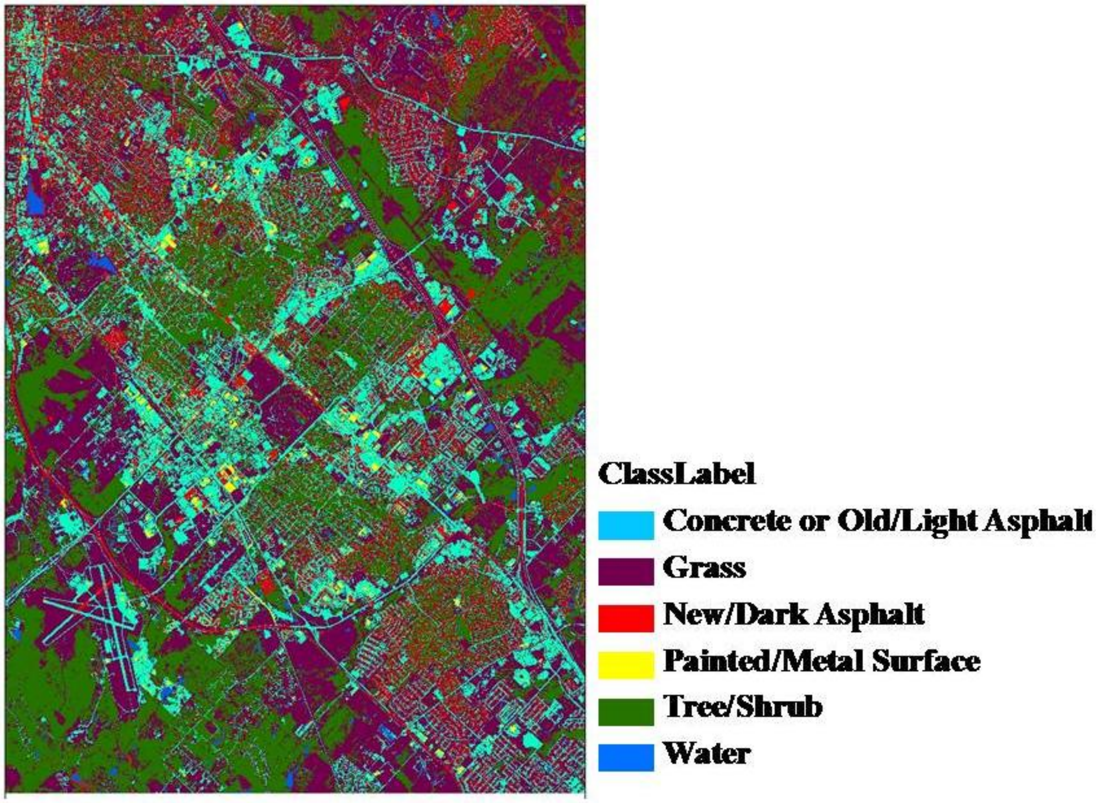

Figure 3. Final classified NAIP image employed by unsupervised classification scheme

Table 1. Final classification type and area results.

Classification Type	Area (m²)
Grass (Natural Grass and Irrigated Grass)	117021918
Tree/Shrub (Tree and Shrub)	68773773
Painted/Metal Surfaces	1504439
Concrete or Light/Old Asphalt	201929938
Dark/New Asphalt	34344686
Water	1876422

The original NAIP image to that of the re-classified impervious surfaces was compared (Figure 4). Building roof tops, streets, buildings are classified by impervious surface type.

Figure 4. Result comparison of NAIP image (upper panel) with reclassification of urban impervious surfaces (lower panel) (adapted from NAIP 2008a).

The accuracy assessment (Table 2) was achieved by generating a stratified random sampling and Kappa analyses. Stratified random sampling gives each class a number of points based on the percentage of each area. The Kappa analysis measures the agreement between the classified image results and the reference data. A total of 160 points were sampled. These points were then viewed in Google Maps to identify their true classification. If the class could not be determined through Google Maps, the point was ground-truthed by visiting the site and identified. The overall accuracy was 85%, and the kappa coefficient was 0.7993 (Table 2). 100% of the grass could be correctly identified as grass, but nearly 42% of the dark asphalt was misidentified. Misclassification happened in areas covered by shadows. These areas were most often incorrectly classified as Dark/New Asphalt. For the accuracy assessment, the test areas were identified as ground cover, not as shadow. Extremely new concrete and bare soil from construction were sometimes misclassified as painted/metal surface.

Table 2. Classification accuracy assessment results.

Class Name	Reference Totals	Classified Totals	Number Correct	Users Accuracy
Grass	72	57	57	100.00%
Tree/Shrub	33	34	33	97.06%
Painted/Metal	6	8	5	62.50%
Dark/Asphalt	10	21	9	42.86%
Concrete/Asphalt	29	32	26	81.25%
Water	7	8	6	75.00%
Overall Accuracy 85.00% Kappa Coefficient 0.80				

Conclusions

Impervious surfaces have been recognized as an indicator to assess urban environments. Many studies have focused on the classifying impervious surfaces based population density and land use type. However, accurate extraction of impervious areas from images still presents a challenge due to the complexity of urban and suburban landscapes. Misclassifications in the extraction of impervious surfaces from images are often due the heterogeneity of urban environments.

In this study, impervious surface distribution and classification were derived from the 2008 NAIP imagery by applying a supervised classification maximum likelihood algorithm and classified each individual impervious surface. Surfaces were classified as grass (natural grass and irrigated grass), tree/shrub (tree and shrub), painted and metal surfaces, concrete or light/old asphalt (concrete and light/old asphalt), and dark and new asphalt. The results from this classification produced a unique impervious surface type classification. The overall accuracy assessment of 85% is good and areas that were most often misclassified were dark and new asphalt. Sometimes new concrete and bare soil were misclassified as metal surface. Shadows from buildings and trees also cause misclassification of impervious surfaces.

Lu and Weng (2006) reported an overall classification accuracy of 83.78% in their attempt to successfully classify five urban land use classes using medium spatial resolution remotely sensed data using a linear spectral mixture analysis. Johnson (2004) reported 75.33-81.33% overall accuracies derived from three different seasonal dates of

Landsat TM multi-spectral imagery. My higher overall accuracy can likely be attributed to my use of a supervised maximum likelihood classification scheme.

Based on my results, this breakdown of classes would be beneficial in predictive hydrological modeling of impervious surfaces and sources of contaminants for urban water quality. My research demonstrates a unique way of extracting impervious surface types from remotely sensed data.

CHAPTER III

MEASURING NUTRIENTS IN SIMULATED RUNOFF IN BRAZOS COUNTY, TEXAS

Introduction

Impervious surfaces not only contribute to enhanced nonpoint source pollution in urban watersheds, but have also been proven to alter the hydrological cycle (Lazaro 1990, Tsihrintzis and Hamid 1997, Brabec et al. 2002, Tong and Chen 2002, Shuster et al. 2005). Urbanization generally increases flow velocity, runoff volume and flooding intensity in urban streams and rivers (e.g. Hall 1984, Leopold 1968). Urban watersheds replace native ground cover with paved and impervious surfaces. Drainage networks from paved surfaces serve as a transportation conduit for an abundance of nutrients and metals.

There is a growing need to focus on monitoring and accurately assessing the effects of urbanization on urban runoff volume and water quality (Spångberg and Niemczynowic 1992, Goonetilleke et al. 2005). The United States Environmental Protection Agency (EPA) stated that nonpoint source pollution is a major contributor to water quality issues (U.S. EPA 1994). Road pollutants, dust and debris, and dry deposition accumulate in runoff from impervious surfaces during rain events and the pollutants in this runoff are known to impair urban stream chemistry. As a measurable contributor to enhancing pollutant runoff, impervious surface coverage, has been intensely studied by the National Urban Runoff Program (NURP) (U.S. EPA 2002).

Runoff from impervious surfaces impairs surface waters chemically, microbiologically and physically. Nutrients such as phosphorous and nitrogen are known contributors in the depletion of water quality. Steele et al. (2010) noted that surface water in urban environments contains higher phosphorous concentrations than rural surface waters. Inputs of phosphorous to surface waters can be linked to fertilizers, waste water treatment plants or failing septic systems, and atmospheric deposition (Steele et al. 2010). Nitrogen sources, in the form of organic nitrogen, are often linked to waste water treatment plants or failing septic tanks, and can be recognized as a major contributor of nitrogen in urban areas (Steele et al. 2010). Over a period of time, organic nitrogen is converted to ammonia nitrogen. In oxygenated watershed soils ammonium-N is converted to nitrites then nitrates if enough labile carbon is available but in reduced or low oxygen soil environments nitrification of ammonium-N cannot occur and the typical reaction is denitrification of any nitrates present in the soil environment. Hence surface water riparian zones are important because they alternate between reducing and oxidating conditions which remove N and ultimately reduce nitrate entering surface waters.

Numerous research studies have determined that surface water chemistry is linked to the percentage land use and land cover in a watershed (e.g. Aitkenhead et al. 1999, Aitkenhead-Peterson et al. 2009 and 2010b, Brabec et al. 2002, Hope et al. 2004, Sansalone et al. 1998, Brun and Band 2000, Scheuler 1994). Several methods have been explored to examine runoff and water quality for impervious surface areas. For example, Sheuler (1994) examined 40 runoff monitoring sites illustrating the relationship between impervious cover and an increased runoff coefficient. Li et al. (2008) designed and simulated urban rainfall to prove the feasibility of implementing urban rainfall management. Infiltration conditions on surfaces can be effectively used to reduce runoff. Roy et al. (2003) found concentrations of total suspended solids (5.10 mg L^{-1}), NO_3/NO_2-N (368 μg L^{-1}), NH_4-N (1.32μg L^{-1}), and soluble reactive phosphorus (77.3 μg L^{-1}) to be significantly and positively correlated with increased urban land cover and decreased forest land in the Etowah River Basin, Georgia, USA. Aitkenhead-Peterson et al. (2009 and 2010b) reported that urban open areas explained between 61 and 71% of the variance in bicarbonate and sodium in urban and rural streams and that high density urban areas typically classified as impervious surfaces are highly and positively correlated with electrical conductivity, dissolved organic carbon (DOC) and sodium in urban streams. In our growing cities, parking lot surfaces generate a significant amount of runoff containing a wide range of nutrients, salts and novel organic carbon compounds (e.g. Kaushal et al. 2005 and 2008). These can be caused by removal of riparian zones that are typically instrumental in denitrification thus reducing nitrate concentrations in receiving waters (Kaushal et al. 2008). Application of NaCl for de-icing in northern urban regions (Kaushal et al. 2005) and leaking parked vehicles, insufficient parking lot cleaning, and little to none continuous flow of traffic (Tsihirintzis and Hamid 1997) also combine to render impervious surface run off to surface waters high in pollutants.

In addition to land use change, rainfall intensity and duration are also critical factors in determining runoff volumes and pollution loads. Urban ecosystems tend to have increased rainfall, for example, urban heat islands tend to increase rainfall over and downwind of major cities in the USA (Heisler and Brazel 2010, Shepherd et al. 2010). Niemcyznomicz (1999) acknowledged the importance of rainfall data accuracy and collection and understanding the fundamental relationships between them. For this reason, it was suggested that hydrological data acquired from meteorological service agencies may be inadequate for urban hydrology and researchers have to create techniques and tools to generate data on a smaller spatial scale and over shorter periods of time. Therefore because of its important role in hydrological processes, rainfall is an important input in modeling and predicting runoff. Simulating rainfall events provides an alternative to a lack of accurate data. One issue in obtaining first flush data over a city is the expense of man-power to collect samples during that first flush event over a wide area or the expense of instrumenting storm drains so that first-flush samples can be collected. Herngren (2005) simulated rainfall to understand event mean concentrations (EMC) on paved surfaces and further to correlate heavy metal distribution among suspended solids particle size in runoff samples. Their study reported that dissolved organic carbon (DOC) and total suspended solids (TSS) influenced the distribution of metal concentration. In addition, they concluded that creating rainfall artificially was a preferred choice for generating rainfall data due to the limited rainfall events in Brisbane, Australia, and the limitations associated with them. Similarly, Hope et al. (2004) quantified the maximum amounts of readily soluble nutrients on 38 parking lot plots and reported high concentrations of DOC (26.1 to 295.9 mg L^{-1}) and that asphalt sites were dominated by NO_3^-N (15.4 mg L^{-1}). Thus simulating rain events has proven feasible in mimicking natural rainfall conditions but more importantly allows researchers to standardize runoff results.

The objectives of this study were to examine the first flush of nutrients in storm runoff by means of a custom constructed rainfall simulator under differing ‘scenarios’ a) two types of impervious surfaces, b) three parking lot traffic intensities and c) days since last rain event. I hypothesized that concrete would have greater nutrient concentration than asphalt when supplied with a similar sized event. I also hypothesized that parking lots with higher parking intensity would have more pollutants than those with low parking intensity because vehicle dry deposition was less. In addition, I hypothesized that first flush contamination concentration is dependent on time since the previous rainfall event.

Materials and Methods

A custom-designed rainfall simulator (Figure 5) was used on several sites which were selected based on their parking surface material and assumed vehicular use in which to simulate rainfall events. The research study sites (Figure 6) were located in College Station, TX, USA which has a population of approximately 68,000. College Station has a humid subtropical climate and averages ~1000 mm rainfall per year in a bimodal pattern with most of the precipitation falling in the spring and fall seasons. Rain events are typically high intensity and of short duration.

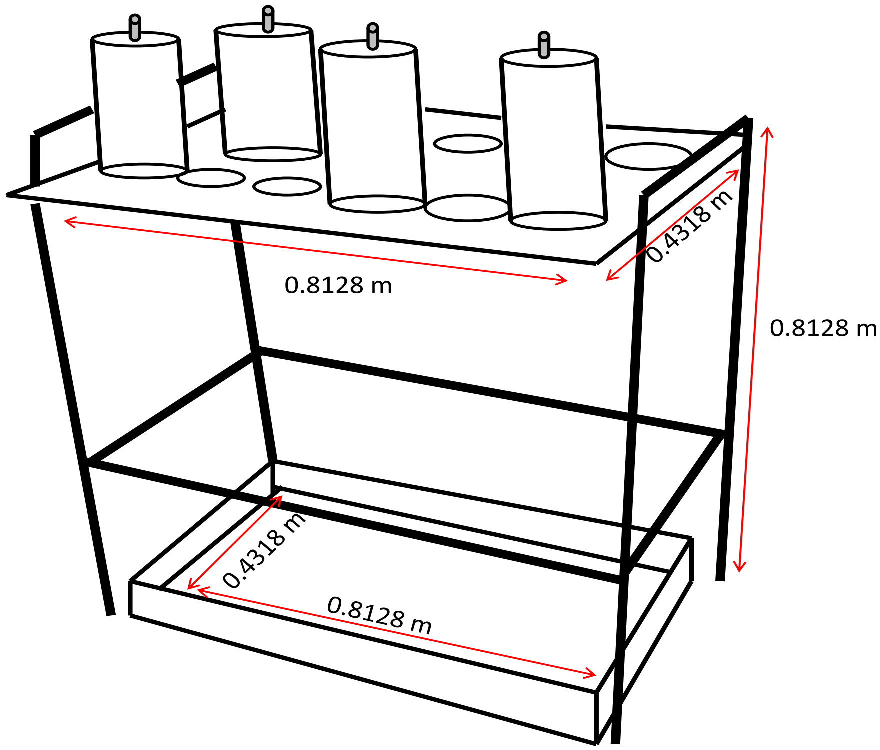

Figure 5. Dimensions of rainfall simulator used in this study.

Figure 6. Parking lot study areas. Site 1 Parking for Recreational area, Site 2Commercial parking for Strip Mall, Site 3 Parking for large shopping Mall and Site 4 Parking for apartment complex (adapted from NAIP 2008a).

I used three variables for parking intensity a) low: recreation parking which is only highly used during weekends and holidays; b) medium: residential parking which is long term parking overnight by the same vehicles and c) high: shop parking: parking at big box stores that will have multiple different vehicles in and out of the parking lot for an extended period of time.

I used two variable for parking surfaces a) concrete and b) asphalt (Table 3) and two variables for time since last rain event a) 7 days and b) 23 days.

Wolf Pen Creek Park and Amphitheater, site (1), is recreational park and amphitheater, hosting crowds up to 10,000. This park hosts some of the community’s outdoor concert series, festivals and fitness recreation. Study site (2) was a parking lot located in a nearby commercial strip development area. Consisting of 8 retail stores, this shopping center receives moderately low-minimum traffic. Study site (3) is home of the areas only and busiest shopping mall. Home of 121 retail stores and 5, 228 parking spots, this concrete/cement parking lot plot area can be attributed with poor surface quality. A close-by apartment community serves as site (4). Known for having frequent flooding, this 150 apartment community has poor concrete/cement surface. Lastly, a popular grocery store in the area is site (5). The asphalt located within this study area is good condition.

Table 3. Parking lot location, identification and classification.

Site ID	Site Location	Site Classification
(1)	96°18′10.772″W 30°37′3.837″N	Recreational park and amphitheater
(2)	96°18′24.444″W 30°37′25.984″N	Commercial strip development, low-minimum traffic
(3)	96°18′11.068″W 30°37′28.035″N	Shopping mall, high traffic density
(4)	96°18′37.165″W 30°37′28.531″N	Apartment community
(5)	96°19′5.371″W 30°36′46.389″N	Grocery shopping center

Field Sampling

A rainfall simulator consisting of a rectangular-framed structure of 0.43 m wide and 0.81 m long hosted 8 1 L Nalgene bottles. Each Nalgene bottle contained 1L of distilled water. Surface runoff was captured within the box structure beneath the simulator using a portable shop-vac vacuum cleaner. At each location sterile whirlpack bags were used for samples of water runoff. Aliquots of unfiltered samples were measured for electric conductivity (EC) and pH within 6 hours of collection. Samples were filtered through pre-washed ashed Whatman GF/F filters and oven-dried for 2-3 days and then reweighed. Suspended solids (mg L^{-1}) were calculated.

Chemical Analysis

Dissolved organic carbon (DOC) and total dissolved nitrogen (TDN) were quantified using high temperature Platinum-catalyzed combustion with a Shimadzu TOC-VCSH and Shimadzu total measuring unit TNM-1 (Shimadzu Corp. Houston, TX, USA). Dissolved organic carbon was measured as non-purgeable carbon which entails acidifying the sample (250 μL 2M HCl) and sparging for 4 min with C-free air. Ammonium was analyzed using the phenate hypochlorite method with sodium nitroprusside enhancement (U.S. EPA method 350.1) and nitrate was analyzed using Cd-Cu reduction (U.S. EPA method 353.3). Alkalinity was quantified using methyl orange (U.S. EPA method 310.2). Alkalinity was converted to the major carbonate species using geochemical software (AqQA, Rockware Inc., Denver, CO) which, in this study was bicarbonate. All colorimetric methods were performed with a Westco Scientific Smartchem Discrete Analyzer (Westco Scientific Instruments Inc. Brookfield, CT, USA). Calcium, magnesium, potassium and sodium were quantified by ion chromatography using an Ionpac CS12A analytical and Ionpac CG12A guard column for separation and 20 mM methanosulfonic acid as eluent at a flow rate of 1 mL min^{-1} and injection volume of 25 μL (DIONEX ICS 1000). Fluoride, chloride and sulfate were quantified using Ionpak AS20 and Ionpak AG20 analytical and guard columns for separation with 35 mM KOH as eluent at a flow rate of 1 mL min^{-1} and an injection volume of 25 μL (DIONEX ICS 1000; DIONEX Corp. Sunnyvale, CA, USA). Dissolved organic nitrogen was estimated by deducting inorganic-N (NH_3-N + NO_3-N) from TDN.

Statistical Analysis

A Univariate analysis of variance with three factors a) days since last rain event, b) parking surface substrate and c) parking intensity and interactions among factors was examined to determine what factors in an urban environment might have a significant effect on urban runoff chemistry. Means and standard deviations of each runoff chemistry analyzed were calculated for a) days since last rain event, b) parking surface substrate and c) parking intensity. Two-tailed Student's two-sample student's t-tests with unequal variance were run to determine significant difference among factors. Pearson bivariate correlation analysis was completed on all the runoff data to examine correlations among nutrients irrespective of parking, substrate surface and days since last rainfall factors.

Results

Local environmental controls on runoff chemistry: Univariate analysis of variance gave some interesting results for the chemistry of our runoff solution using a rainfall simulator. Surface type which was either concrete or asphalt had a significant effect on runoff dissolved organic carbon, ammonium-N, sodium, magnesium, calcium, fluoride and sulfate (Table 4). Parking intensity which was defined as very low for residential areas to high for 'big box' parking lots had an effect on runoff alkalinity and fluoride (Table 4). The most significant affect on runoff chemistry was days since the last rain event. Here all nutrients tested with the exception of sodium and fluorides were significantly affected by the number of days since the last rain event (Table 4). Interactions between factors were found for surface and days where DOC, ammonium-N, sodium, magnesium, calcium fluoride and sulfate were significantly affected. Parking intensity and day interactions were found for runoff chemistry alkalinity, sodium, calcium and fluoride (Table 4).

Concrete typically produced higher concentrations of all nutrients than did asphalt (Table 5). Sodium was the only nutrient however that was significantly higher in runoff from concrete (Table 5). Density of vehicles or type of parking lot had a significant effect on runoff alkalinity where we found that alkalinity concentrations were significantly higher in recreational parking areas than in residential areas (Table 5). Days since the last rain event also had a significant effect on runoff chemistry where DOC, nitrate-N, ammonium-N, orthophosphate-P, potassium, magnesium, calcium, chloride, sulfate and DON were all significantly higher in runoff after 23 days with no rain compared to runoff after 7 days with no rain (Table 5).

Discussion

The major aim for this study was to examine the first flush of nutrients in storm runoff using rainfall simulation at five study sites in the Bryan/ College Station region. Rainfall simulation allowed for field sampling to mimic natural rainfall and runoff conditions. The rainfall simulator was highly mobile due to its size, and was easily transportable. The rainfall simulator allowed for control over variables such as intensity, duration, and sampling area type although I only examined one rainfall intensity and duration for my study. Additionally, the rainfall simulator provided a time and cost-efficient method to examine parking lot runoff. The rain simulator provided 2.808 mm rain over an average 30.54 ±3.9 seconds which is equivalent to an average of 341.6 ± 45.1 mm hr or 13.4 ± 1.8 inches per hour, much higher than the intensity reported by Herngren (2005) whose rainfall simulator give multiple settings of rainfall intensity ranging from 14 to 200 mm hr^{-1}. Herngren (2005) achieved an average discharge rate of between 13.9 to 15.1 L min^{-1}, slightly lower than our average rate of 16.8 ±1.91 L min^{-1}. I did not examine factors such as drop size and kinetic energy of raindrops in this study. Moore et al. (1983) also used a rainfall simulator with a high discharge Veejet 80100 nozzle which produced a rainfall intensity of around 580 mm hr^{-1} when spraying continuously over a plot, almost twice the intensity of our rainfall simulator. Pulsed

Table 4. Results of univariate analysis of variance with three factors. Bold typeface indicates a significant effect. Ns is not significant.

	DOC	DON	NO_3-N	NH_4-N	PO_4-P	Alkalinity	Na^+	K^+	Mg^{2+}	Ca^{2+}	Cl^-	F^-	SO_4^{2-}
						Significance							
Surface Type	**0.013**	0.54	0.83	0.3	0.09	0.13	**0.003**	0.66	0.01	< 0.001	0.29	0.004	0.049
Parking Intensity	0.15	0.60	0.91	0.72	0.75	**0.021**	0.26	0.3	0.08	0.16	0.25	**0.001**	0.284
Days since last rain	**0.007**	**0.001**	**0.001**	**0.001**	**0.001**	**0.015**	0.8	**0.012**	**<0.001**	**<0.001**	**0.007**	0.073	**<0.001**
Surface * Parking	ns	ns	ns	ns	ns	ns	ns	ns	ns	Ns	ns	ns	Ns
Surface * Days	**0.002**	0.18	0.18	**0.02**	0.22	0.89	**0.006**	0.85	**0.005**	**<0.001**	0.42	**0.045**	**0.006**
Parking * Days	0.13	0.5	0.82	0.16	0.5	**0.004**	**0.004**	0.286	0.2	**0.02**	0.35	**0.013**	0.073
Surface * Parking * Days	ns	ns	ns	ns	ns	ns	ns	ns	ns	Ns	ns	ns	Ns
Mean Square Error	45.1	0.05	0.001	0.005	0.0002	9.03	0.94	1.78	0.005	0.54	1.99	0.000	0.84
Adj. R^2	0.58	0.51	0.57	0.56	0.79	0.61	0.49	0.27	0.64	0.91	0.42	0.58	0.65

Table 5. Mean concentrations of nutrients in runoff according to a) surface substrate, b) parking type and c) days since last rain. Values in parenthesis are standard deviation. Different lower case letters indicate significant difference in runoff chemistry within each of the individual factors.

	DOC mg L^{-1}	DON mg L^{-1}	NO_3-N mg L^{-1}	NH_4-N mg L^{-1}	PO_4-P mg L^{-1}	Alkalinity mg L^{-1}	Na^+ mg L^{-1}	K^+ mg L^{-1}	Mg^{2+} mg L^{-1}	Ca^{2+} mg L^{-1}	Cl^- mg L^{-1}	F^- mg L^{-1}	SO_4^{2-} mg L^{-1}
Surface													
Asphalt	8.0^{a} (6.5)	0.31^{a} (0.29)	0.12^{a} (0.06)	0.13^{a} (0.10)	0.03^{a} (0.02)	18.4^{a} (2.9)	4.5^{a} (0.6)	0.8^{a} (0.5)	0.09^{a} (0.04)	2.2^{a} (0.7)	1.9^{a} (0.5)	0.01^{a} (0.01)	1.10^{a} (0.9)
Concrete	12.1^{a} (11.9)	0.45^{a} (0.35)	0.13^{a} (0.07)	0.14^{a} (0.11)	0.04^{a} (0.03)	21.8^{a} (5.4)	5.6^{b} (1.5)	1.7^{a} (1.9)	0.15^{a} (0.15)	3.8^{a} (3.0)	3.3^{a} (2.2)	0.01^{a} (0.02)	1.55 (1.8)
Parking													
Recreational	10.0^{a} (7.7)	0.57^{a} (0.34)	0.14^{a} (0.07)	0.15^{a} (0.08)	0.05^{a} (0.03)	25.2^{b} (6.0)	5.4^{a} (0.8)	2.5^{a} (2.8)	0.12^{a} (0.11)	3.9^{a} (3.8)	4.2^{a} (3.2)	0.00^{a} (0.00)	1.4^{a} (1.1)
Shopping	12.0^{a} (12.0)	0.36^{a} (0.34)	0.12^{a} (0.06)	0.15^{a} (0.12)	0.04^{a} (0.02)	19.4^{ab} (3.3)	5.2^{a} (1.6)	1.0^{a} (0.6)	0.14^{a} (0.14)	3.2^{a} (2.1)	2.2^{a} (0.9)	0.01^{a} (0.002)	1.6^{a} (1.8)
Residential	4.6^{a} (0.8)	0.21^{a} (0.10)	0.08^{a} (0.01)	0.06^{a} (0.01)	0.03^{a} (0.03)	16.6^{a} (2.8)	4.7^{a} (0.3)	1.2^{a} (0.6)	0.09^{a} 0.07)	1.9^{a} (1.2)	2.4^{a} (0.2)	0.00^{a} (0.00)	0.35^{a} (0.25)
Days													
7	6.1^{a} (5.3)	0.21^{a} (0.16)	0.08^{a} (0.03)	0.08^{a} (0.04)	0.02^{a} (0.01)	19.1^{a} (3.3)	4.9^{a} (0.8)	0.8^{a} (0.4)	0.06^{a} (0.05)	1.8^{a} (1.0)	2.0^{a} (0.5)	0.01^{a} (0.02)	0.54^{a} (0.55)
23	18.0^{b} (12.5)	0.70^{b} (0.31)	0.19^{b} (0.04)	0.24^{b} (0.11)	0.07^{b} (0.02)	23.0^{a} (6.1)	5.6^{a} (2.0)	2.4^{b} (2.2)	0.23^{b} (0.14)	5.6^{b} (2.4)	4.0^{b} (2.6)	0.00^{a} (0.01)	2.79^{b} (1.65)

rainfall to give intermittent rainfall has been used in other rain simulator studies (e.g. Floyd 1981, Grierson and Oades 1977, Moore et al. 1983).Some rainfall simulator studies use distilled water and others collect rainfall or produce synthetic rainwater for experimentation. One difference between my study and that of Herngren (2005) was that he used a minimum slope of 2.5% and collected water downslope of his collecting trough thus emulating runoff whereas my sites had no slope and runoff water was vacuumed up. My runoff collection efficiencies were extremely poor compared to Herngren (2005). My collection trough had rubberized sealant and there was no evidence of leakage from the weighted down collection trough yet my collection efficiency was below 5% compared to a collection efficiency of 33 to 97% reported by Herngran (2005). Mean temperatures in the Herngren study were 20.9º C in July and 28.9º C in December compared to our average temperatures of 36º C during simulated rain events which may have caused larger than expected evaporation of rain water.

Typically rainfall is reported as mm or inches for a 24 hour period with no indication of the duration of the individual event. However the general consensus is that high intensity rain events are typically of short duration. Locatelli and Hobbs (1995) reported an event which deposited 305 mm (12 inches) of rain in 42 minutes in Holt, Missouri in 1947. High-intensity and short-duration rainfall events, derived from data collected between 1990 and 2008; show an increase in exceptional rainfall events in Italy (Floris et al. 2010). Violent rain showers are categorized as those producing > 50 mm hr in Great Britain (Met Office 2007). Thus the simulated rainfall intensity of my simulator may be considered relevant for extreme events of high intensity short duration rainfall.

Change in rain event intensity can be due to the urban heat island effect (Shepherd et al. 2010). The urban heat island can warm cities between 0.6º and 5.6º C above the surrounding suburbs and rural areas thus inducing additional shower and thunderstorms. Furthermore some cities can induce an annual precipitation increase of around 51%. Dixon and Mote (2003) examined the urban heat island-initiated storm events in Atlanta, Georgia. Most events reported in this study occurred during the night and near high density urbanized areas.

Runoff collection was attempted during an actual rainfall event. This method of collection presented many challenges such as stagnant puddles at collection sites after the rain event had terminated and changes in rainfall duration and intensity over the course of the day. In attempt to solve for such problems, methods such as a stormwater team for collection and placement of collection bottles in stormwater drains were considered. Manpower, along with the cost to employ such techniques proved to be overwhelming and the rainfall simulator method was chosen as the best method in reproducing relatively natural rainfall events to collect stormwater runoff.

Runoff was characterized by the characteristics of the surface, dry atmospheric deposition, rainfall intensity and duration. Dry atmospheric deposition is significantly increased in the urban environment from the dust, aerosol and gas particles accumulated on the grounds surface (Göbel et al. 2007, Hope et al. 2004). Findings from my study suggested that there is a significant increase amount of accumulation of pollutants on parking lot surfaces after 23 days since the last rain event. The predominance of nutrients such as DOC, nitrate-N, ammonium-N and dissolved organic nitrogen may be attributed to gaseous nitrogen oxides from vehicle combustion and management of surrounding landscapes.

Parking intensity significantly increased alkalinity and fluoride concentrations in my study. This might be attributed to pollutant sources from road abrasion and drip loss (grease, brake fluid, antifreeze, etc.). However as bicarbonate and fluoride are signatures of municipal tap water in my research region (Aitkenhead-Peterson et al. 2010b), irrigation of turf and landscaped strips in parking lots likely led to water runoff onto the parking lot which consequentially evaporated in the high Texas temperatures resulting in bicarbonate and fluoride build-up. Parking lot substrate in this study had a significant effect on runoff DOC, ammonium, sodium, magnesium, calcium, fluoride and sulfate concentrations where concrete typically produced higher concentrations of nutrients than asphalt. This might be attributed to pollutants being more strongly attached to the asphalt. My rainfall velocities may not have been enough to wash off additional pollutants from the asphalt. Asphalt surfaces are characterized by having deeper, rougher pores than concrete.

The results reported here are precursors to further work. This study can be improved by 1) increasing conducting more rainfall simulations events, 2) increasing parking lot type and replication, and; (3) repeating the study addressing seasonal variability.

Conclusions

My rainfall simulator was successfully used to simulate rainfall at five study sites in this study. However, a number of limitations were observed with the use of the rainfall simulator and data collection. These were:

(1) low collection efficiencies, which can be attributed to higher summer temperatures and water being absorbed by pavements,

(2) Limited variety in rainfall intensity compared to natural rainfall,

(3) Limited variations in sites selected; and

(4) Limited data collection over seasonal periods of time.

The limitations noted above can be reduced or improved by increasing the number of study sites and increasing replications at each site with various rainfall intensities. Additionally, rainfall simulation should be conducted during every season to properly address seasonal variations in runoff quality. For example, traffic intensities for Brazos County, TX increases during the fall and spring and decreases during the summer and winter months. This essentially can increase or decrease runoff nutrient concentrations.

Also, in this study, the first flush of nutrients from storm runoff under three scenarios has been quantified:

(1) Days since the last rain event had the most significant effect on surface water quality.

(2) Parking intensity had an effect on runoff alkalinity and fluoride.

(3) Concrete produced higher DOC, DON, K, Ca runoff concentrations than did asphalt.

CHAPTER IV

EVALUATING THE RELATIONSHIP BETWEEN LAND USE AND SURFACE WATER QUALITY USING BASINS PLOAD

Introduction

Surface runoff serves as sources of non point source pollution (Yong and Chen, 2002). During a rain event, as water drains from an impervious surface, pollutants and contaminants are wash-off and carried from the land surface. This becomes a source of non point source pollution. With this phenomena, the quality of water in receiving water bodies are often degraded and it is conceivable that land-use has a direct affect on water quality.

Section 303(d) of the Clean Water Act as regulated by US EPA Water Planning and Management Regulations require states to identify water within their jurisdiction that do not meet WQ limits. States are required to develop Total Maximum Daily Loads (TMDLs) for those specific pollutants of concern. TMDLs are the allowable amount of pollutants a stream can receive and still meet Federal mandated water quality standard and met its specific use(s).

As a result, when identifying one of the most studied aspects of impervious land cover is its relationship with runoff and water quality it is better to understand the process. In a study of its effects, predictive modeling is the modern approach to linking water pollution to urbanization utilizing spatially generated maps (Lenzi and Di Luzio 1997). Models are often used as an extrapolating mechanism to estimate and predict future outcomes of hydrological processes and the evolution of hydrological variables such as water quality and quantity over time. Modelers can examine and evaluate the predicted outcomes and impact of management practices and development on future hydrological responses. Additionally, the use of models allows the loadings into a surfaces' waterbody to be predicted.

Models are tools that can used to support the development of TMDLs (Borah et al. 2006). Models examine the source of pollutants and water, anthropogenic impacts on land cover and use, and the possibility of changing the use on future outcomes. Engel et al. (1993) evaluated three NPS pollution models integrated with GIS. Their model simulated watershed responses to a series of varying rain events. The correlation coefficients for the Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS) hydrograph response compared with the actual response with a correlation coefficient between 0.87 and 0.98. In another study, Lenzi and Luzio (1997) used the Agriculture Non-Point Source (AGNPS) model to examine runoff and soil erosion in the Alpone watershed. This model properly measured estimates of nitrogen and phosphorous and provided realistic estimates of nutrient runoff.

There is an increasing interest in applying remote sensing and Geographic Information Systems (GIS) to map and monitor urbanization, land use/land cover change and the effects on the hydrological cycle (Jat et al. 2009), furthermore, GIS is a useful tool for estimating non point source pollution over spatial and temporal variability.

The United States Environmental Protection Agency created a multi-purpose environmental analysis system for use by regional, state and local stakeholders for watershed studies. Better Assessment Science Integrating Point and Non Point Sources (BASINS) is a decision making support mechanism utilized by integrating management alternatives, environmental examination, and analysis support (US EPA 2001a). Designed to be flexible, BASINS supports GIS based tools and operates in a GIS environment. Tong and Chen (2002) used BASINS to model the effects of land use on water quality in the East Fork Little Miami River Basin, a tributary to the Ohio River. Their study simulated total nitrogen, total phosphorus and *Fecal Coliform* using BASINS Non Point Source Model. All their simulated values were close to USGS monitored values reported in a modeling scenario using L-THIA.

In this study, GIS will be applied as an automated tool for estimating pollutants in Brazos County, Texas. Developed by CH2M HILL, BASINS Pollutant Loading Application (PLOAD) v3.0 (2001) mechanism is used to evaluate pollutant loadings within a particular watershed, limiting watershed scales to 2.6 km^2.

PLOAD, a simplified, GIS-based model, has the capability of estimating non point source pollution for urban and suburban watersheds on an annual basis using a GIS interface that can be used by planners and managers. PLOAD has the ability to estimate any user-specified pollutant, i.e., total suspended solids, nutrients, metals and fecal coliform. PLOAD requires both GIS and tabular data, land use data, watershed boundary data, pollutant loading data tables, and impervious spatial data, PLOAD can evaluate the data and illustrate the distinct relationship between land use and water quality impacts (PLOAD 2001b).

The objective of this study was to spatially explore a correlation between impervious areas and the effects on water quality utilizing Better Assessment Science Integrating Point and Non Point Sources (BASINS) Pollutant Loading Application (PLOAD), Geographic Information Systems and Remote Sensing using a watershed-based approach, and to model the impacts of different land types in a local watershed. The aims of this study were to further enhance our understanding of the effects of land use on hydrological processes.

Study Area

For this study, PLOAD v.3 (US EPA 2001b) was used. This study consisted of two parts: predicted watershed annual loads using 2001 National Land Cover Data (NLCD) data set and 2008 National Agriculture Imagery Program digital ortho quarter quad tiles (DOQQs) classified impervious surface image.

Three (3) independent watersheds located in Brazos County, Texas were selected (Figure 7). Tributaries to the Brazos River, this study encompass 21114 acres located in the cities of Bryan and College Station, Texas and their local surrounding rural areas. It is located at (northern point – N 30˚43′7.188″ W 96˚21′29.053″ and southern point N 30˚33′55.833″ and W 96˚19′26.364″). The study is located in a humid subtropical climatic zone which averages 1000 mm rainfall per year. Rainfall events are typically high intensity and of short duration.

As the Brazos Valley population grows, land use is undergoing significant changes. As of the 2000 Census, Bryan and College Station metropolitan area population was 184, 885 and an estimated population of 212, 268 in 2009.

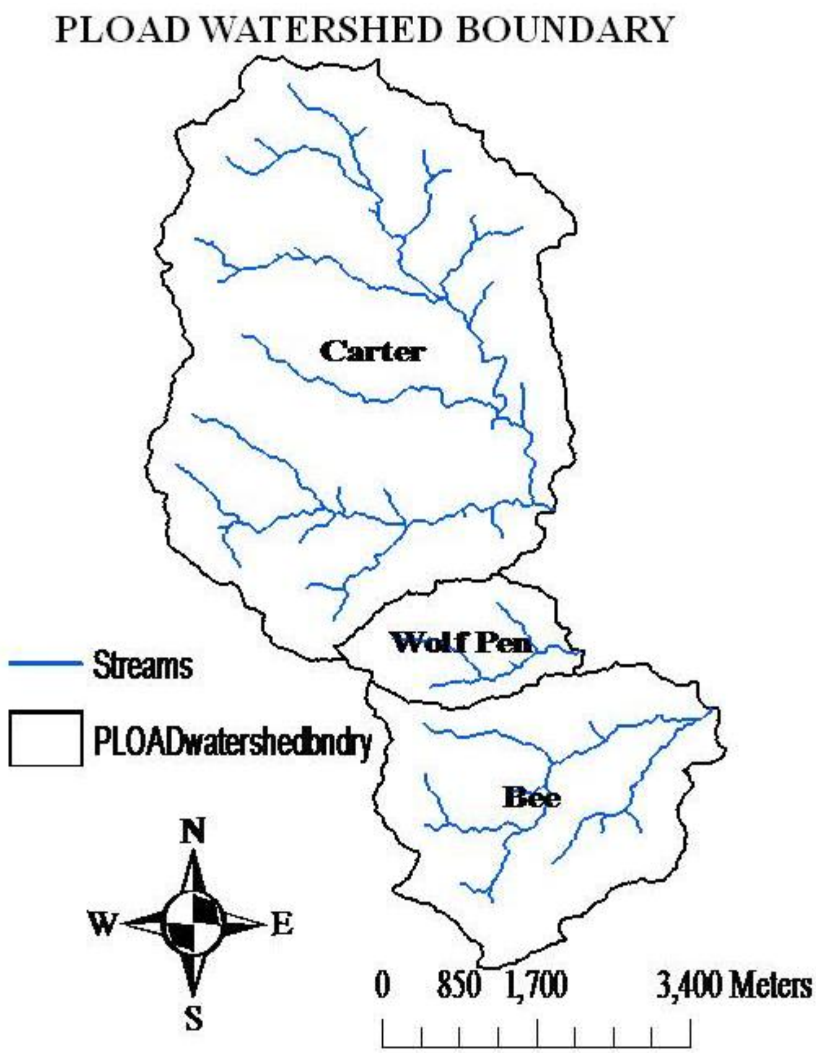

Figure 7. Watershed boundaries for PLOAD model.

Materials and Methods

Data Preparation

Input data files for PLOAD were organized based on GIS data supplied by the Spatial Sciences Laboratory (SSL), Texas A&M University, City of College Station, Texas and City of Bryan, Texas GIS Departments and tabular data. The 2004 National Sediment Quality Database (NSQD) version 1.1 (Table 6) was utilized. Pitt et al. (2004) collected and evaluated stormwater data from nationwide National Pollutant Discharge Elimination System (NPDES) municipal separate storm sewer system (MS4) stormwater permit holders from 17 states across the U.S. and 3,770 separate storm events. Values were derived from more than 200 municipalities and collected over a 10-year period. NSQD data set includes a summary of the national EMC values obtained. Relevant regional Event Mean Concentration (EMC) data tables (Table 7) were compiled from existing published values in mg/L as provided in the 1998 Future Needs Assessment Report for Austin, Texas (Barrett et al. 1998). Barrett et al. (1998) examined 18 watersheds with varying land uses of commercial, industrial, single-family residential, multifamily residential, office, transportation, and developed. This study calculated EMC values for Austin, Texas urban watersheds as a part of the City of Austin Stormwater Monitoring Program to develop estimates of local pollutant loadings. This regional data set is provided by the PLOAD user's manual. Additionally, local area pollutant loading values were collected through rainfall simulation and field sampling as completed in Chapter II (Table 8) were used in the simulation of runoff. Imperviousness tables were taken from the United States Department of Agriculture's Technical Release

55 document (U.S. SCS 1986) in the format of impervious fraction (0.00 to 1.00) (Table 9).

Table 6. 2004 National Stormwater Quality Database NSQD, version 1.1 (Pitt et al. 2004).

Landuse	TDS (mg L^{-1})	TSS (mg L^{-1})	NH_3 (mg L^{-1})	$NO_2 + NO_3$ (mg L^{-1})	TKN (mg L^{-1})	TP (mg L^{-1})
Residential	72	49	0.32	0.60	1.40	0.30
Mixed Residential	86	68	0.39	0.60	1.35	0.27
Commercial	74	42	0.50	0.60	1.60	0.22
Mixed Commercial	70	54	0.60	0.58	1.39	0.26
Industrial	92	78	0.50	0.73	1.40	0.26
Mixed Industrial	80	82	0.43	0.57	1.00	0.20
Institutional	52.5	17	0.31	0.60	1.35	0.18
Freeways	77.5	99	1.07	0.28	2.00	0.25
Mixed Freeways	174	81	nd	0.60	1.60	0.26
Open Space	125	48.5	0.18	0.59	0.74	0.31
Mixed Open Space	109	83.5	0.51	0.70	1.12	0.27

Table 7. Event mean concentration data table complied from regional studies used in our PLOAD model (Barrett et al. 1998).

Land use Type	Ammonia-N (mg L^{-1})	BOD (mg L^{-1})	DP (mg L^{-1})	Nitrate (mg L^{-1})	TKN (mg L^{-1})	TP (mg L^{-1})	TSS (mg L^{-1})
Commercial	0.35	16.75	0.27	0.66	2.28	0.45	210.30
Industrial	0.31	11.67	0.15	1.46	1.68	0.63	205.30
Multiple Family Residence	0.26	14.50	0.32	0.50	1.35	0.40	206
Office	0.22	14	0.14	0.89	1.58	0.22	66
Single Family Residence	0.22	8.60	0.16	0.76	1.24	0.31	181
Transportation	0.40	8	x	0.05	1.15	0.26	231.50
Undeveloped	0.74	4	0.04	1.23	0.88	0.15	95

Table 8. Field sampling event mean concentration data table and roof EMC adapted values (Aitkenhead-Peterson et al. 2010a).

Land use Type	NO_3-N	NH_3-N	PO_4-P	Alkalinity	Na^+	K^+	Mg^{2+}	Ca^{2+}	NO_3^-	SO_4^{2-}
	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})	(mg L^{-1})
Commercial	0.12	0.15	0.04	19.43	5.16	0.98	0.14	3.20	0.59	1.58
Recreational	0.08	0.06	0.03	16.64	4.67	1.21	0.09	1.89	1.27	0.35
Multiple Family Residential	0.14	0.15	0.05	25.20	5.40	2.46	0.14	3.88	1.52	1.42

Table 9. Imperviousness data table used in our PLOAD model. This table reports the percent imperviousness associated with each land use.

Level 2 Classification	Impervious Percentage
Residential	0.5
Commercial and Services	0.85
Industrial	0.72
Trans, Comm, Utilities	0.65
Industrial and Commercial Complexes	0.75
Mixed or Urban Built-up	0.6
Other Urban or Built-Up	0.15
Cropland and Pasture	0.02
Orch, Grov, Vnyrd, Nurs, Orn	0.02
Confined Feeding Ops	0.25
Other Agriculture Land	0.02
Herbaceous Rangeland	0.02
Shrub and Brush Rangeland	0.02
Mixed Rangeland	0.02
Deciduous Forest Land	0.02
Streams and Canals	1
Lakes	1
Reservoirs	1
Forested Wetland	0.02
Non-forested Wetland	0.02
Bare Rock Exposed	1
Strip Mines	0.5
Transitional Areas	0.5

The map with 3 independent watersheds was obtained by the SSL and was used as the watershed boundary. Using the Soil and Water Assessment Tool (SWAT) watershed boundaries were delineated at the catchment level. A hydrological modeling extension to ArcGIS 9.1 Desktop was used to generate a polygon shape file with catchment boundaries. Land cover data sets provided for the study were available in raster (grid) format and were converted to vector (polygon files) using the Spatial Analyst extension in ArcGIS 9.1. The 2001 NLCD land use and impervious data (Figure 8) for the study area were obtained from the Landsat Thematic Mapper data set acquired by the Multi-Resolution Land Characteristics Consortium (MRLC). The 2008

NAIP (Figure 9) imagery was classified using a supervised classification and converted to vector (polygon) format as reported in Chapter II.

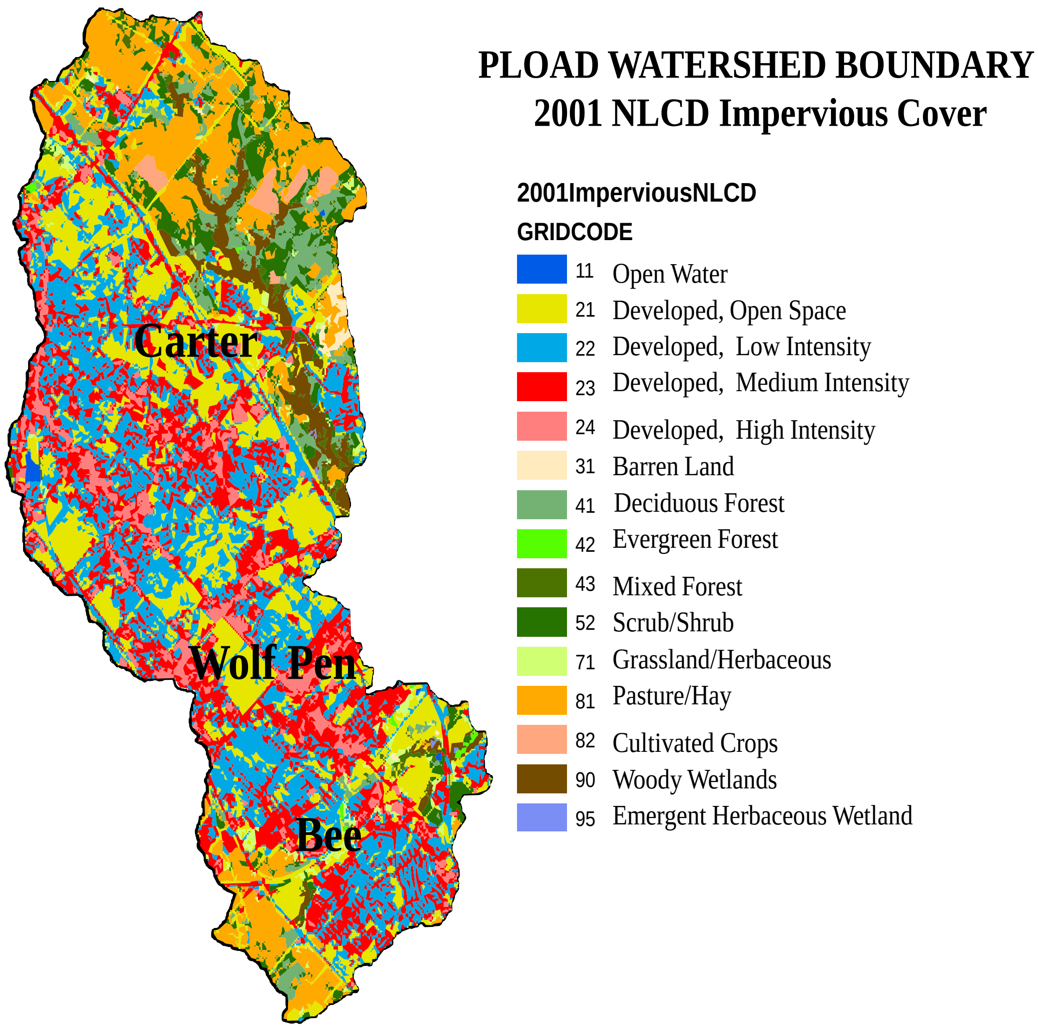

Figure 8. PLOAD boundaries for the three independent watersheds with 2001 NLCD impervious cover.

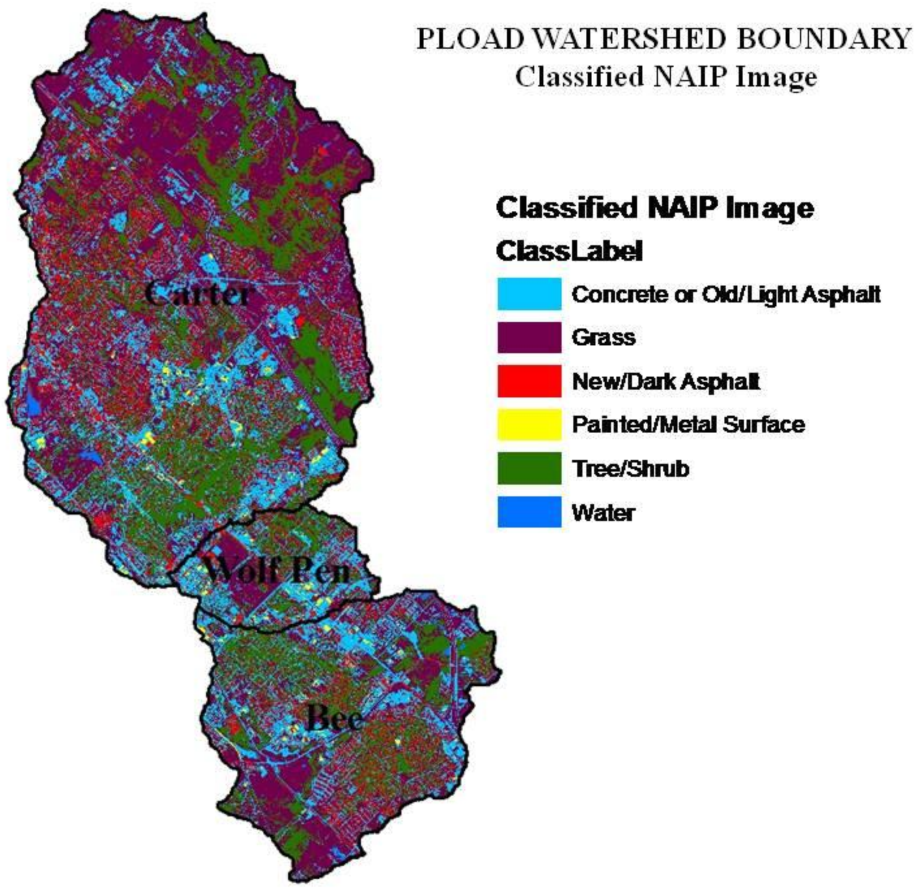

Figure 9. PLOAD boundaries for the three independent watersheds with classified NAIP impervious cover.

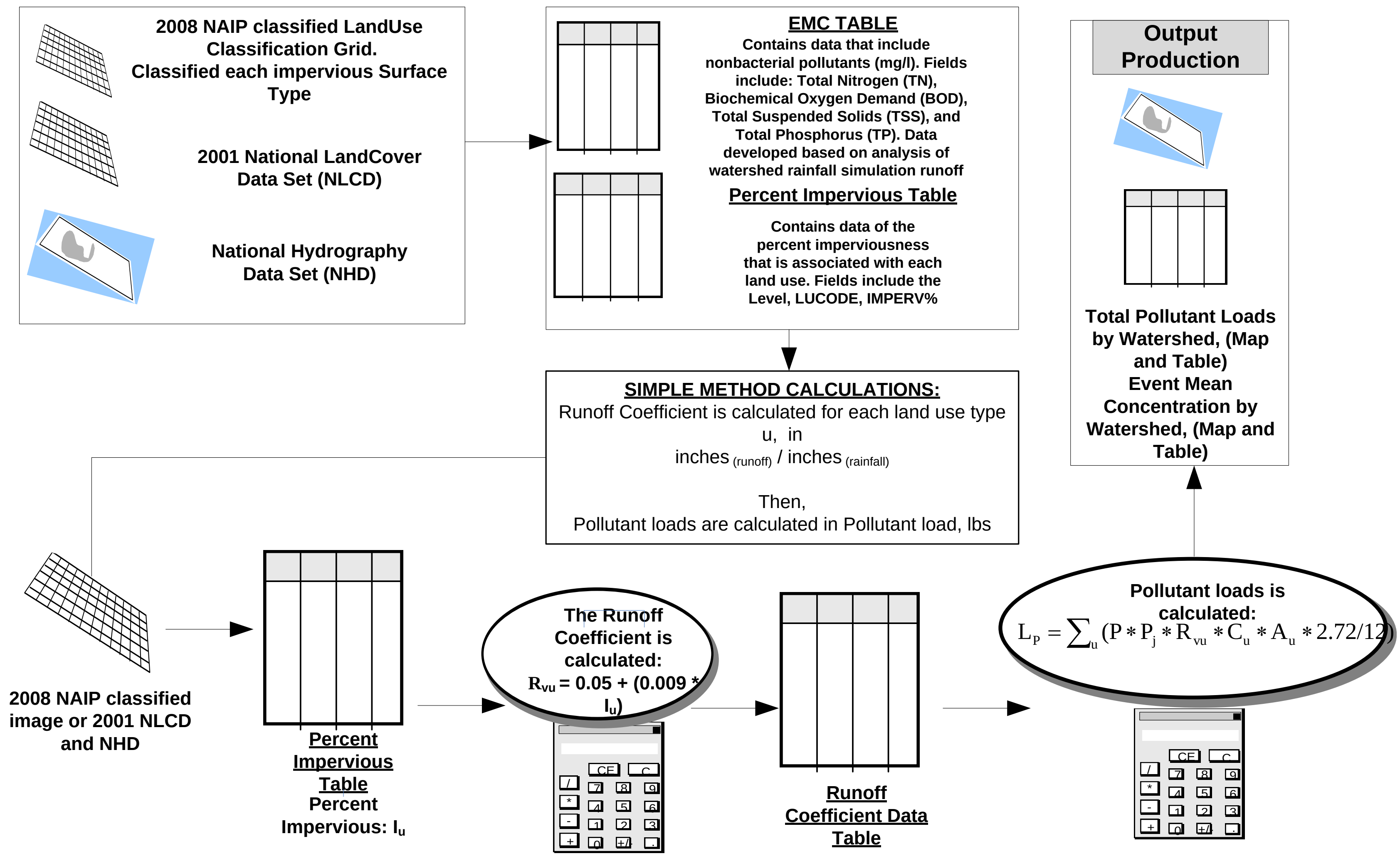

Figure 10. PLOAD conceptual framework used to determine scenario modeling direction.

The Analyses

This study developed a series of predicted annual pollutant loads scenarios to use PLOAD. The idea was to model several scenarios that reflect data availability and accuracy. PLOAD has the ability to produce maps with total pollutant loads per watershed in lb/yr (Figure 10). All formulas and equations that will require utilizing PLOAD will come from the PLOAD user's manual (U.S. EPA 2001b). There are two main equations that are required to calculate loads for each of the specified pollutant type, using the "simple method." First, the runoff coefficient for each land use type must be derived with the equation:

$$R_{vu} = 0.05 + (0.009 * I_u) \qquad (2)$$

where: R_{vu} = Runoff Coefficient for land use type u, inches $_{(runoff)}$ / inches $_{(rainfall)}$

I_u = Percent Imperviousness

The pollutant loads are then calculated with the following equation:

$$L_P = \sum_U (P * P_J * R_{VU} * C_U * A_U * 2.72/12) \qquad (3)$$

Where: Lp = Pollutant load, lb/yr

P = Precipitation, in/yr (assumed 46 for study area)

P_J = Ratio of storms producing runoff (default = 0.9)

R_{VU} = Runoff Coefficient for land use type u, inches $_{(runoff)}$ / inches $_{(rainfall)}$

C_U = EMC for land use type u, mg/1

A_U = Area of land use type u, in ac

(PLOAD converts areas from sq m to ac prior to using the information in the above equation)

EMCs are single indexes used to characterize constituent concentrations of pollutants. Using values from the state of Texas, these values represent a flow concentration that will be calculated as the total pollutant load divided by the total runoff volume for an event duration t_r.

To begin the analysis, for the first scenario (Figure 10), the commonly used 2001 NLCD land cover map (Di Luzio et al. 2005, Geza and McCray 2008, White et al. 2010) for the 3 independent watersheds was selected. This area was clipped by the watershed study area boundary. PLOAD prompts specified user parameters. Watershed boundary and land-use polygons files were selected. The 3 independent watersheds were selected for evaluation. The simple method calculation method was selected and prompted user annual precipitation and ratio of storms (Figure 11). National, regional, and local EMC values were used to evaluate data numbers. Pollutants loads were evaluated without best management practices and selected out puts were produced.

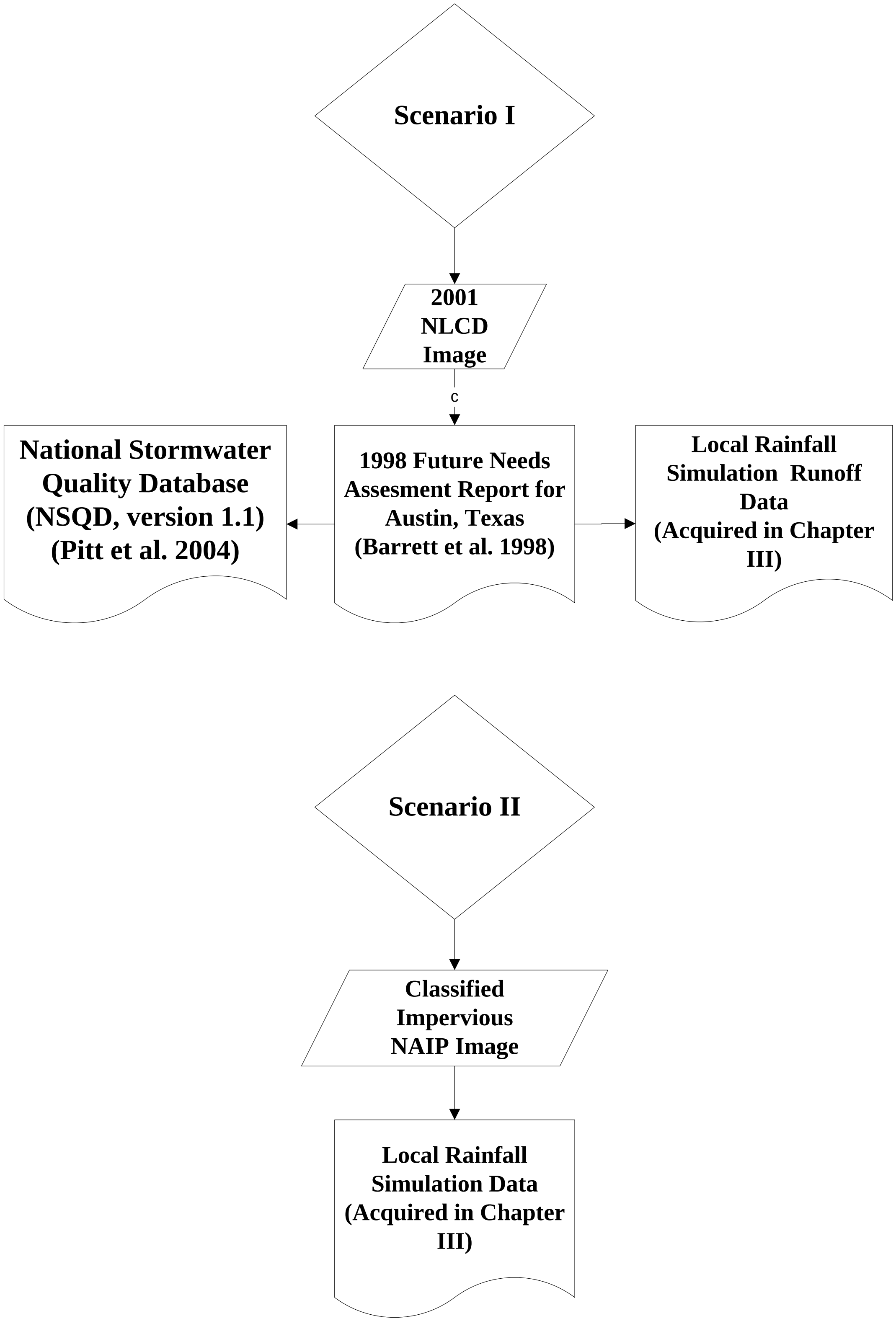

Figure 11. Scenario I and II flow chart.

The second scenario (Figure 10) utilized the impervious surface classified image created in Chapter II for the 3 local independent watersheds. This scenario applied the EMC values collected from field sampling data and selected maps and tabular outputs were produced. The purpose of these scenarios was to develop the capacity for using this model with local and regional data to demonstrate the appropriateness of accurate, up-to-date data. Pitt et al. (2004) indicated that stormwater managers need to establish a local monitoring program to obtain reliable estimates of stormwater quality. Factors such as landuse classification, seasonality, rainfall intensity and duration, runoff amounts all affect the reported pollutant concentrations in national and regional reports. Di Luzio et al. (2005) assessed the impact of input data variation on water runoff and sediment yield outputs. Results from this study showed land use land cover maps have a significant effect on predicted runoff concentrations and sediment loads. The simulations of annual pollutant loads under the two scenarios were conducted and output maps with total pollutant loads per watershed in lbs/yr were produced. Additionally, tabular output summary tables with total pollutant were for the study area in lb/yr.

GIS analysis predicted yearly pollutant loads for the watershed selected. In scenario I the 2001 NLCD along with national, regional, and local water quality data (Pitt et al. 2004 and Barrett et al. 1998), PLOAD estimated predicted loads for Wolf Pen, Bee and Carter Creek Watersheds (Table 10). The result of the modeling application estimates pollutant loads over a period of a year. For example, Wolfpen can be expected to produce loads of over 203 lbs per year of NH_3-N, 28369 lbs per year of total suspended solids, and 126.44 lbs per year of total phosphorus when modeling with Pitt et al. (2004) national data set.

Table 10. PLOAD estimated output loads for scenario I.

		NH_3-N (lbs/yr)	NO_2+NO_3 (lbs/yr)	NO_3^- (lbs/yr)	TKN (lbs/yr)	TP (lbs/yr)	TSS (lbs/yr)
Wolfpen							
	National	203	309.53	x	678.74	126.44	28369
	Regional	124	x	321.18	761.72	760.46	72273
	Local	25	x	282.7	x	x	x
Bee							
	National	507	804	x	1716.28	334.55	75758
	Regional	305	x	839.02	1843.89	389.5	173341
	Local	48	x	749.96	x	x	x
Carter							
	National	1130	1799.25	x	3931.06	763.71	164622
	Regional	717	x	2016.06	4355.19	870.04	377705
	Local	134	x	1953.86	x	x	x

The results of the modeling application in Scenario II estimated yearly pollutant loads for the three selected watersheds (Table 11). Scenario II utilized the re-classified NAIP imagery from Chapter I. This image allows for the user to gain a better estimate of which surface types in urban areas are producing higher nutrient concentration. For example, Carter Creek was estimated to produce 110 lbs per year of NO_3-N and 101 lbs per year for NH_4-N. Additionally, results produced from scenario II showed (Figures 12 and 13) that Wolf Pen, a completely 100% urbanized area, produced more NO_3-N and NH_3-N than other watersheds. This can be attributed to recent construction of new apartments and strip developments. Additionally, several pet owners' visits Wolf Pen Amphitheater and animal feces can also increase pollutant concentrations. Lastly, Wolf Pen is irrigated and regularly fertilized which increased levels of nitrogen, phosphorous and potassium.

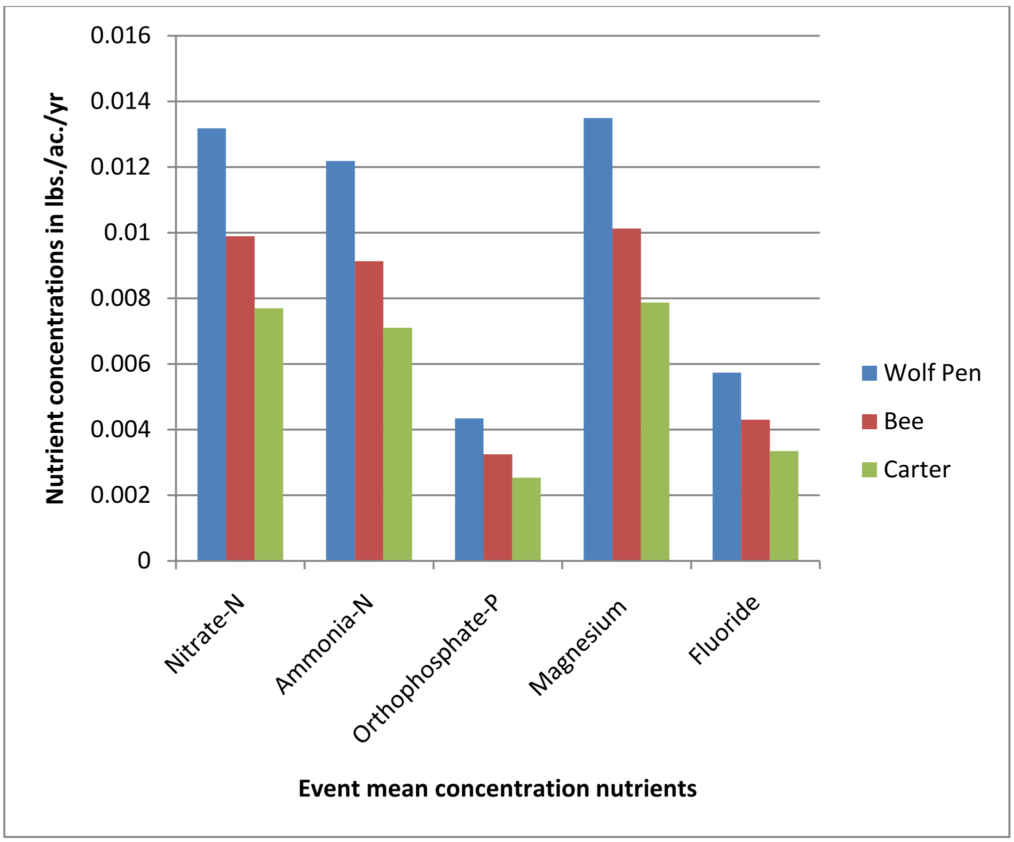

Figure 12. Comparison of watersheds nutrient concentrations results in lbs./ac./yr.

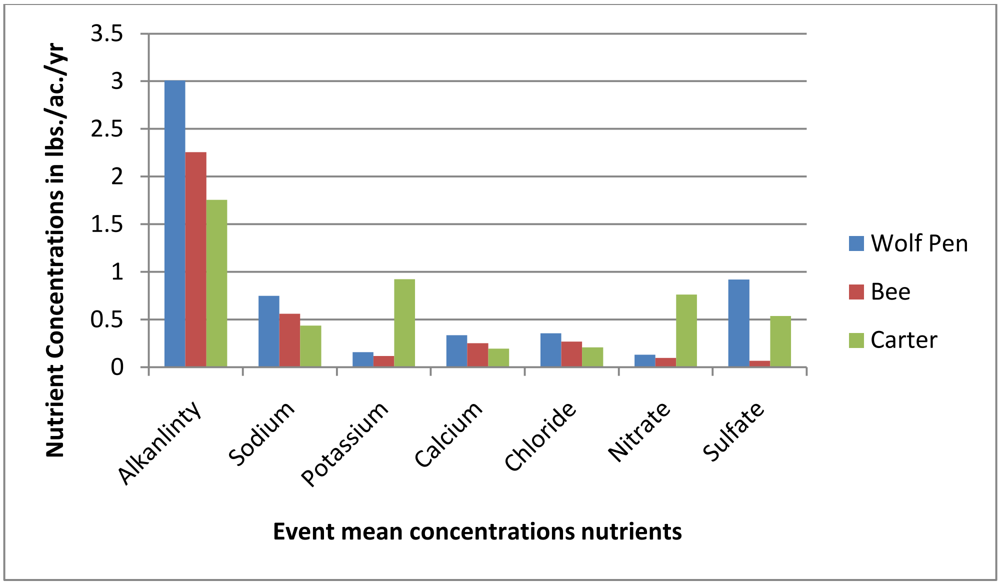

Figure 13. Comparison of watersheds EMC results in lbs./ac./yr.

Table 11. PLOAD estimated outputs from scenario II.

Watershed	NO_3-N (lb/yr)	NH_3-N (lb/yr)	PO4-P (lb/yr)	Alkalinity (lb/yr)	Na^+ (lb/yr)	K^+ (lb/yr)	Mg^{2+} (lb/yr)	Ca^{2+} (lb/yr)	NO_3^- (lb/yr)	SO_4^{2-} (lb/yr)
Wolfpen	21	20	7	4891	1216	258	22	546	212	150
Bee	52	48	17	11890	2957	627	53	1328	516	364
Carter	110	101	36	24989	6215	1317	112	2792	1084	765

The comparison of the estimated NH_4-N pollutant load between data set types in scenario I was found to report a significant difference (Figure 14). For example, Wolfpen NH_4-N estimated values acquired from the national data in scenario I were approximately 62 % higher than values acquired from regional data. Additionally, NH_4-N estimated national values were approximately 700% higher than those collected locally from rainfall simulation.

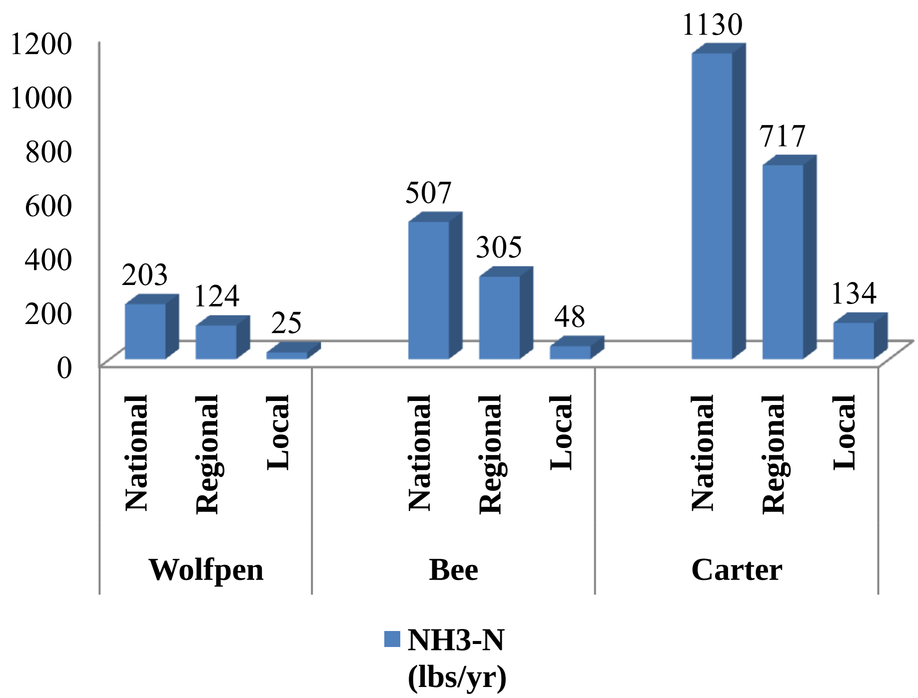

Figure 14. Comparison of the estimated NH_3-N pollutant load from scenario I. Scenario I employed runoff data from the National NSQD, Austin, TX and local rainfall simulation data sets.

Discussion

The estimated pollutant loads and observed data in the modeling application provide users with resourceful information in deciding data applicability for a watershed, water quality prediction model.

In this study, PLOAD was used to estimate pollutant loads for three watersheds in Brazos County, TX. Pollutant loads estimated from national, regional, and local data reported a vast difference. The pollutant load differences between the three data sets may be attributed to data collection and methodology. For example, the NSQD was collected from ‘grab sampling’ during the first part of 3,770 separate storm events over a ten-year period. The events varied in intensity and duration and were collected over several parts of the U.S. Some communities within this study collected grab samples during the first 30 minutes of a storm event. Others were collected as composite samples. This data set contained factors that may affect stormwater pollutant concentrations and quite likely contribute to the different pollutant loads observed. National data sets were separated into five land use categories, residential, mixed residential, commercial, mixed commercial and industrial. Mixed land uses were not taken into consideration in their data set and will be evaluated at a later time. Almost 2/3rds of the monitoring sites in the National data set contained percent impervious data. Additionally, some samples represent “first flush” while other samples represented composite sampling techniques. The regional data lacked information on the sample period and sampling techniques. Local data was obtained using the data generated in Chapter III. Limitations from that study include data lacking seasonal variation and limited site selection. The local data set only sampled parking lots and not other impervious surfaces such as roof runoff which would have been a valuable addition to the study and easier to collect relative to parking lot runoff. The data for the local study only represented the "first flush" of runoff under higher rainfall intensities utilizing a rainfall simulator. The local data would also have benefited by using different rainfall intensities.

Goldshleger et al. (2009) combined data sets from case studies in Israel with data sets from Australia and the USA to generalize the relationship between runoff, rainfall and impervious areas. Although the data sets they used had different measuring systems and methodologies, their study produced gross estimates of storm runoff in urban regions with three hydrological models. My methodology was similar to that of Goldshleger et al. (2009) in that the data used in the PLOAD model came from three very different sources with differing methodologies for collection of data. The difference in my study relative to that of Goldshleger et al. (2009) was that I wished to compare data collected at different resolutions; national, regional and local to allow recommendations for the resolution needed for modeling nutrient runoff from impervious surfaces.

It is important when drawing conclusions for urban and city ordinances that local data is used, if possible. Scenario I in my results illustrated the practical application of capturing local land use data when using programs such as PLOAD to model pollutant runoff. Furthermore data used from local runoff chemistry may prevent misleading decision making that can be made from predictive modeling.

When basing pollution loading in urban watersheds on runoff collected from impervious surfaces, other factors such as runoff from urban open areas such as games parks and neighborhood lawns under turfgrass or landscapes are not taken into account as contributing to urban freshwater pollution as demonstrated by Aitkenhead-Peterson et al. (2009, 2010b). Use of local data changed the estimates for NO_3^- and NH_3-N runoff. While this may be a result of bias because the local data was collected from parking lot surfaces, it nevertheless demonstrates the contribution of nutrients from impervious surfaces in urban and suburban watersheds. Wolfpen creek watersheds houses the Texas A&M golf course as well as several neighborhood parks and greenspace for the amphitheater. These green spaces in Wolfpen watershed are irrigated regularly with municipal tap water high in bicarbonate and sodium which may be inducing sodic soil conditions, the result is release and runoff of carbon and orthophosphate to impervious surfaces as well as grassy swales and surface waters (Aitkenhead-Peterson et al. 2009, 2010b). Runoff of fertilizer N from these highly managed greenspaces in Wolfpen is also highly likely. The consequence of this irrigation runoff to local impervious surfaces, especially during hot summer months when evaporation is high, is a buildup of nutrients on impervious surfaces, ready to be mobilized during a rain event. Furthermore, Wolfpen was undergoing significant construction of new lofts, condominiums and apartments during sampling time which may also have contributed to a higher pollution load. Inversely, Bee and Carter watersheds have 30% less urban open greenspace areas and most of these are older sub-divisions with neighborhood parks that are not as intensely managed or irrigated thus reducing the contribution of fertilizer runoff to impervious surfaces.

As rainfall frequency, volume and intensity are important characteristics in estimating runoff volume and concentration of constituents, differences in flow rates and therefore the runoff produced when using data from the national, regional and local data sets may affect the accuracy of the PLOAD model. Combining data sets with additional national, regional and a revised local data set could possibly be used to reflect similar collection methodologies and land use types in future studies. The local data set was limited in site selection and seasonality. The regional data set lacked information in collection techniques and the national data set was collected using various collection methods and a combination of smaller datasets. Therefore, limitations are taken into consideration to increase PLOAD's capabilities in estimating pollutant loads for local, regional and national data sets.

CHAPTER V

SUMMARY

As communities increase in population size, more land is covered with impervious surface to fit the need of the growing city. There is a direct negative correlation between urbanization and water quality. Impervious surfaces such as hard-packed soils, concrete and asphalt all impact the transport of chemicals to downstream waterbodies. Concrete produces the highest percentage of runoff flow as opposed to hard-packed soils, which produce less runoff than concrete and asphalt. Rainfall frequency, volume and intensity are important characteristics in estimating runoff volume and concentration of constituents. Arid or semi-arid regions are known to produce high nutrient EMCs. The most common pollutants impairing water quality from impervious are sediments, nutrients, heavy metals and oxygen demanding matter. Evaluating all the factors that affect runoff from an urban environment can assist land use planners in making effective land use policies to help reduce the effects of urbanization on water quality.

The first objective of this study was to effectively use ENVI's remote sensing software to accurately determine impervious surfaces to enhance water quality modeling. Results indicated that the classified image had an overall accuracy assessment of 85%. The results from this classification are beneficial in pinpointing exact impervious types and the source of pollutants emitted from them. Asphalt accuracy was lowered due to shadows.

This dissertation also aimed to establish a relationship between impervious surfaces and water quality, while focusing on surface materials such as asphalt and concrete. The use of rainfall simulation in the examination of first flush of nutrients in storm runoff allowed for field sampling to mimic natural rainfall and runoff condition. This method control physical factors and increase the mobility of site selection. However, my rainfall runoff efficiencies were extremely poor as compared to the Herngren (2005) study. Concrete produced higher DOC, DON, K, Ca runoff concentrations than did asphalt. Additionally, days since last rainfall event had the most significant effect on surface water quality. Parking intensity had an effect on runoff and alkalinity.

Lastly, this study spatially explored the correlation between impervious area and the effects on surface water quality using BASINS PLOAD modeling application. This study demonstrated the importance of using local data in hydrological modeling. Results shown that using local data coupled with classified impervious type image yields a better result and more detailed outputs.

Limitations and Future Research

Although the methodology and relationships established throughout this research will strengthen the knowledge of impervious surfaces and the effects on surface water quality, there still remain a number of critical areas that have not been addressed through this research. Therefore, it is recommended that future research to be undertaken in the following areas:

(1) The collection and examination of seasonal variability on samples collected from rainfall simulation parking lot sites. Samples were collected in only one season and results shown the number of dry days prior to rain event had a significant impact on surface water quality

(2) Increasing the number of selected sites for rainfall simulation to included various parking intensities and surface types

(3) Random selections of study site areas

(4) Employing an unsupervised classification to extract impervious surface types areas to compare the difference in methodology.

(5) Validation of the PLOAD model to include more regional and local parking lot study areas to compare the accuracy of using local, up-to-date data in estimating urban runoff. Additionally, include other land use types, i.e., pervious and impervious surfaces, to increase the models' accuracy and reduce bias.

REFERENCES

Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieletiner, J., Zobrist, J., and Srinivasan, R., 2007. Modeling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *Journal of Hydrology,* 333, 413-430.

Adams, B.J. and Papa, F., 2000. *Urban Stormwater Management Planning with Analytical Probabilistic Models*. New York, NY: John Wiley and Sons, Inc.

Aitkenhead, J.A., Hope, D., and Billet, M.F., 1999. The relationship between dissolved organic carbon in streamwater and soil organic carbon pools at different spatial scales. *Hydrological Processes*, 13, 1289-1302.

Aitkenhead-Peterson, J.A., Dvorak, B.D., Volder, A., Stanley, N.C., 2010a. Chemistry of growth medium and leachate from green roof systems in south-central Texas. *Urban Ecosystems*, DOI 10.1007/211252-010-01374.

Aitkenhead-Peterson, J.A., Nahar, N., Harclerode, C., and Stanley, N., 2010b. Chemistry of urban and rural watersheds in central Texas. *Urban Ecosystems*, DOI 10.1007/s11252-010-0147-2 (in press).

Aitkenhead-Peterson, J.A., Steele, M.K., Nahar, N., and Santhy, K., 2009. Dissolved organic carbon and nitrogen in urban and rural watersheds of south-central Texas: land use and land management influences. *Biogeochemistry*, 96, 119-129.

Alley, W.M. and Veenhuis, J.E., 1983. Effective impervious area in urban runoff modeling. *Journal of Hydraulic Engineering*, 109 (2), 313-319.

Arnold, C. L. and Gibson, C.J., 1996. Impervious surface coverage: the emergence of a key environmental indicator. *Journal of the American Planning Association*, 62 (2), 243-258.

Avery, T.E. and Berlin, G.L., 1992. *Fundamentals of Remote Sensing and Airphoto Interpretation*. 5th Edition. Upper Saddle River, NJ: Prentice-Hall, Inc.

Bannerman, R.T., Owens, D.W., Dodds, R.B., and Hornewer, N.J., 1993. Sources of pollutants in Wisconsin stormwater. *Water Science Technology*, 28 (3-5), 241-259.

Barrett, M.E., Quenzer, A.M., and Maidment, D.R., 1998. Water quality and quantity inputs for the urban creeks future needs assessment. Center for Research in Water Resources, Bureau of Engineering Research, The University of Texas at Austin.

Basnyat, P., Teeter, L., Lockaby, B.G., and Flynn, K.M., 2000. Land use characteristics and water quality: a methodology for valuing of forested buffers. *Environmental Management*, 26 (2), 153-161.

Benz, U.C., Hofmann, P., Willhauck, G., Linjefelder, I., and Heymen, M., 2004. Muli-resolution, object-oriented fuzzy analysis of remote sensing for GIS ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58, 239-258.

Berthier, E., Andrieu, H., and Creutin, J.D., 2004. The role of soil in the generation of urban runoff: Development and evaluation of a 2D model. *Journal of Hydrology*, 299, 252-266.

Bhaduri, B., Harbor, J., Engel, B., and Grove, M., 2000. Assessing watershed-scale, longterm hydrologic impacts of land-use change using a GIS-NPS model. *Environmental Management*, 26 (6), 643-658.

Bird, S.L., Exum, L.R., and Alberty, S.W., 2000. Generating high quality impervious cover data. *Quality Assurance*, 8, 91-103.

Borah, D.K., Yagow, G., Saleh, A., Barnes, P.L, Rosenthal, W., Krug, E.C., and Hauck, L.M., 2006. Sediment and nutrient modeling for TMDL development and implementation. *American Society of Agricultural and Biological Engineers*, 49 (4), 967-986.

Brabec, E., Schulte, S., and Richards, P.L., 2002. Impervious surfaces and water quality: a review of current literature and its implications for watershed planning. *Journal of Planning Literature*, 16 (4), 499-514.

Brett, M.T., Arhonditsis, G.B., Mueller, S.E., Hartley, D.M., Frodge, J.D., and Funke, D.E., 2005. Nonpoint source impacts on stream nutrient concentrations along a Forest to Urban Gradient. *Environmental Management,* 35 (3), 330-342.

Brun, S.E. and Band, L.E., 2000. Simulating runoff behavior in an urbanizing watershed. *Computers, Environment and Urban Systems*, 24, 5-22.

Burton, G.A. and Pitt, R.E., 2002. *Stormwater Effects Handbook: A Toolbox for Watershed Managers, Scientists, and Engineers*. Boca Raton, FL: CRC Press, LLC.

Carlson, T.N. and Arthur, S.T., 2000. The impact of land use – land cover changes due to urbanization on surface microblimate and hydrology: a satellite perspective. *Global and Planetary Change*, 25, 49-65.

Center for Watershed Protection (CWP), 2003. Impacts of impervious cover on aquatic systems. *Watershed Protection Monograph No.1, March 2003*. Elliot City, MD: Center for Watershed Protection.

Chen, J. and Adams, B.J., 2007. Development of analytical models for estimation of urban stormwater runoff. *Journal of Hydrology*, 336, 458-469.

Davies-Colley, R.J. and Smith, D.G., 2001. Turbidity, suspended sediment, and water clarity: a review. *Journal of the American Water Resources Association*, 37 (5), 1085-1101.

Deguchi, C. and Sugio, S., 1994. Estimations for percentage of impervious area by the use of satellite remote sensing imagery. *Water Science Technology*, 29 (1-2), 135-144.

Deletic, A., 1998. The first flush load of urban surface runoff. *Water Research*, 32 (8), 2462-2470.

Deletic, A., Maksimovic, C., and Ivetic, M., 1997. Modeling of storm wash-off of suspended from impervious surfaces. *Journal of Hydraulic Research*, 35 (1), 99-118.

Dixon, P. G. and Mote, T. L., 2003. Patterns and causes of Atlanta's urban heat island-initiated precipitation. *Journal of Applied Meteorology*, 42, 1273–1284.

Di Luzio, M., Arnold, J.G., and Srinivasan, R., 2005. Effect of GIS data quality on small watershed stream flow and sediment simulations. *Hydrological Processes*, 19, 629-650.

Draper, S.E. and Rao, S.G., 1986. Runoff prediction using remote sensing imagery. *Water Resources Bulletin*, 22 (6), 941-949.

Driver, N.E. and Tasker, G.D., 1988. Techniques for estimation of storm-runoff loads, volumes, and selected constituent concentrations in urban watersheds in the United States. Water Supply Paper 2363. U.S. Geological Survey, Reston, VA.

Echols, S., 2008. Split-flow theory: Stormwater design to emulate natural landscapes. *Landscape and Urban Planning,* 85, 205-214.

Engel, B.A., Srinivasan, R., Arnold, J., Rewerts, C., and Brown, S.J., 1993. Nonpoint Source (NPS) pollution modeling using integrated with Geographic Information Systems (GIS). *Water Science Technology*, 28 (3-5), 685-690.

Field, R., 1985. Urban runoff: pollution sources, control and treatment. *Water Resources Bulletin,* 21 (2), 197-206.

Floris, M., D'Alpaos, A., Squarzoni, C., Genevois, R., and Marani, M., 2010. Recent changes in rainfall characteristics and their influence on thresholds for debris flow triggering in the Dolomitic area of Cortina d'Ampezzo, north-eastern Italian Alps. *Natural Hazards Earth System Science*, 10, 571-580.

Floyd, C.N., 1981. A mobile rainfall simulator for small plot field experiments. *Journal of Agricultural Engineering Resources*, 26, 307-314.

Geza, M. and McCray, J.E., 2008. Effects of soil data resolution on SWAT model stream flow and water quality predictions. *Journal of Environmental Management*, 88, 393-406.

Gnecco, I., Berrata,C., Lanza, L.G., and LaBarbera, P., 2005. Stormwater pollution in the urban environment of Genoa, Italy. *Atmospheric Research,* 77, 60-73.

Göbel, P., Dierkes, C., and Coldewey, W.G., 2007. Stormwater runoff concentration matrix for urban areas. *Journal of Contaminant Hydrology*, 91, 26-42.

Goldshleger, N., Shoshany, M., Karnibad, L., Arbel, S., and Getker, M., 2009. Generalising relationships between runoff-rainfall coefficients and impervious areas: an integration of data from case studies in Israel with data sets from Australia and the USA. *Urban Water Journal*, 6 (3), 201-208.

Goonetilleke, A., Thomas, E., Ginn, S., and Gilbert, D., 2005. Understanding the role of land use in the urban stormwater quality management. *Journal of Environmental Management,* 74, 31-42.

Graham, P. H., Costello, L. S., and Mallon, H.J., 1974. Estimation of imperviousness and specific curb length for forecasting stormwater quality and quantity. *Journal Water Pollution Control Federation, 46* (4), 717-725.

Grierson, L.T. and Oades, J.M., 1977. A rainfall simulator for field studies of runoff and soil erosion. *Journal of Agricultural Engineering*, 22, 37-44.

Hall, M.J., 1984. *Urban Hydrology*. London: Elsevier Applied Science Publishing.

Hall, M.J. and Ellis, J.B., 1985. Water quality problems of urban areas. *GeoJournal*, 11, 265-275.

Heisler, G.M. and Brazel, A.J. 2010. The urban physical environments: Temperature and urban heat islands. p. 29-56. In: J. Aitkenhead-Peterson and A. Volder, eds. *Urban Ecosystem Ecology*. Madison, WI: American Society of Agronomy, Inc.

Herngren, L., 2005. Build-up and wash-off process kinetics of PAHs and heavy metals on paved surfaces using rainfall simulation. Ph.D. Thesis. Queensland University of Technology, Brisbane, Australia, Faculty of Built Environment and Engineering.

Hope, D., Naegeli, M.W., Chan, A.H., and Grimm, N.B., 2004. Nutrients on asphalt parking surfaces in an urban environment. *Water, Air, and Soil Pollution: Focus*, 4, 371-390.

Jat, M.K., Khare, D., Garg, P.K., and Shankar, V., 2009. Remote sensing and GIS-based assessment of urbanization and degradation of watershed health. *Urban Water Journal*, 6 (3), 251-263.

Johnson, M.P., 2001. Environmental impacts of urban sprawl: a survey of the literature proposed and research agenda. *Environmental and Planning A*, 33, 717-735.

Kaushal, S.S, Groffman, P.M., Band, L.E., Shields, C.A., Morgan, R.A., Palmer, M.A., Belt, K.T., Swan, C.M., Findlay, S.E., and Fisher, G.T., 2008. Interaction between urbanization and climate variability amplifies watershed nitrate export in Maryland. *Environmental Science Technology*, 42, 5872-5878.

Kaushal, S.S., Groffman, P.M., Likens, G.E., Belt, K.T., Stack, W.P., Kelly, V.R., Band, L.E., and Fisher, G.T., 2005. Increased salinization of fresh water in the northeastern United States. *Proc. Natl. Acad. of Sci. of USA* , 102 (38), 13517–13520.

Lazaro, T.R., 1990. *Urban Hydrology: A Multidisciplinary Perspective*. Revised Edition. Lancaster, PA: Technomic Publishing Company, Inc.

Lee, J.H., Bang, K.W., Ketchum, L.H., Choe, J.S., and Yu, M.J., 2002. First flush analysis or urban storm runoff. *The Science of the Total Environment*, 293, 163-175.

Lee, S.M., Min, K.D., Woo, N.C., Kim, Y.J., and Ahn, C.H., 2003. Statistical models for the assessment of nitrate contamination in urban groundwater using GIS. *Environmental Geology,* 44, 210-221.

Lee, V. and Olsen, S., 1985. Eutrophication and management initiatives for the control of nutrient inputs to Rhode Island coastal lagoons. *Estuaries,* 8 (2B), 191-202.

Lenzi, M.A. and Di Luzio, M., 1997. Surface runoff, soil erosion and water quality modeling in the Alpone watershed using AGNPS integrated with a Geographic Information System. *European Journal of Agronomy*, 6, 1-14.

Leopold, L., 1968. Hydrology for urban land use planning- A guide on hydrologic effects of urban land use. U.S. Geological Survey Circular 554, Washington, DC.

Li, J., Zeng, B., Wang, Y., and Shen, L., 2008. Physical simulation of urban rainfall infiltration. *Journal of China University of Mining & Technology*, 18, 0293-0295.

Li, M. H., Dvorak, B., and C.Y. Sung. 2010. Bioretention, low impact development, and storm water management. p. 413–430. In: J. Aitkenhead-Peterson and A. Volder, eds. *Urban Ecosystem Ecology*. Madison, WI: American Society of Agronomy, Inc.

Locatelli, J. D. and P.V. Hobbs, 1995. A world record rainfall rate at Holt, Missouri: Was it due to cold frontogenesis aloft? *Weather and Forecasting*, 10, 779-785.

Lu, P. and Weng, Q., 2006. Use of impervious surface in urban land-use classification. *Remote Sensing of Environment*, 102, 146-160.

Mahler, B.J., Van Metre, P.C., Wilson, J.T., 2004. Concentrations of Polycyclic Aromatic Hydrocarbons (PAHs) and major trace elements in simulated rainfall runoff from parking lots, Austin, Texas, 2003. U.S. Geological Survey, Open-File Report 2004-1208, version 2 Austin, Texas.

Maniquiz, M.C., Lee, S., Lee, E., Kong, D., and Kim, L., 2009. Unit loss rate from various construction sites during a storm. *Water Science Technology*, 59, 2187-2196.

Martin, M.E., Plourde, L.C., Ollinger, S.V., Smith, ML., McNeil, B.E., 2008. A generalizeable method for remote sensing of canopy nitrogen across a wide range of forest ecosystems. *Remote Sensing of Environment*, 112, 3511–3519.

Met Office, 2007. News Release: UK weather forecast [online]. Available from: http://www.metoffice.gov.uk/corporate/pressoffice/2007/pr20070104.html [Accessed 1 September 2010].

Monday, H.M., Urban, J.S., Mulawa, D. and Benkelman, C.A., 1994. City of Irvine utilizes high resolution multispectral imagery for N.P.D.E.S. compliance. *Photogrammetric Engineering & Remote Sensing*, 60 (4), 411-416.

Moore, I.D., Hirschi, M.C., and Bartfield, B.J., 1983. Kentucky rainfall simulator. *Transactions of the ASAE*, 26 (4), 1085-1089.

Morse, C.C., Haryn, A.D., and Cronan, C., 2003. Impervious surface area as a predictor of the effects of urbanization on stream insect communities in Maine, U.S.A. *Environmental Monitoring and Assessment*, 89, 95-127.

National Agriculture Imagery Program (NAIP), 2008a. Digital ortho quarter quads (DOQQs) acquired from the United States Department of Agriculture, Geospatial Data Gateway [online]. Available from: http://datagateway.nrcs.usda.gov [Accessed 30 May 2010].

National Agriculture Imagery Program (NAIP), 2008b. National Agriculture Imagery Program (NAIP) information sheet [online]. Available from: http://www.fsa.usda.gov/Internet/FSA_File/naip_2007_infosheetpdf.pdf [Accessed 30 May 2010].

Nelson, E.J. and Booth, D.B., 2002. Sediment sources in an urbanizing, mixed land-use watershed. *Journal of Hydrology*, 264, 51–68.

Niemczynowicz, J., 1999. Urban hydrology and water management – present and future challenges. *Urban Water*, 1, 1-14.

Pappas, E.A., Smith, D.R., Huang, C., Shuster, W.D., and Bonta, J.V., 2008. Impervious surface impacts to runoff and sediment discharge under laboratory rainfall simulation. *Catena,* 72, 146-152.

Pilgrim, D.H., Chapman, T.G., and Doran, D.G., 1988. Problems of rainfall-runoff in arid and semi-arid regions. *Hydrological Sciences*, 33 (4), 379-400.

Pitts, R. andVoorhees, J., 2002. SLAMM, the Source Loading and Management Model. In: R. Field and D. Sullivan, eds. *Wet-Weather in the Urban Watershed: Technology and Management*. Boca Raton, FL: CRC Press, LLC, 1-29.

Pitt, R., Maestre, A., and Morgecho, R., 2004. The National Stormwater Quality Database (NSQD, version 1.1) [online]. Available from: http://rpitt.eng.ua.edu/Research/ms4/Paper/recentpaper.htm [Accessed 1 August 2010].

Rabalais, N.N., Turner, R.E., Justić, D., Dortch, Q., Wiseman, W.J., and Sen Gupta, B.K., 1996. Nutrient changes in the Mississippi River and system response on the adjacent continental shift. *Estuaries*, 19 (2B), 386-407.

Rao, S.G. and Draper, S.E., 1983. Estimations of percent imperviousness of urban basins using remote sensing data. *Hydrological Applications of Remote Sensing and Remote Data Transmission*. Proceedings of the Hamburg Symposium, August 1983. IAHS Publ. No. 145: 667-676.

Richards, J.A. and Jia, X., 1999. *Remote Sensing Digital Image Analysis: An Introduction*. 4th edition. Berlin: Springer-Verlag.

Rogers, P., 1994. Hydrology and water quality. In: W.B. Meyer and B.L. Turner, eds. *Changes in Land Use and Land Cover: A Global Perspective*. Cambridge, U.K.: Cambridge University Press, 231-258.

Ross, B. B., and Dillaha, T.A.. 1993. *Rainfall Simulation/Water Quality Monitoring for Best Management Practice Effectiveness Evaluation.* Blacksburg: Virginia Polytechnic Institute and State University.

Roy, A.H., Rosemond, A.D., Paul, M.J., Leigh, D.S., and Wallace, J.B., 2003. Stream macro invertebrate response to catchment urbanisation (Georgia, U.S.A.). *Freshwater Biology*, 48, 329-346.

Sansalone, J.J., Hird, J.P., Carthledge, F.K., and Tittlebaum, M.E., 2005. Event-based stormwater quality and quantity loadings from elevated urban infrastructure affected by transportation. *Water Environment Research*, 77 (4), 348-365.

Sansalone, J.J. and Kim, J.Y., 2008. Transport of particulate matter fractions in urban source area pavement surface runoff. *Journal of Environmental Quality*, 37 (5), 1883-1893.

Sansalone, J.J., Koran, J.M., Smithson, J.A., and Buchberger, S.G., 1998. Physical characteristics of urban roadway solids transported during rain events. *Journal of Environmental Engineering*, 124 (5), 427-440.

Schiff, R. and Benoit,G., 2007. Effects of Impervious cover at multiple spatial scales on coastal watershed streams. *Journal of the American Water Resources Association,* 43 (3), 712-730.

Schueler, T.R., 1994. The importance of imperviousness. *Watershed Protection Techniques*, 1 (3), 100-111.

Shaver, E., Horner, R., Skupien ,J., May, C., and Ridley, G., 2007. *Fundamentals of Urban Runoff Management: Technical and Institutional Issues* 2nd Edition. Madison, WI: North American Lake Management Society.

Shepherd J.M., Stallins J.A., Jin M.L., and Mote T.L., 2010. Urbanization: Impacts on clouds, precipitation and lightening. p. 1-28. In: J. Aitkenhead-Peterson and A. Volder, eds. *Urban Ecosystem Ecology*. Madison, WI: American Society of Agronomy, Inc.

Shuster, W.D., Bonta, J., Thurston, H., Warnedmuende, E., and Smith, D.R., 2005. Impacts of impervious surface on watershed hydrology: a review. *Urban Water Journal*, 2 (4), 263-275.

Sickman, J.O., Zanoli, M.J., and Mann, H.L., 2007. Effects of urbanization on organic carbon loads in the Sacramento River, California. *Water Resources Research,* 43, W11422.

Slonecker, E.T., Jennings, D.B., and Garofalo, D., 2001. Remote sensing of impervious surfaces: a review. *Remote Sensing Reviews*, 20, 227-255.

Smith, M.L., Martin, M.E., Plourde, L., and Ollinger, S.V., 2003. Analysis of hyperspecteral data for estimating of temperate forest canopy nitrogen concentrations: comparison between an airborne (AVHIRIS) and a spaceborne (Hyperion) sensor. *IEEE Transactions on Geoscience and Remote Sensing*, 40 (6), 1332-1337.

Sonzogni, W.C., Chesters, G., Coote, D. R., Jeffs, D.N., Konrad, J.C., Ostry, R.C., and Robinson, J.K.,1980. Pollution from land runoff. *Environmental Science Technology*, 14, 148-153.

Spångberg, Ǻ. and Niemczynowicz, J., 1992. High resolution measurements of pollution wash-off from an asphalt surface. *Nordic Hydrology*, 23, 245-256.

Steele, M.K., McDowell, W.H., Aitkenhead-Peterson, J.A., 2010. Chemistry of urban, suburban, and rural surface waters. p. 297-339. In: J. Aitkenhead-Peterson and A. Volder, eds. *Urban Ecosystem Ecology*. Madison, WI: American Society of Agronomy, Inc.

Stoel, T.B., 1999. Reining in urban sprawl. *Environment*, 41(4), 6-11.

Texas Water Research Institute (TWRI), 2010. Carters and Burton creek water quality [online]. Available from: http://cartersandburton.tamu.edu [Accessed 31 August 2010].

Tong, S.T.Y. and Chen, W., 2002. Modeling the relationship between land use and surface water quality. *Journal of Environmental Management*, 66, 377-393.

Trench, E.C. and Kiesman, S.S., 1998. *Surface-Water Quality Information in Connecticut: Answering Key Scientific and Management Questions (Fs-088-98).* U.S. Geological Survey, in cooperation with the Connecticut Department of Environmental Protection, East Hartford, CT.

Tsihirintzis, V. and Hamid, R., 1997. Modeling and management of urban stormwater runoff quality: a review. *Water Resources Management,* 11, 137-164.

U.S. Environmental Protection Agency (U.S. EPA). 1983. Results of nationwide urban runoff program: executive summary. WH-554, Water Planning Division, U.S. Environmental Protection Agency, Washington, DC.

U.S. Environmental Protection Agency (U.S. EPA). 1993. Handbook - Urban Runoff Pollution Prevention and Control Planning. EPA-625-R-93-004. Washington, DC.

U.S. Environmental Protection Agency (U.S. EPA), 1994. The quality of our Nation's Water: 1992. U. S. Environmental Protection 841-S-94-002, Office of Water, Washington, DC.

U.S. Environmental Protection Agency (U.S. EPA), 2001a, PLOAD Version 3.0. An ArcView tool to calculate nonpoint sources of pollution in watershed and stormwater projects user's Manual. U.S. Environmental Protection Agency, Office of Water, Washington, DC.

U.S. Environmental Protection Agency (U.S. EPA), 2001b, BASINS Version 3.0. Better assessment science integrating point and nonpoint sources user's manual. U.S. Environmental Protection Agency #EPA-823-B-01-001, Office of Water, Washington, DC.

U.S. Environmental Protection Agency (U.S. EPA), 2005. Using Smart Growth Techniques as Stormwater Best Management Practices. Environmental Protection Agency, EPA 231-B-05-002, December 2005.

U.S. Environmental Protection Agency (U.S. EPA), 2006. Protecting water resources with higher –density development. U. S. Environmental Protection 231-R-06-001, Office of Water, Washington, DC.

U.S. Soil Conservation Service (U.S. SCS), 1986. Urban hydrology for small watersheds, Technical Release 55, Washington, DC.

Wang, Y., Choi, W., and Deal, B.M., 2005. Long-term impacts of land-use change on non point source pollutant loads for the St. Louis Metropolitan Area, USA. *Environmental Management*, 35 (2), 194-205.

White, J.D., Prochnow, S.J., Filstrup, C.T., Scott, J.T., Byars, B.W., and Zygo-Flynn, L., 2010. A combined watershed-water quality modeling analysis of the Lake Waco reservoir: I. Calibration and confirmation of predicted water quality. *Lake and Reservoir Management*, 26 (2), 147-158.

Wu, C. and Murray, A.T., 2003. Estimating impervious surface distribution by spectral mixture analysis. *Remote Sensing of Environment*, 84, 493-505.

Yang, L., Huang, C., Homer, C.G., Wylie, B.K., and Coan, M.J., 2003. An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. *Canadian Journal of Remote Sensing*, 29 (2), 230-240.

Young, D., 2006. Development of an ArcGIS-Pollutant Load Application (PLOAD) tool. M.S. Thesis. Texas A&M University, College Station, TX, Spatial Sciences Laboratory.

Young, K. and Thackston, E., 1999. Housing density and bacterial loading in urban streams. *Journal of Environmental Engineering*, December, 1177-1180.

Yuan, F. and Bauer, M.E., 2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface heat island effects in Landsat Imagery. *Remote Sensing of Environment*, 106, 375-386.

Zhao, J.W., Shan, B., and Yin, C., 2007. Pollutant loads of surface runoff in Wuhan City Zoo, an urban tourist area. *Journal of Environmental Science*, 19, 464-68.

APPENDIX A

ID	X	Y		Reference
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ID#8	761874.50000000000	3388759.50000000000	2	
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ID#97	760031.50000000000	3384982.50000000000	0	shadow from constructioin equipment on bare soil
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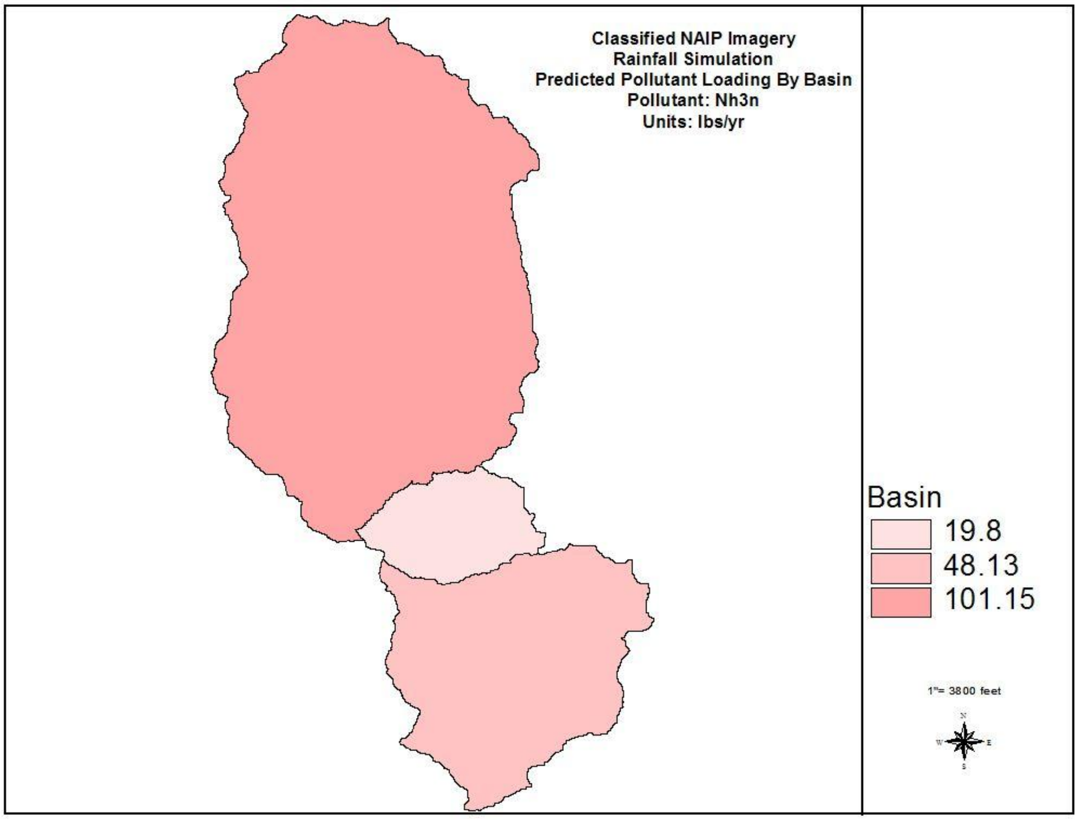
APPENDIX B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Predicted Pollutant Loading By Basin
Pollutant: Nh3n
Units: lbs/yr
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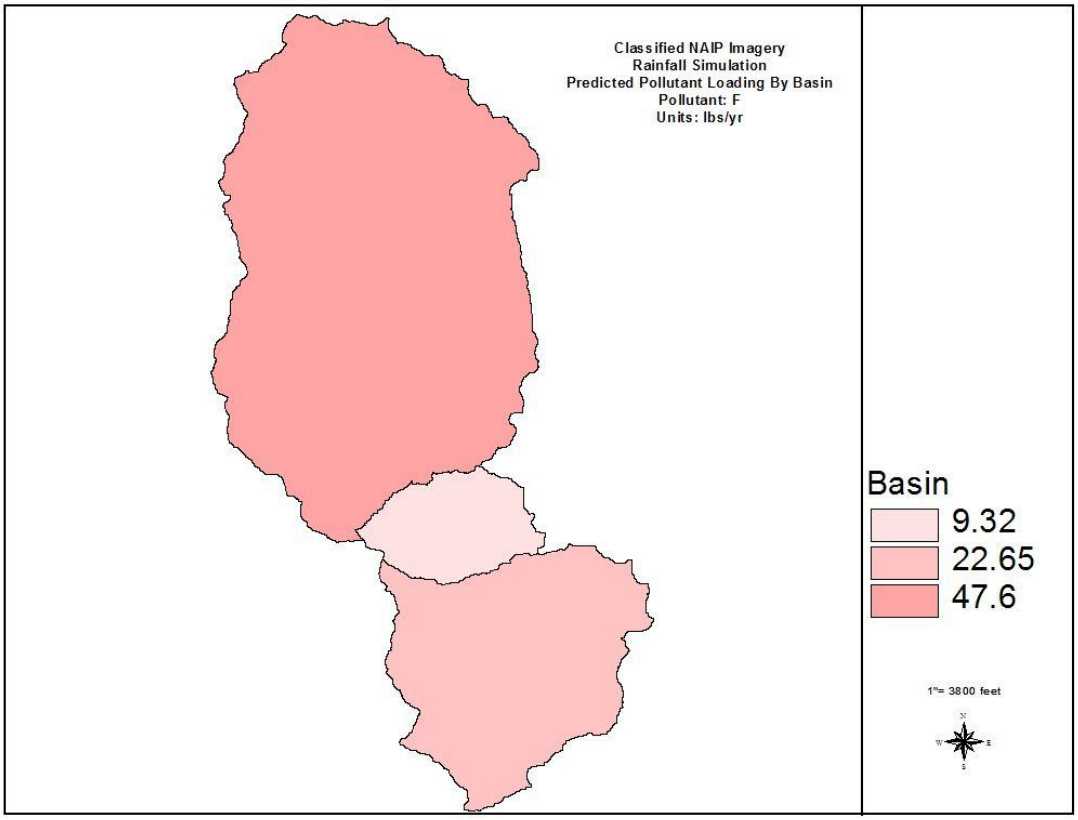
101.15
1"= 3800 feet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Rainfall Simulation
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Units: lbs/yr
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47.6
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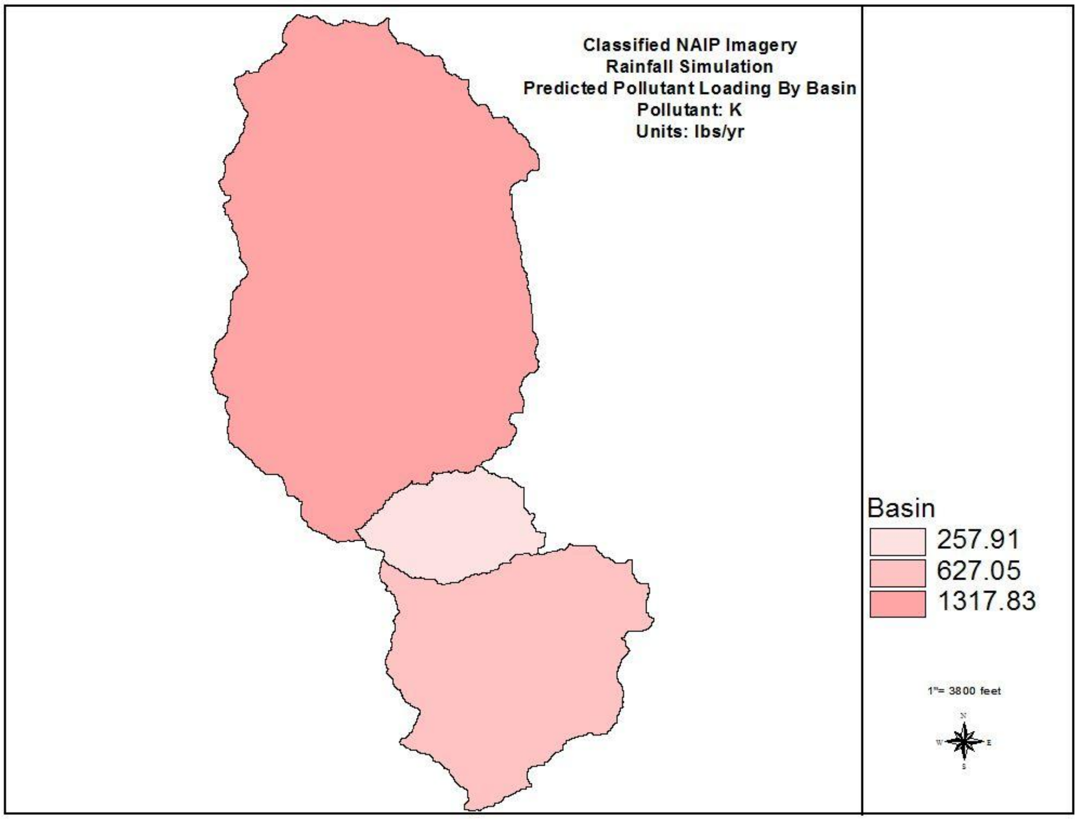
N
W
E
S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Rainfall Simulation
Predicted Pollutant Loading By Basin
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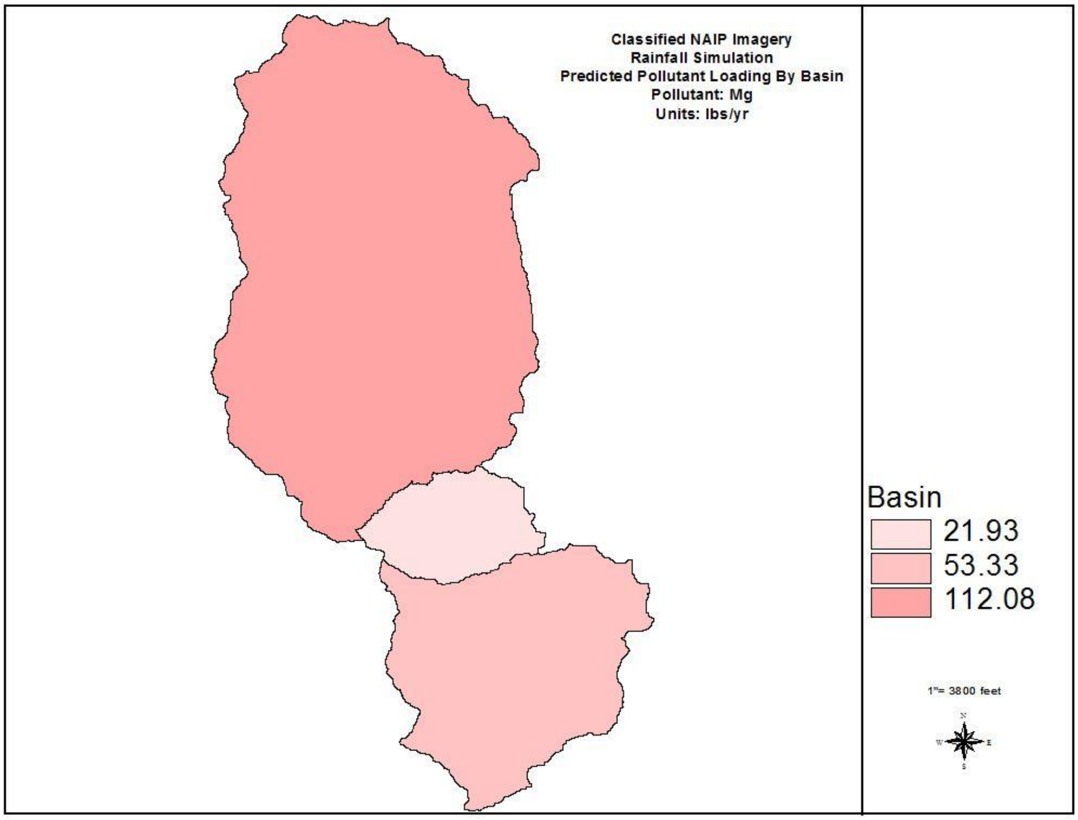
W
E
S


Classified NAIP Imagery
Rainfall Simulation
Predicted Pollutant Loading By Basin
Pollutant: Mg
Units: lbs/yr
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112.08
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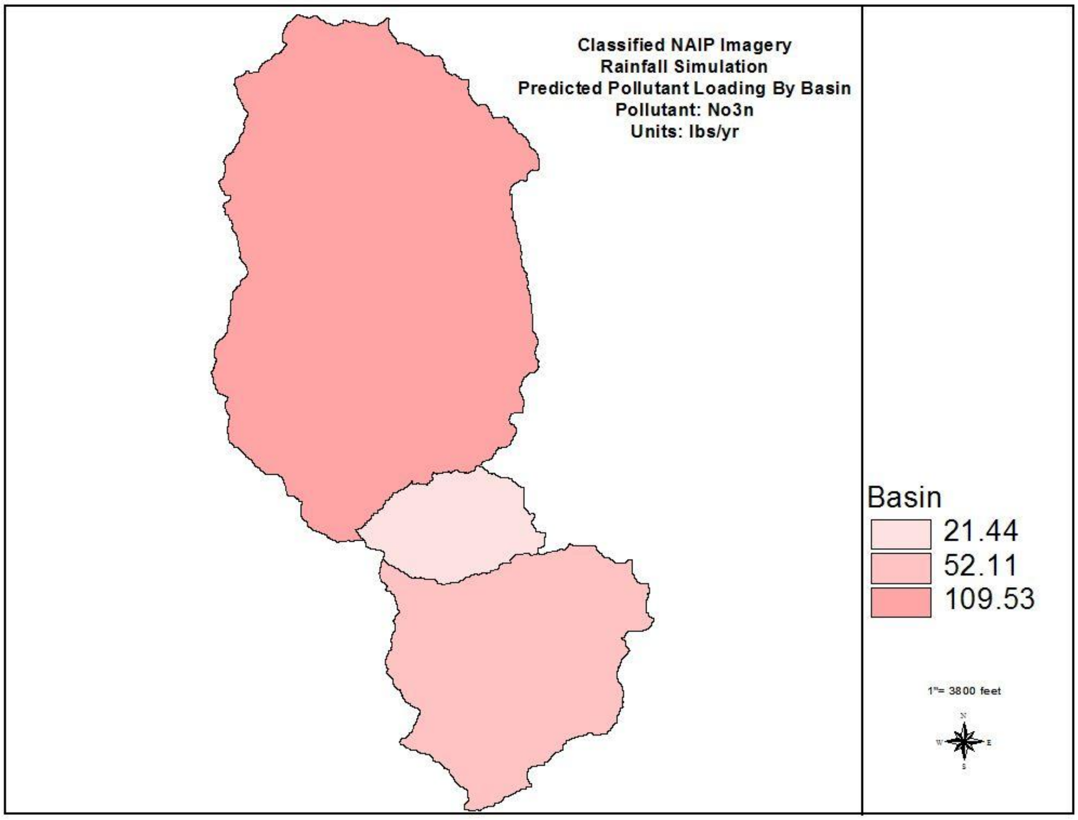
N
W
E
S


Classified NAIP Imagery
Rainfall Simulation
Predicted Pollutant Loading By Basin
Pollutant: No3n
Units: lbs/yr
Basin
21.44
52.11
109.53
1"= 3800 feet

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Texas A&M University Diversity Fellowship, 2006-2009
Texas Water Research Institute Mills Scholarship, 2006
Philip B. Lucas Fellowship, 2006-2007
Department of Forest Science, Outstanding Master's Student of the Year, 2006